Fachbereich Erziehungswissenschaft und Psychologie

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Setting letters and words into context:

An Associative Read-Out Model

Auf der Suche nach dem Sinn des Lesens:

Buchstaben und Wörter im Kontext

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For my mother Gerlinde Hofmann

(† 17.1.2000)

Zusammenfassung

Wie der deutsche Untertitel dieser Dissertation *„Auf der Suche nach dem Sinn des Lesens"* verdeutlichen soll, hängt das erfolgreiche Wiedererkennen geschriebener Wörter von mentalen *Repräsentationen* unterschiedlicher Größen und deren Zusammenspiel ab (Ziegler & Goswami, 2005). Der *Buchstabe „s"* in „Lesens" kann mit einem aus dem *Kontext* vorhersagbaren *Wort* wie „Lebens" im Konflikt stehen. Ziel der vorliegenden Dissertation war es diese drei Determinanten der Bedeutung von Wörtern in einem einheitlichen Modell der Worterkennung zu fassen: Buchstaben, Wörter und Sinnzusammenhänge zwischen Wörtern.

Die theoretische Basis dieser Dissertation bilden „Interactive Activation Models" (IAMs, McClelland & Rumelhart, 1981). Das ursprüngliche Modell kann die zum Wiederkennen von Buchstaben notwendigen Prozesse simulieren (z.B. McClelland & Rumelhart, 1981). Doch auch das Zusammenfügen solcher sub-lexikalischen Repräsentationen zu lexikalischen Repräsentationen ganzer Wörter lässt sich in diesen Modellen darstellen, um damit menschliches Verhalten vorherzusagen (z. B. Grainger & Jacobs, 1996). Während IAMs sowohl orthographische als auch phonologische Prozesse des Lesens bereits abbilden können (z. B. Coltheart, Rastle, Perry, Langdon, & Ziegler, 2001; Perry, Ziegler & Zorzi, 2007), ist die Quantifizierung möglicher Einflüsse des sprachlichen Kontextes auf das Wiedererkennen von Wörtern noch problematisch. Assoziationen zwischen Wörtern, wie z. B. die semantische Relation von „Organ" zu seinem Unterbegriff „Lunge", wurden zwar verbaltheoretisch postuliert (Coltheart, Curtis, Atkins, & Haller, 1993; McClelland & Rumelhart, 1981; Jacobs & Grainger, 1994). Bisher wurden sie jedoch noch nicht zur quantitativen Vorhersage von Verhaltensdaten in ein solches Modell implementiert.

Am Anfang dieser Dissertation stand die Frage, ob die Auftretenshäufigkeiten von Buchstaben (Grainger & Jacobs, 1993) und anderer sub-lexikalischer Repräsentationen den Prozess der Worterkennung beeinflussen. Studie 1 behandelt diese Frage im Überblick über bisherige Artikel. Die darin enthaltenen Korpus-Analysen (Baayen, Piepenbrock, & Gullikers, 1995) stellen ferner diverse sub-lexikalische Frequenzen für das Deutsche bereit, i.e. type und token Buchstaben- und Phonem-, Bigramm- und Biphonem-, sowie orthographische und phonologische Silben-Frequenzen für Wortformen und Lemmata.

Studie 2 wendet sich den Eigenschaften ganzer Wörter zu, und „beleuchtet" neuronale Korrelate der Worterkennung mittels funktioneller Nah-Infrarotspektroskopie (fNIRS; z. B. Steinbrink, Villringer, Kempf, Haux, Boden & Obrig, 2006). Wie auch in den Studien 3 und 4 kommt eine lexikalische Entscheidungsaufgabe zum Einsatz, in der die Versuchspersonen entscheiden sollen, ob die dargebotene Buchstabenfolge ein Wort ist oder nicht (Nichtwort). Wörter lösten einen höheren Blutsauerstoffverbrauch im superioren Frontallappen und im linken inferioren Parietallappen aus als Nichtwörter. Die Funktion ersterer Region lässt mit entscheidungsrelevanten Prozessen der visuellen Worterkennung beschreiben (Fiebach, Ricker, Friederici, & Jacobs, 2007). Die Funktion letzterer Region betrifft wahrscheinlich die Integration orthographischer, phonologischer und semantischer Repräsentationen – ein Prozess der so nur für Wörter stattfindet (vgl. Binder et al., 2003). Weiterhin wiesen die optischen Bildgebungsbefunde auf einen erhöhten Sauerstoffverbrauch im linken inferioren Frontallappen bei seltenen im Vergleich zu häufigen Wörtern hin. Dies lässt sich dadurch erklären, dass seltene Wörter nicht eindeutig identifiziert werden, was zu Konflikten zwischen gleichzeitig aktivierten lexikalisch-semantischen Repräsentationen führt. Die Auflösung dieses Konfliktes bei der Auswahl einer Bedeutung aus vielen möglichen Bedeutungen stellt gemäß Thompson-Schill und Botvinick (2006) die wesentliche Funktion des linken inferioren Frontallappens dar.

In Studie 3 wird ein anderer lexikalischer Konflikttypus, sowie dessen hirnelektrischen Korrelate mit einem IAM simuliert (Jacobs, Rey, Ziegler, & Grainger, 1998). Da sich die Aussagen dieser Studie auf Nichtwörter stützen, kommt diese Modellvorstellung gänzlich ohne eine Bedeutungsrepräsentation aus. Je mehr orthographisch und phonologisch definierte Wortform-Repräsentationen durch ein Nichtwort aktiviert werden, und umso stärker deren Aktivierungen sind, desto größer ist der Konflikt zwischen diesen lexikalischen Repräsentationen (Botvinick, Braver, Barch, Carter, & Cohen, 2001). Wie von der „conflict monitoring theory" vorhergesagt (Yeung, Botvinick, & Cohen, 2004), stieg die zweite Negativierung des ereigniskorrelierten Potentials (EKPs) graduell an, wenn die Nichtwörter stärkere lexikalische Konflikte auslösten. Diese im Zeitfenster von 400 bis 600 ms nach Reizdarbietung gefundenen Negativierungen lassen sich – wie von Botvinick et al. (2001) vorhergesagt (vgl. Ridderinkhof, van den Wildenberg, Segalowitz, & Carter, 2004) – auf Quellen im anterioren cingulären Cortex und im mittleren Frontallappen zurückführen (Pascual-Marqui, 2002). Die IAM-Simulationen sagen auf Item-Ebene voraus, welches Nichtwort welche mittleren Reaktionszeiten, Fehlerraten, und EKP-Negativierungen auslöst. Damit erschließt diese Studie die Item-Ebene – als eines der ambitioniertesten IAM-Model-Evaluationskriterien -- nun auch für neurophysiologische Variablen (vgl. Rey, Dufau, Massol, & Grainger, 2009).

Studie 4 untersucht EKPs und Pupillenerweiterungen bei der Verarbeitung affektiver Bedeutungskonnotationen von lexikalischen (i.e. Wort-) Repräsentationen. Negativ geladene Wörter lösten bei hohem Erregungspotential (arousal) schnellere und bei niedrigem Erregungspotential langsamere Reaktionen aus als neutrale, niedererregende Wörter. Hingegen ließ sich bei positiv valenten Wörtern auch ohne ein erhöhtes Erregungspotential eine Vereinfachung der Worterkennung beobachten. Die pupillometrischen Analysen verliefen ergebnislos. Vergleicht man dieses Ergebnis mit anderen Studien (Kuchinke, Võ, Hofmann, & Jacobs, 2007; Võ et al., 2008), lässt sich

dieser negative Befund als Hinweis auf eine Rolle der Pupille als Indikator kognitiver Anstrengung deuten (Beatty, 1982; Briesemeister, Hofmann, Tamm, Kuchinke, Braun, & Jacobs, 2009). Es spricht gegen eine direkte Beteiligung der Pupillendilation bei affektiven Prozessen (Hess, 1965). Weiterhin wurden beide antworterleichternden Bedingungen – also niedererregend positive und hocherregend negative Wörter – schon 80-120 ms nach Reizdarbietung von erhöhten EKP-Negativierungen begleitet. Dies weist darauf hin, dass affektive Bedeutungskonnotationen den Zugriff auf ein hypothetisches mentales Lexikon erleichtern (Sereno & Rayner, 2003). Die EKP-Effekte hocherregend negativer Wörter ließen sich auf Quellen im linken fusiformen Gyrus (vgl. Kronbichler, Hutzler, Wimmer, Mair, Staffen, & Ladurner, 2004) und mittleren Temporallappen zurückführen. Da letztere Region mit semantischen Prozessen in Verbindung gebracht wird (Price, 2000), lässt sich dieses Ergebnis als Hinweis auf eine Hypothese von Maratos, Allan und Rugg (2000) deuten. Diese besagt, dass die Effekte affektiver Wörter im Wesentlichen durch deren stärkere semantisch-assoziative Verknüpftheit zu anderen Wörtern ausgelöst werden.

Studie 5 untersucht den Einfluss von assoziierten Wörtern im Reizmaterial auf das Wiedererkennen gelernter und nicht-gelernter Wörter. Schon Hebb (1949) hatte postuliert, dass häufig gemeinsam auftretende Reize wahrscheinlich als assoziiert gelten können. Deshalb wurden in dieser Studie – basierend auf psycholinguistischen Ansätzen – zwei Wörter jeweils als 'assoziativ verknüpft' definiert, wenn sie signifikant häufig gemeinsam in den Sätzen eines der größten deutschen Korpora auftreten (Quasthoff, Richter, & Biemann, 2006). Gelernte und nicht-gelernte Wörter, die viele solcher signifikant ko-okkurrenten Reize im Experiment aufwiesen, erzielten höhere Wiedererkennensraten als solche mit wenigen assoziierten Wörtern. Auch im Simulationsmodell wurden signifikante Ko-okkurrenzen von Wortpaaren zur Definition von Assoziationen eingesetzt, um die assoziative Aktivierungsausbreitung zwischen den Wörtern im Experimentalverlauf, und damit den Einfluss des sprachlichen Kontexts auf

die Einzelworterkennung zu simulieren (Anderson, 1983; Collins & Loftus, 1975). Gleichzeitig wurde ein signalentdeckungstheoretischer Ansatz in das Modell integriert (Jacobs, Graf & Kinder, 2003), und dessen Annahme größerer Gedächtnissignale für gelernte Wörter übernommen (z. B. Green & Swets, 1966). Aus der Aktivierung vieler aktiver Gedächtnisrepräsentationen im Modell entstand deren starke Kompetition. Dies führte dazu, dass jede Wortrepräsentation in der Summe ein inhibitorisches Signal erfährt. Eine solche „Netto"-Inhibition wird in einem IAM durch die Aktivierung der Repräsentation selbst skaliert, um die Aktivierungsänderung zu bestimmen. So resultieren aus den erhöhten Gedächtnissignalen für gelernte Wörter unmittelbar deren erhöhte Aktivierungsvarianzen, was der ad-hoc Annahme ungleicher Signalvarianzen der klassischen Signalentdeckungstheorie entspricht (Green & Swets, 1966). Dieser Ansatz kann daher den in Wiedererkennensaufgaben typischen Befund einer Steigung kleiner 1 für z-transformierte „Receiver Operation Characteristics" erklären (z-ROC; Glanzer et al., 1999). Diese Steigung der z-ROC Steigung spiegelt die größere Gedächtnissignalvarianz gelernter Reize wider (z.B. Shiffrin & Steyvers, 1997; McClelland & Chappel, 1998). Für die Simulation wurden die freien Parameter so angepasst, dass das Modell die empirisch erhaltenen z-ROCs vorhersagen kann. Das resultierende „Associative Read-Out Model" (AROM) ist darüber hinaus auf der Ebene der konkreten einzelnen Items in der Lage vorherzusagen, welches Wort mit welcher Wahrscheinlichkeit erinnert wird. Die Wiedererkennensrate eines Wortes steigt mit der Anzahl assoziierter Wörter im Stimulusmaterial an, die als assoziative Hinweisreize dienen können. Da viele der am stärksten assoziierten Wörter im Modell eine semantische Relation zu dem präsentierten Wort aufwiesen (z.B. Synonymie), kann das AROM als das erste IAM gelten, das auch semantische Prozesse abbilden kann.

Mit der Definition der Bedeutung eines Wortes durch dessen gemeinsame Auftretensgeschichte mit anderen Wörtern, erschließen sich viele neue Fragestellungen

für deterministische Simulationsmodelle der Sprachverarbeitung: Kann das AROM menschliches Verhalten genauer vorhersagen, wenn dessen assoziativer Wiederfindensprozess („recollection") durch die im Modell ohnehin schon enthaltenen (orthographischen) Vertrautheitsinformationen (familiarity) ergänzt wird (Jacobs et al., 2003; Yonelinas, 1994)? Zeichnen sich affektiv geladene Wörter wirklich im Wesentlichen dadurch aus, dass diese mehr semantisch-assoziative Verknüpfungen zu anderen Wörtern aufweisen? Da die Reihenfolge der präsentierten Wörter für den Sinn, den ein Wort auslöst, als kritisch gelten kann, besteht die wesentlichste zukünftige Herausforderung in der Fixierung der zeitlichen Struktur der Sprache im Modell (Elman, 1990, 2004; Rumelhart, 1967). Damit ließe sich das Wiedererkennen von Wörtern im Satzkontext modellieren. Ein solches Modell könnte beispielsweise Aufschluss über die Frage geben, ob der linke inferiore Frontallappen tatsächlich sensitiv auf Bedeutungskonflikte reagiert (Thompson-Schill & Botvinick, 2006), wie sie zum Beispiel durch das letzte Wort des Satzes „Auf der Suche nach dem Sinn des Lesens" ausgelöst werden.

Summary

The successful recognition of written words crucially depends on mental representations of different sizes, and their interplay (Ziegler & Goswami, 2005). Letters form words, and words are embedded into context. So, when you read "The road to hell is paved with good inventions", you expected 'intentions' from the context of this famous proverb. This expectation is in conflict with what you actually read, i.e. 'inventions'. Thus, a letter changes a word, which also changes the whole meaning of the phrase. The aim of this thesis was to integrate all of these three representation levels into a single computational model of word recognition: letters, words, and language context. All of these are necessary for words to generate meaning.

This enterprise is theoretically based on interactive activation models (IAMs, McClelland & Rumelhart, 1981). The original model simulated the recognition of letters. When putting these sub-lexical units together, words can be formed. The successor model predicted performance during word recognition (Grainger & Jacobs, 1996). While IAMs can excellently account for the orthographic and phonological processes of reading (Coltheart, Rastle, Perry, Langdon, & Ziegler, 2001; Perry, Ziegler & Zorzi, 2007), quantifying the influence of the context of other words still seems to be an unanswered challenge for this type of model. Associations between words like the semantic relation of 'organ' to his hypernym 'lung' have been posited in a verbal-theoretical fashion (Coltheart, Curtis, Atkins, & Haller, 1993; McClelland & Rumelhart, 1981). However, they were never implemented for the quantitative performance predictions that are possible with IAMs (Jacobs & Grainger, 1994).

Study 1 addressed the influence of the frequencies of sub-lexical units on word recognition. It reviews previous empirical work on that issue. Moreover, analyses of the CELEX-corpus provided type and toke letter and phoneme, bigram and biphoneme, as well as orthographic and phonological syllable frequencies for German word forms and lemmata (Baayen, Piepenbrock, & Gullikers, 1995).

Study 2 used functional Near-infrared Spectroscopy (fNIRS) to 'enlighten' the brain processes elicited by whole-word, lexical representations. As in the Studies 3 and 4, participants performed lexical decisions, at which they decide whether the presented letter string is a word, or not (nonword). The results indicated a greater oxygen consumption to words than to nonwords in the superior frontal and left inferior parietal gyri. The first region's function was associated with decision-related processes of word recognition (Fiebach, Ricker, Friederici, & Jacobs, 2007). The second region's function most likely concerns the integration of orthographic, phonological and semantic representations (e.g., Binder et al., 2003), which is a process that only occurs in word stimuli. Moreover, the results index a greater oxygen consumption in the left inferior frontal gyrus for low frequency in comparison to high frequency words. This can be explained by low frequency words being more equivocally recognized, which leads to a conflict between concurrently activated lexico-semantic representations. Thompson-Schill and Botvinick (2006) proposed that the critical function of this region consists of resolving this conflict during the selection of an appropriate meaning.

Study 3 relied on an IAM to simulate a different type of conflict between lexical representations (Jacobs et al., 1998). These simulations were used to predict electrophysiological findings. Because this Study's conclusions are based on nonwords, semantic representations likely don't play any role. The idea was that the more orthographically and phonologically defined word form representations are activated by a nonword, and the stronger the activations of the word representations are, the keener is the competition between them (Botvinick, Braver, Barch, Carter, & Cohen, 2001). As

predicted by the conflict monitoring theory (Yeung, Botvinick, & Cohen, 2001), the second negative deflection of the event-related potential (ERP) increased parametrically with the amount of conflict elicited by the nonwords. Source localization attributed these ERP effects to the anterior cingulate and the medial frontal gyri (Pascual-Marqui, 2002; Ridderinkhof, van den Wildenberg, Segalowitz, & Carter, 2004). The model predicted which nonword elicits which RTs, error-rates, and ERP amplitudes on an item-level. Thus, the study bridged the gap between fine-grained, quantitative model predictions and the actual neural response (cf. Rey, Dufau, Massol, & Grainger, 2009).

Study 4 investigated ERPs and pupil dilation responses during the processing of affective connotations of words. High-arousal negative words elicited faster, and low-arousal negative words elicited slower RTs than (low-arousal) neutral words. In contrast, response facilitation to positive words was apparent even when arousal was low. The analysis of the pupil data elicited no significant effects. When compared to other studies (Kuchinke, Võ, Hofmann, & Jacobs, 2007; Võ et al., 2008), this (zero) finding suggests that the pupil dilates in cognitively demanding situations (Beatty, 1982; Briesemeister, Hofmann, Tamm, Kuchinke, Braun, & Jacobs, 2009), rather than being driven by affective processing itself (Hess, 1965). Moreover, positive and high arousal negative words elicited a greater ERP negativity in a time frame from 80 to 120 ms. As both of these conditions also facilitated the behavioral responses, the study provides converging evidence that affective processes facilitates the access to a hypothetical mental lexicon (Sereno & Rayner, 2003). The ERP arousal effects in negative words were source-localized in the left fusiform (vgl. Kronbichler, Hutzler, Wimmer, Mair, Staffen, & Ladurner, 2004) and middle temporal gyri. Because the latter region was associated with semantic processing (Price, 2000), this result points at a hypothesis by Maratos, Allan, and Rugg (2000). The effects elicited by affective words may be explained by the greater semantic-associative connectivity to other words.

Study 5 tested whether learned and non-learned words are more often recognized, when they have a greater amount of associated items in the stimulus set. According to Hebbian learning (Hebb, 1949), two words were defined 'associated' when they co-occur significantly often together in the sentences of one of the largest German corpora (Quasthoff, Richter, & Biemann, 2006). As expected, a greater amount of associated items elicited more 'yes' responses during the recognition of learned and non-learned words. Moreover, co-occurrence statistics were used to implement associations between words into an IAM. Accordingly, associative spreading activation between the word stimuli accounted for the influence of the experimental word context on word recognition (Anderson, 1983; Collins & Loftus, 1975). Moreover, a signal detection approach was integrated into the model. According to signal detection theory, learned items obtained greater memory signals than non-learned words (Green & Swets, 1966). To allow for associative interactions between all items, their associative representations were initialized in an active state. Therefore, a strong competition between them resulted. As a consequence, each word representation obtained an inhibitory signal, in sum. Such a 'net' inhibition is scaled by the activation of the representation itself in an IAM, to obtain the final activation change. Thus the learned items greater activation variability results from their greater initial memory signal, in comparison to non-learned representations. This corresponds to the unequal variance ad-hoc assumption in classical signal-detection theory (Green & Swets, 1996), which explains why the z-transformed Receiver Operation Characteristics (z-ROC) typically reveals a slope lower one during recognition memory (Glanzer, Kim, Hilford, & Adams, 1999). The slope of the z-ROC mirrors a greater signal strength variance for learned items (e.g., Shiffrin & Steyvers, 1997; McClelland & Chappel, 1998). When the model parameters were optimized to account for the empirical z-ROCs, the obtained "Associative Read-Out Model" (AROM) can predict which word is remembered with which probability. Recognition rates increase as a function of the amount of associated

items in the stimulus set, because the associates cue the retrieval of a word. Many of the model's most strongly associated items reflected a semantic relation to the presented word, e.g., synonymy. Therefore, the AROM can be considered as the first IAM with a fully implemented semantic layer.

By defining the meaning of a word by its co-occurrence history with other words, many questions become addressable by deterministic models of language processing: Can the AROM better account for human performance, when its associative "recollection" process is complemented by the available (orthographic) familiarity information (Jacobs et al., 2003; Yonelinas, 1994)? Does the critical feature of affectively loaded words indeed consist of their stronger associative-semantic wiredness to other words? However, the actual word sequence is critical for the meaning elicited by a word (Elman, 1990, 2004; Rumelhart, 1967). Therefore, the essential future challenge lies in fixing "the structure of time" (Elman, 1990). By doing so, word recognition could be modeled in sentence context. Such a model could prove useful for answering the question whether the inferior frontal gyrus indeed responds sensitively to conflicts between differential meanings (Thompson-Schill & Botvinick, 2006). Such a conflict could be elicited by the last word of the sentence "The road to hell is paved with good inventions."

General Introduction

Word recognition is such a highly automated process that readers may easily forget what complex task they perform. To name only a few of the sub-processes engaged in reading, it contains perceiving visual features, composing these to letters, integrating the letters into words, imagining the sound of the pronounced words, decomposing these to syllables and the smallest sound units, imagining the referent on which it relates, retrieving this information from long-term memory, and connecting the single words' meaning to the meaning of other words.

However, such cognitive processes do not yet capture how words can affect the human being. When considering that something read can completely change the apperception the world, it is hard to believe that one day all processes elicited by written words can be fully understood. To put it into Jonathan Ive's words:

"When something exceeds your ability to understand how it works, it sort of becomes magical." (http://www.youtube.com/watch?v=sYpK6GecpcU&feature=related)

And the issue of science is to de-mystify this magic, to approximate constantly towards a better understanding of how things work.

Extending the theoretical base: Interactive Activation Models

Computational models provide one way to bring order into the various processes involved in reading. When processes become too complex to be handled in a verbal-theoretical fashion, programming down how things appear to work favors theoretical clarity and falsifiability (Jacobs & Grainger, 1994).

The theoretical base of this thesis consists of the prototype of a so-called localist connectionist model: the interactive activation model (IAM, McClelland & Rumelhart, 1981). However, before turning to the description of this model, the terms localist and connectionist require definition.

The basic idea of connectionist models is that there are mental representations. These are represented by variables, often called units or nodes. The value of the variable is called activation. These variables are connected, which represents cognitive processes that act on these representations. These representations can receive information from other representations, as well as they transmit it to other units.

Two types of representations can be distinguished in connectionist models: distributed and local representations. In a model using distributed representations, a single real-world entity is represented by multiple variables (e.g., Seidenberg & McClelland, 1989). Local representation variables, in contrast, reflect a single real-world entity, e.g. a letter or a word (e.g. Grainger & Jacobs, 1998; Page, 2000).

The original interactive activation model and the identification of letters

The IAM contains three layers (McClelland & Rumelhart, 1981; cf. Grainger & Jacobs, 1996; Figure 1). Each of these layers contains one type of local representation variable. The first layer represents visual features, such as "I" as a straight line at a particular position, e.g. in the middle of a letter. The second layer contains letters, which are defined by the activation of visual features. For instance, "T" is composed of two straight lines, and when both of these become activated, they likely activate the letter representation of "T". The third layer represents orthographic word forms, such as "TRIP", which receive activation from certain letters at particular positions.

The connections between these representation variables can be excitatory, e.g. when "I" as visual feature is apparent in the middle of a letter position, it activates the letter "T". Alternatively, connections can be inhibitory: The line "I" in the middle of a letter position is evidence against an "N" at this position, because this letter does not contain that particular visual feature. Therefore, the visual feature representation "I" inhibits the letter representation "N".

McClelland and Rumelhart (1981; Figure 1) designed this model to explain human performance in tasks at which letters have to be recognized. Reicher (1969) and Wheeler (1970) had shown that letters are better identified when they are embedded in words as compared to meaningless letter strings. McClelland and Rumelhart (1981) explained this word superiority effect by excitation from the word to the letter layer. When a word is presented, its letter unit receives excitatory activation from the word representation. Therefore, the letter activation is higher. This activation can be interpreted as evidence for a particular mental representation. The higher activation of a letter predicts the perceptual advantage of perceiving letters contained in words.

Though there are other perceptual identification tasks that were modeled by the IAM. For example, Grainger and Jacobs (1996) simulated performance in a progressive demasking task, in which words have to be recognized.
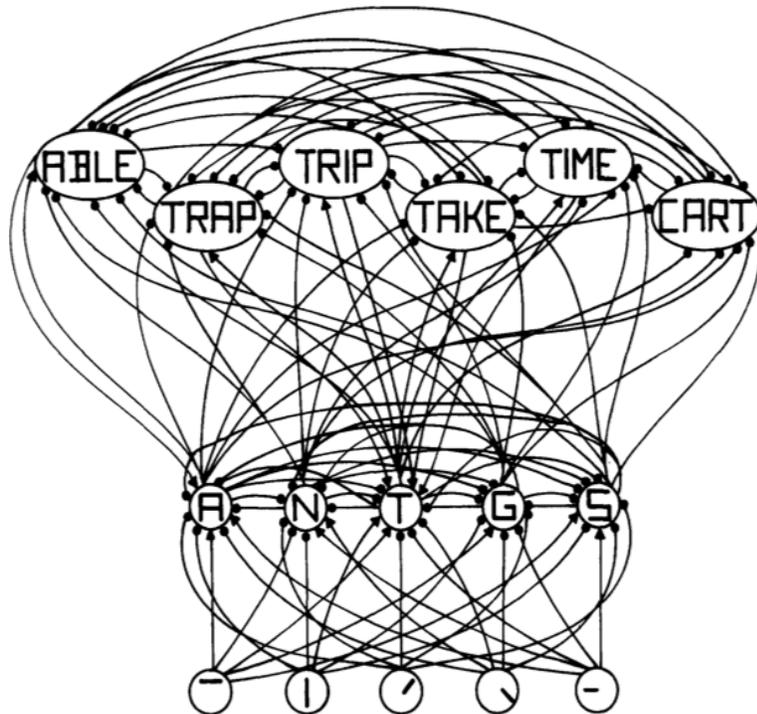
Figure 1: Schematic representation of the basic architecture of the Interactive Activation Model (taken from McClelland & Rumelhart, 1981). Visual word stimuli are presented to the feature layer (lowest representations). The visual features activate letter units of the respective letter position at the letter layer (middle). The letter units then activate the visual word units at the orthographic word layer (upper). The units are connected by excitatory (arrowed line ends) and inhibitory connections (dotted line ends).

The Multiple Read-Out Model and the recognition of words

The Multiple Read-Out Model (MROM, Grainger & Jacobs, 1996) contains an unchanged IAM. This corresponds to the modeling strategy of "nested incremental modeling" (Jacobs & Grainger, 1994). If this strategy is applied, a new model is based on its predecessor[1]. This allows the new model to account for all effects its predecessor can. All of the models presented in the following contain an IAM.

The probably most important achievement of the MROM is, that it captured word recognition performance in an IAM framework. Whereas the original IAM was primarily designed for letter recognition (but cf. Rumelhart & McClelland, 1982), the MROM used the same architecture to predict human performance when more than one letter must be identified: words.

Typically, the MROM is used to predict performance in the lexical decision task (LDT), at which participants decide whether a presented letter string is a word, or not (nonword). This model-based theoretical perspective suggests that the critical difference between these two types of stimuli is, that words are contained in the word layer, whereas nonwords are not. This difference between words and nonwords – i.e. that only the former are contained in the hypothetical "mental lexicon" – is often termed lexicality.

To illustrate the major advantages of the MROM, its dynamic perspective can be beneficial. Transmitting evidence between the layers – such as from the feature to the letter, or from the letter to the orthographic word layer – occurs in time. In the model, processing cycles illustrate the dynamics of information transmission during the recognition of sub-lexical and lexical stimuli. This dynamic perspective allows the MROM to predict human performance during the lexical decision task.

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[1]More exactly, nested modeling is defined as: "a new model should be related to or include, at least, its own, direct precursors and be tested against the old data sets that motivated the construction of the old model before testing it against new ones" (Jacobs & Grainger, 1994, pp. 1329).

The novel modeling elements of the MROM consist of decision mechanisms that operate on multiple sources of lexical information in time. The activation of an orthographic word representation can thus be regarded as lexical activation function (cf. Figure 2): If a particular word representation – e.g of the word "blur" – crosses that criterion, the model simulates the identification of this particular word.

However, when the word "blur" is presented, not only the representation of this word gains activation, but also representations of similar words, like "slur" or "blue". By summing the activation of these word units, a second source of information is simulated (Grainger & Jacobs, 1996). It can be termed familiarity (Jacobs, Graf, & Kinder, 2003). Performing lexical decisions based on this source of information may phenomenally correspond to a global feeling that the stimulus is a word, in absence of its concrete identification (cf. Yonelinas, 1994). To make a decision, familiarity is evaluated by a variable criterion. If it's crossed, a 'yes' response is executed. The cycle at which one of these sources of information crosses the identification threshold or a familiarity criterion, a 'yes' response is executed. A third mechanism is used for the 'no' response: When no 'yes' response is executed within a certain amount of time, the model responds 'no'.

Word, High Σ (blur)
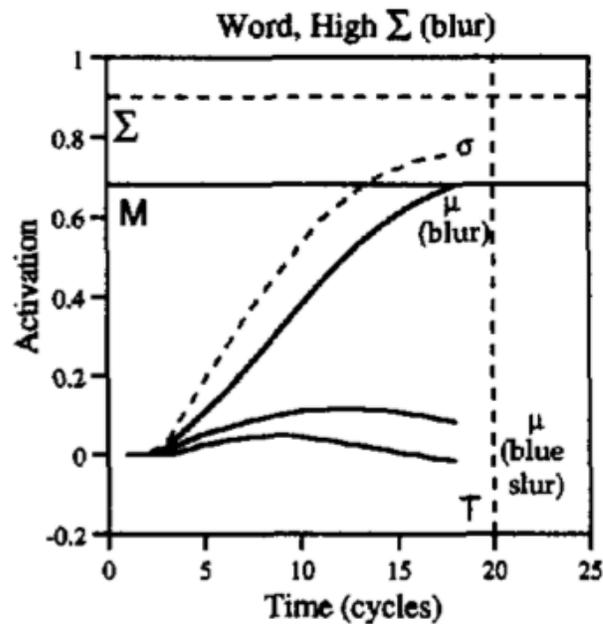
Figure 2 shows the lexical activation functions in the orthographic word layer of the MROM (Figure taken from Grainger & Jacobs, 1996). The word "blur" was presented to the model. Apart from the word representation "blur", also representations of orthographically similar words were activated ("blue", "slur"). There are three decision mechanisms, that are applied to the dynamic activation functions of lexical information accumulation. The identification criterion ('M') is indicated by the solid horizontal line: When "blur" crosses that criterion at cycle 18, a 'yes' response is executed. The cycles at which responses are executed served for simulating response times. Alternatively, a 'yes' response can be executed when the summed activation of the three activated representations (dashed curve) reaches the familiarity-criterion (dashed horizontal line, 'Σ'). If no response is executed within a certain amount of time, the temporal deadline executes a 'no' response (dashed vertical line, 'T').

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The identification information and the familiarity information of the MROM have been related to Yonelinas' (1994) famous dual-process measurement model (Jacobs et al., 2003). Yonelinas (1994) describes the term "familiarity" by the evidence variable in the most simple signal detection model (Green & Swets, 1966; Jacobs et al., 2003, cf. Figure 3). Familiarity is defined by two signal strength distributions of equal variance. When the MROM's 'yes' response probabilities of differential familiarity criteria are plotted for word stimuli on a y-axis, and for nonword stimuli on an x-axis, so-called Receiver Operation Characteristics can be simulated (ROC, Jacobs et al., 2003). By transforming them to z-space, the z-ROC's slope denotes the relationship of the signal strength variances, when they are normally distributed (Green & Swets, 1966).

To be able to address the function of the familiarity mechanism in absence of the identification mechanism, Jacobs et al. (2003) introduced a process-purity assumption for the lexical decision task (cf. e.g., Wixted, 2007). Using a data-limited variant of this task, they assumed that very short stimulus exposures make the identification of the stimulus very unlikely. Thus, decisions should be based exclusively on a global feeling of familiarity, as implemented by the summed activations of all word representations (Grainger & Jacobs, 1996; Jacobs et al., 2003). The process-purity assumption was confirmed. The empirical data of the data-limited lexical decision task provided a slope of one, just like the MROM's familiarity as the summed lexical activations (Jacobs et al., 2003). Thus, a critical feature of familiarity was simulated (Jacobs et al., 2003; Yonelinas, 1994). An increase in familiarity increases the total (familiarity) signal strength level, but not its variability (Yonelinas, 1994, but cf. e.g, Glanzer, Kim, Hilford, & Adams, 1999). However, the theoretical perspective of a dual-process model would assume recollection as a second source of information, when recognition would not be based on familiarity solely. This has not yet been investigated in an IAM, though the MROM's word identification mechanism is a likely candidate for a second source of information (Jacobs et al., 2003).

The MROM was designed to account for a considerable amount of effects during lexical decision. For instance, it accounted for high frequency words to elicit faster and more accurate responses than low frequency words by McClelland and Rumelhart's earlier assumption of a higher lexical base-level activation for high-frequency words (Grainger & Jacobs, 1996). Another prominent example is that 'yes' responses are more likely when many orthographically similar words exist, e.g. orthographic neighbors which differ from the stimulus in exactly one letter. Grainger and Jacobs (1996) also proposed to model naming by an IAM, because naming and lexical decision can be assumed to recruit a subset of common processes.
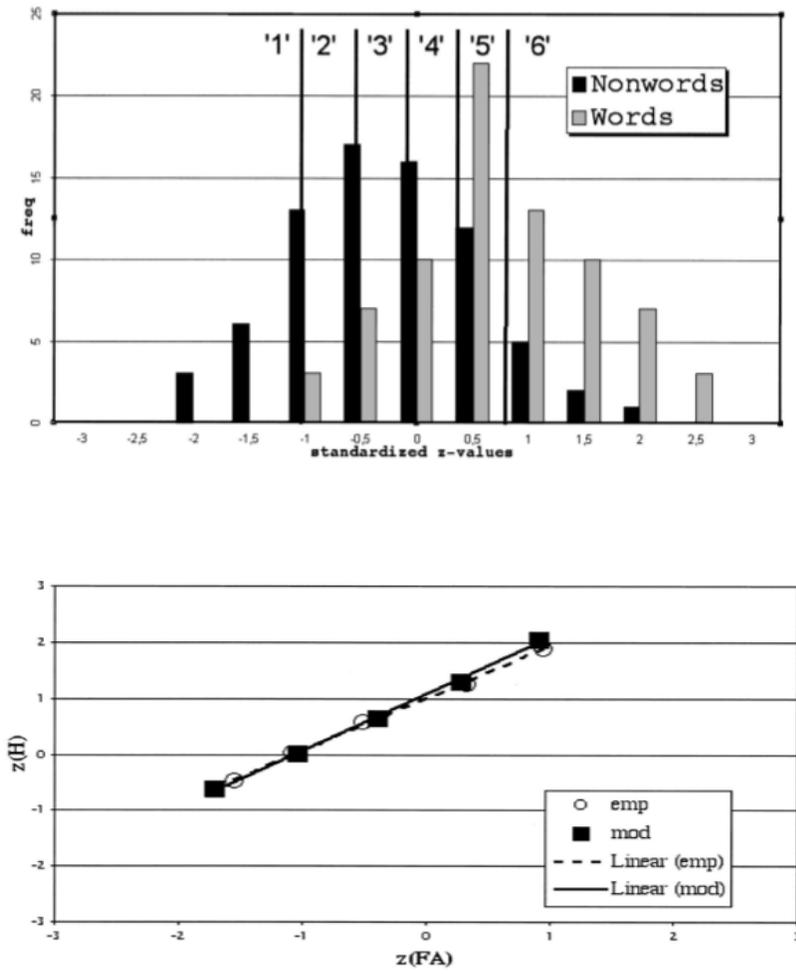
Figure 3: The upper panel shows the distributions of 'familiarity' of the MROM, which were elicited by a set of word and nonword stimuli (Figure taken from Jacobs et al., 2003). The 'yes'-response probabilities are simulated by the summed frequencies ('freq') of the items of which the familiarity values cross the respective criterion ('1' to '6'). The lower panel opposes the z-transformed probabilities for words [z(H) for hits] on the y-axis, to those to nonwords on the x-axis [z(FA) for false alarms]. These are the modeled z-ROCs (mod). The empirical z-ROCs were obtained by a confidence judgment: How sure is the presented stimulus a word, ranging from '1' ('sure no') to '6' ('sure yes'). Empirical z-ROCs are generated by accumulating all '2' to '6' responses as 'yes' response probability for the most liberal response criterion (most upper right dot) to the most conservative criterion (most lower left dot), at which only '6' counts as 'yes'.

Dual-route models and phonological representations in visual word recognition and reading aloud

Van Orden's (1987) famous article "a ROWS is a ROSE" showed that the recognition of written words is mediated by phonological information, even though this information is not necessary to recognize these visual stimuli. Ever since, phonology has attracted much research in the field of visual word recognition. Localist connectionist models reflected that trend: An MROM extended by phonological units (Jacobs, Rey, Ziegler, & Grainger, 1998) can account for the finding that nonwords are identified slower, when they trigger the phonological representation of a real word (cf. Braun, Hutzler, Ziegler, Dambacher, & Jacobs, 2009; Briesemeister, Hofmann, Tamm, Kuchinke, Braun & Jacobs, 2009; Ziegler, Jacobs, & Klueppel, 2001). During naming, however, phonological representations can be investigated more naturally, because the sound-based phonological representation is necessary to read a word aloud.

To simulate naming, an IAM was implemented in the so-called dual route cascaded model (DRC, Coltheart, Rastle, Perry, Langdon, & Ziegler, 2001; cf. Figure 4). The dual routes consisted of a direct-access lexical route, which basically consists of an IAM, and an assembled phonology route, which generates a phonological representation by rule-based grapheme-phoneme correspondences (GPC). For a high frequency word, the DRC assumes that the orthographic word form is directly matched to the lexical whole-word phonology. For a low frequency word, in contrast, the DRC posits that GPC rules generate a phonological representation. As the GPC route is generally thought to be slower, low frequency words take more time to be named. Moreover, this accounts for the finding that irregularly spelled low frequency words are more prone to elicit an erroneous regular pronunciation than high-frequency words, at which phonological representations are directly retrieved.

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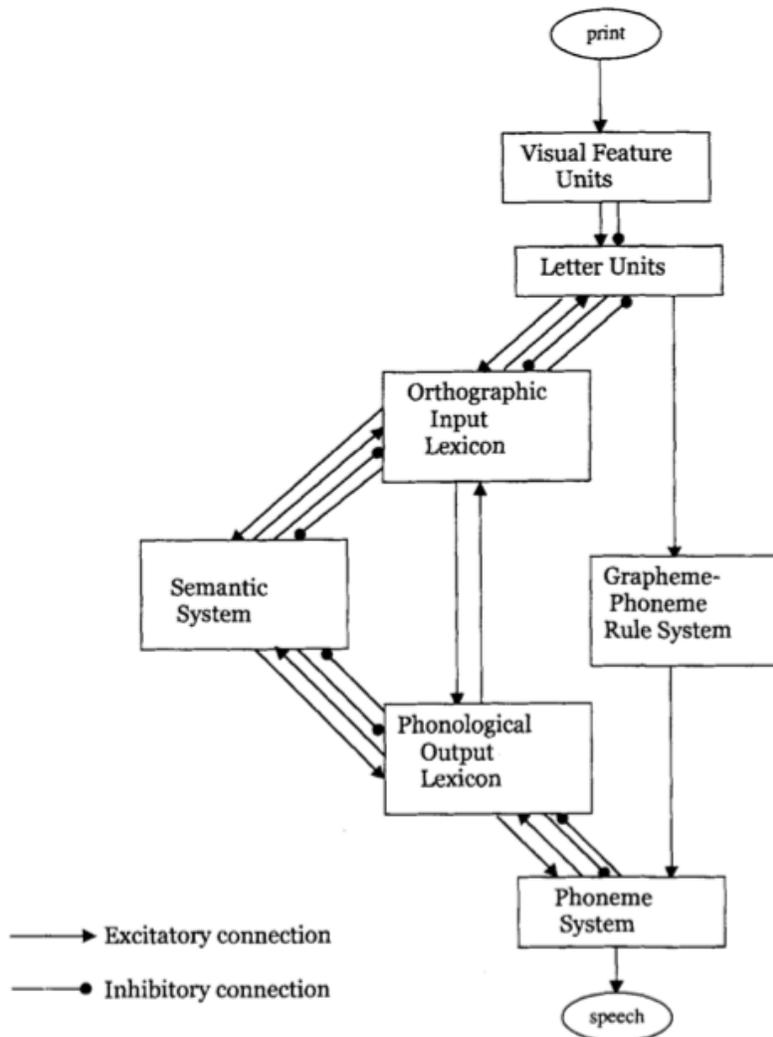
Figure 4 shows the dual route cascaded model (Figure taken from Coltheart et al., 2001). The right route is the "slow" GPC route, particularly required for naming low frequency words and nonwords: Phonological "assembly" works by rules translating graphemes to phonemes. The left route is the so-called direct route. Its visual feature, letter and orthographic (input) lexicon basically correspond to an IAM. Each entry in this input lexicon has its phonological counterpart. The semantic system is only shown for completeness of the theory. It has not yet been implemented.

However, the DRC has been challenged (Coltheart et al., 2001). Relying always on rules cannot explain why reading aloud nonwords sometimes bears pronunciations that reflect irregular rather than regular phonology (Perry, Ziegler, & Zorzi, 2007). Zorzi, Houghton and Butterworth's (1998) continuous dual-process model (CDP) described a solution to that problem. It fully relies on localist representations, but adopts a learning mechanism from the literature of distributed representations (Plaut, McClelland, Seidenberg, & Patterson, 1996). While the CDP is trained to learn orthography-to-phonology mapping, it applies a "delta-rule" that adjusts the connection strengths between orthographic and phonological representations proportional to the amount of error between correct pronunciation and actual pronunciation (cf. Widrow & Hoff, 1960). The CDP is trained with a corpus that "knows" which word is spelled in what way, much like a child that learns phonology by observing its parents. Thus, the model learns the correspondence of graphemes to phonemes, which is not a trivial task, because letters can represent a grapheme, or can be part of it. For example, the "C" at an initial position of the word "cease" is pronounced /s/. In contrast, when an "H" follows, "CH" is pronounced /tS/ like in "chair" (cf. Baayen, Piepenbrock, & Gulikers, 1995, for phonological notation, cf. Figure 5).
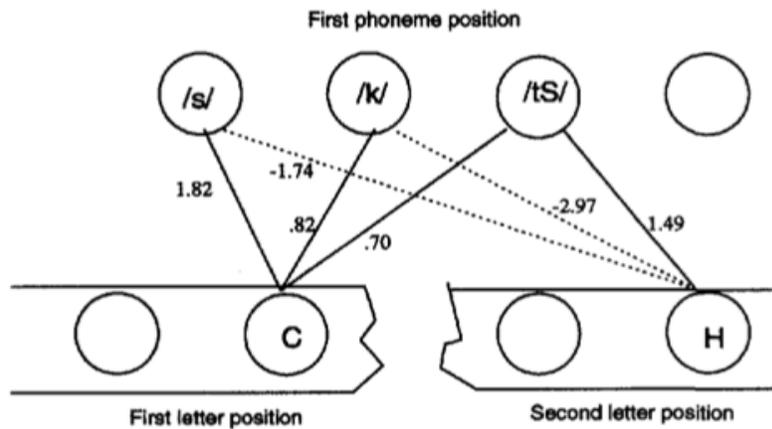
Figure 5 shows how the mapping of graphemes to phonemes was learned (Figure taken from Zorzi et al., 1998). If a "C" is in the initial position of a word it excites the possible phoneme /s/ like in "cease" (excitatory connections correspond to solid lines). However, if an "H" follows, this pronunciation receives inhibition (dotted lines), and the pronunciation /tS/ like in "chair" becomes activated.

The generalization of the DRC and the CDP, i.e. the CDP+ model (Perry et al., 2007), captured an even broader range of empirical phenomena. The probably most important breakthrough was the CDP+'s unchallenged capability of predicting item-level variance (Spieler & Balota, 1997). By simulating the naming latencies for each letter string to be named, this model extends the range of criteria, based on which the success of a model can be evaluated. Thus a good IAM does not only account for empirical phenomena in a qualitative fashion, but it must also face the challenge to predict performance in a fine-grained quantitative fashion.

The CDP+ demonstrates that models of visual word recognition and naming should compete with respect to the amount of item-level variance accounted for. When this is taken as one of the key criteria a successful computational model of word recognition must fulfill, quantitative competition between models can facilitate the evaluation of theoretical progress in the evolution of computation models (Balota & Spieler, 1998; Hofmann, Tamm, Braun, Dambacher, Hahne, & Jacobs, 2008; Jacobs & Grainger, 1994; Perry et al., 2007; Rey, Courrieu, Schmidt-Weigand, & Jacobs, 2009).

All of these models were built on the IAM and discussed meaning and semantics as a source of additional variance. However, they did not implement it. Like the original IAM, they are aware of "higher level input", but framing this source of information in an IAM was the major challenge of this thesis. It has not yet been taken on by any localist connectionist model (cf. Figure 6).
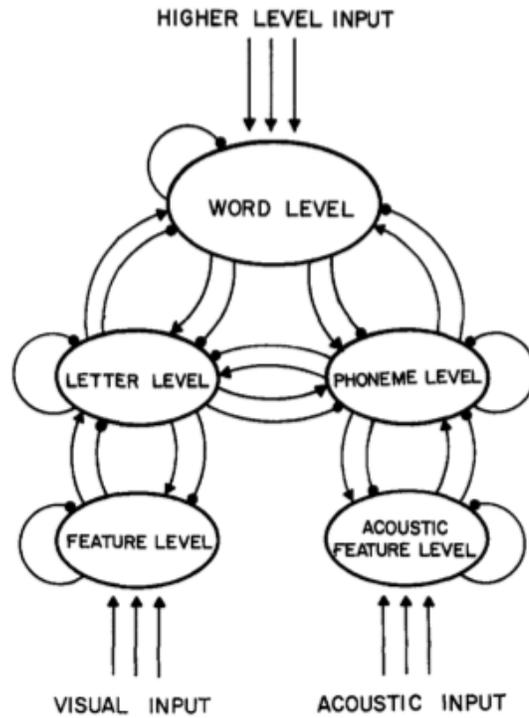
Figure 6 shows a verbal theoretical version of the IAM (taken from McClelland & Rumelhart, 1981). It already sketched the role of "higher level input", such as semantics (Rumelhart & McClelland, 1982). However, semantics was not yet implemented.

How to model (semantic) associations during word recognition?

Dealing with higher level input in a verbal, but not in a computationally concrete fashion, surely was a limitation of the original IAM and its successors (McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982). One might speculate that this limitation was one of the reasons why the original IAM "was abandoned by its creators" (Coltheart et al., 2001, p. 206). An argument for this speculation can surely be derived from their later work (e.g., Seidenberg & McClelland, 1989; Rumelhart & Todd, 1993). For instance, Seidenberg and McClelland (1989) define "meaning" as something "hidden" from the plain sight on local representation variables. Meaning is defined by associations evolving between more or less namable entities (Seidenberg & McClelland, 1989). Though it is fascinating that such simple learning principles can generate higher order representations (cf. e.g., Elman, 1990, 2004), an aim of this thesis was to complement the literature by a fully transparent approach. Therefore, the model developed here will exclusively rely on local representation variables. The challenge consisted of computationally defining contextual between-word associations like the semantic relationship of "lung" to its hypernym "organ". This approach targeted human performance predictions in a fully deterministic fashion. However, before we turn to that enterprise, let's consider how other approaches dealt with 'semantics'.

In the earliest days of connectionism, hand-crafted connections demonstrated semantic networks (e.g., Quillian, 1967), which already sketched semantic taxonomies for verbal-level theories (Collins & Quillian, 1969; Collins & Loftus, 1975). Empirical research on these models often relies on subjective performance measures. For example, a target word was presented and a group of participants named the first words that came to their minds (Roediger & McDermott, 1995). Another group of participants learned these freely associated words. As a consequence, they erroneously retrieved the target word (e.g., Kimball, Smith, & Kahana, 2010). Although such a definition of

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"association" can serve well for proof-of-concept studies, it cannot reflect all potential associative relations. This is necessary, when human performance predictions on an item-level would be one of the key model evaluation criteria (Perry et al., 2007; Spieler & Balota, 1997). Consider that each word pair can have a semantic relation. So checking for the relationships between 100 words means testing 100 * 100 = 10,000 potential relations. Moreover, attributing a word to a particular taxonomic category can be ambiguous. This can be demonstrated when considering a duckbill (Eco, 2003). Different observers may classify it as a fish – because of its gills – or as mammal – because it breast-feeds (cf. General Discussion). In addition, it lays eggs that look like those of birds! In sum, Eco (2003) would likely propose that it would depend on the subjective taxonomy of each individual observer whether two words are semantically related, or not.

Associations can be defined more easily in an objective fashion. Hebb (1949) suggested that two stimuli that occur often together are likely to be associated. Moreover, *"Firth suggested that "you shall know a word by the company it keeps" and that human beings learn at least part of the meaning of a word from "its habitual collocation" with other words (Firth, 1957, p. 11)"* (cited from Andrews, Vigliocco, & Vinson, 2009, p. 465).

Inspired by other applications – such as 'semantic' technologies that complete google search queries from likely co-occurring words – the present thesis will define two words as being associated, when they occur significantly often together in the sentences of a large corpus (Quasthoff, Richter, & Biemann, 2006). Whether these significantly co-occurring words are semantically related or not can be evaluated by each observer in a post-hoc fashion. Associatedness simply reflects the likelihood of a semantic relation.

The potentially most successful approaches to semantics were based on such co-occurrence statistics, as well. Landauer and Dumais (1997) represent the meaning

of a word by performing an analysis on the latent factors that determine the co-occurrences of words in documents. They assume that the meaning of a word is represented by its loadings on several hundred latent factors. Alternatively, each of these factors can be considered as a dimension in a high-dimensional space. Accordingly, semantic similarity can be determined by the distance between two words. A more recent approach used a dimensional approach to semantics in a Bayesian framework (Griffiths, Steyvers, & Tennenbaum, 2007). For a recognition memory task, this so-called topic model predicted the 'yes' rate difference of a learned word in comparison to the same word when non-learned. In this regard, the topic model already comes close to an item-level of prediction. However, knowing whether the variance accounted for results from new or old items, is crucial. The lack of separate predictions for old and new items results from the fact that the topic model is a purely representational model. It does not make any assumptions about the cognitive processes acting on these representations (Steyvers, Griffiths, & Dennis, 2006).

A more recent approach calculates the latent factors that determine both, the co-occurrence in text corpora and free association performance (Andrews et al., 2009). This might provide an even more realistic world knowledge representation (Andrews et al., 2009). However, approaches that rely on non-namable abstracted factor loadings cannot be used in a fully localist model, because this would require that every representation variable refers to a single real-world entity (Grainger & Jacobs, 1998). Dimension-reduction, however, distributes the meaning representation of a word across several variables, much as connectionist models relying on distributed representations (e.g., Harm & Seidenberg, 2004; Seidenberg & McClelland, 1989).

Thus, rather than targeting the "semantics" by latent dimensions that do not refer to a single meaningful entity, local representations will provide an epistemically transparent approach: During any step in the computations, the observer can evaluate, whether the processes that act on the meaning relationships between the words provide

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face validity. There are no hidden or abstract factor representations that have no meaning by themselves. Connected units representing concrete words can be more directly related to the embodied nature of semantics (cf. Schrott & Jacobs, 2001): Neurons that reflect mental representations are connected in the brain. In contrast, it is questionable whether the brain hosts a semantic space of about several hundred dimensions (but cf. Landauer & Dumais, 1997).

Moreover, Gamallo and Bordag (2010) called into question whether the reduction of the latent dimensions does improve model performance, when compared to using the original co-occurrence statistics from which the dimensions were derived (cf. Bullinaria & Levy, 2007). Thus, computational resources might be better invested into increasing the size of the corpus – which clearly can improve the model performance (Rapp & Wettler, 1991) –, rather than into the computationally effortful reduction of the "semantic" dimensionality (Gamallo & Bordag, 2010).

On the other hand, dimension-reduction allows for integrating the most reliable information from corpus-linguistic and subjective measures (Andrews et al., 2009). Therefore, the dispute about dimension-reduction or not seems far away from being settled. However, when targeting the optimization of performance predictions, a model based on simple co-occurrence statistics should be at least considered as theoretical alternative to the existing co-occurrence-based dimension-reduction approaches (Andrews et al., 2009; Griffiths et al., 2007; Landauer & Dumais, 1995). A simple co-occurrence approach is more compatible with the theoretical framework of traditional associative spreading activation between local representations (e.g. Collins & Loftus, 1975; Collins & Quillian, 1969, Figure 1).

In addition to being a representational model of "semantics", an IAM includes a memory processing model. Unifying a processing model of memory and a representational model of semantics is a vision Mark Steyvers and colleagues already

had (Steyvers et al., 2006). The present thesis will provide one possible answer to that vision.

Overview of the present studies and their methods

The first study made sub-lexical frequency measures available for German (Study 1). This allowed for controlling confounding variables at a sub-lexical level in other studies of this thesis. Then, three studies were conducted on the lexical, whole-word representation level: Lexicality and word frequency were investigated by optical imaging (Study 2). Competing lexical units in a computational model accounted for behavioral and electrophysiological data (Study 3), and affective features of words were investigated in Study 4. The results of this study pointed towards the so-called semantic cohesiveness hypothesis of affective word processing (Maratos, Allan, & Rugg 2000). It suggests that much of the influence, that affective words exert on behavioral or neural observables, can actually be accounted for by their greater amount of associative-semantic relations to other words. Therefore, Study 5 examined associative connections between words.

Study 1: Sub-lexical frequency measures provided by corpus analyses

Phonological representations can be assumed to be activated incidentally, even though phonological processing is not (psycho-)logically necessary for lexical decision (Van Orden, 1987). This is probably the case, because learning to speak is driven by phonological representations, which are the fundamental memory representations of language. Language and semantics have been learned via phonological representations in the first place. Therefore, their influence on the processing of orthographic representations remains (Ziegler & Goswami, 2005). The CDP and the CDP+ learn GPCs by training (Perry et al., 2007; Zorzi et al., 1998). As the amount of occurrences of a grapheme shapes its orthographic-phonological association strength,

graphemes of high frequency are probably more stably connected to their phonological representation. In German, nearly all graphemes correspond to letters and bigrams. Therefore, the CDP would probably predict that words composed of higher frequency letters or bigrams can be read faster than those composed of low frequency sub-lexical units.

Indeed, as the literature review of this study will show, the frequency of sub-lexical units considerably affects visual word recognition performance. Because there was no openly accessible database of orthographic and phonological sub-lexical frequency measures for German, the first step of this thesis involved the calculation of letter and phoneme frequencies, bigram and biphoneme frequencies, and orthographic and phonological syllable frequencies. The sub-lexical frequency measures were derived from the CELEX corpus (Baayen et al., 1995). To extract the relevant pieces of information from huge amounts of data, the corpus-analytic methods applied in this thesis relied on PERL and UNIX-shell scripts (cf. also Study 5).

Without the extracted sub-lexical frequency measures, it would have been impossible to test whether the behavioral facilitation to high frequency words in Study 2 would have resulted from the frequency of the whole words, rather than from the frequency of its constituents. For instance, high frequency words might be composed of high frequency bigrams on average, which might account for the word frequency effect. To rule out such confounding effects, the aforementioned sub-lexical measures were used as control variables in all of the present studies that assessed word recognition by manipulating psycholinguistic variables. Consider that Study 2 will also address the hemodynamic word frequency effect in the left inferior frontal gyrus (IFG). The aim of controlling for sub-lexical measures was to rule out that the expected word frequency effect in the IFG results from confounds at a sub-lexical representation level.

Study 2: Word frequency, lexicality and optical imaging

Fiebach, Friederici, Müller, and Von Cramon (2002) found low frequency words to engage a greater IFG activation than high frequency words. This is probably the best-replicated effect of functional magnetic resonance (fMRI) studies of word recognition (Fiebach, Friederici, Müller, Von Cramon, & Hernandez, 2003; Carreiras, Mechelli, & Price, 2006; Ischebeck, Indefrey, Usui, Nose, Hellwig, Taira, 2004; Nakic, Smith, Busis, Vythilingham, & Blair, 2006; Prabhakaran, Blumstein, Myers, Hutchison, & Britton, 2006). Fiebach et al. (2002) functionally associated this region with grapheme-to-phoneme conversion (Coltheart et al., 2001). However, as the CDP+ learns GPCs by the exposure of the words to the model (Perry et al., 2007), this process should be affected by the frequency of exposure of the graphemes, usually corresponding to letters and bigrams in German (cf. Figure 5). Therefore, the experimental control of sub-lexical frequencies in this study should constrain the IFG's lexical frequency effect to result from whole-word frequency. Thus, Study 2 tested whether low frequency words still engage a greater activation in the IFG than high frequency words, when the sub-lexical letter and bigram frequencies do not differ between conditions. Thus, the IFG was the first target region of this study. Second, as the MROM assumed different decision mechanisms for words and nonwords, lexicality effects can be expected in decision-related brain regions, such as the superior frontal gyrus (SFG, e.g., Fiebach, Ricker, Friederici, & Jacobs, 2007). Third, the left inferior parietal gyrus (IPG) can be assumed to act as a hub that integrates orthographic, phonological and semantic representations (e.g. Price, 2000; Binder et al., 2003). Therefore, word stimuli should elicit a larger neural activation than nonwords in both of these regions, which has been repeatedly shown in fMRI studies of word recognition (e.g., Binder, Frost, Hammeke, Bellgowan, Rao, & Cox, 1999; Ischebeck et al., 2004). The aim of Study 2 was to test

the hypotheses with respect to the function of these three target regions, using a method novel to the research field of word recognition.

Optical imaging is a relatively young method that uses light in the near-infrared wavelength spectrum to measure which brain region consumes oxygen (Villringer & Dirnagl, 1995). Therefore, it is also often called Near-Infrared Spectroscopy (NIRS). To collect NIRS data, light sources and detectors are arranged side by side on the skull. Since near-infrared light is diffuse, some light quants penetrate the cortical tissue on an arched path to the neighboring detectors. If the tissue properties would not change, an approximately equal amount of quants would arrive at a detector. However, as hemoglobin absorbs light, concentration changes can be measured. Because the red, oxygenated hemoglobin absorbs a different part of the light spectrum than the blue deoxygenated hemoglobin, using two lasers of different wavelengths allows for inferring on concentration changes of both, oxygenated [oxy-Hb] and deoxygenated hemoglobin [deoxy-Hb] (Villringer & Dirnagl, 1995).

By comparing the neuroimaging data of two experimental conditions, which differ only with respect to a single alleged process, it is possible to draw inferences about which brain region may respond to which process. Though functional NIRS (fNIRS) has its disadvantages in comparison to other methods allowing for similar conclusions – such as positron-emission tomography (PET) or fMRI – it also provides some advantages. The major benefit is its non-invasiveness: Light in the near-infrared part of the spectrum is less invasive than natural sunlight, because the latter contains also a bit more "dangerous" components of the light spectrum such as ultraviolet. Therefore, this method can even be used to assess the heartbeat of prenatal fetuses (Kisilevsky et al., 2009). The method thus appears optimally suitable to assess the hemodynamic responses of the brain at all live ages, which is a promising perspective for developmental neuroscience (Lloyd-Fox, Blasi, & Elwell, 2010). The major disadvantage

is the limited spatial resolution in the range of a few cubic centimeters, and only cortical regions close to the skull being investigable.

Another main advantage of NIRS is its quietness. For example, a magnetic resonance tomograph typically elicits acoustic noise louder than 110dB sound pressure level (Counter, Olofsson, Grahn, & Borg, 2005). In contrast, the optical tomograph used in Study 2 elicited a background noise of about 56dB. Because word recognition is commonly assumed to rely on sound representations (e.g., Van Orden, 1987), it might be particularly prone to interact with the relatively loud fMRI scanner environment. Therefore, if the first fNIRS study of word recognition confirms previous fMRI studies, the concern can be rejected that the relatively loud scanner environment of fMRI studies has led to qualitatively different results than in an environment with an increased ecological validity. Corresponding results with both methods would thus allow for testing conclusions drawn from fMRI studies using fNIRS.

Optical imaging allows for peeking deep into the mechanics of the hemodynamic response by allowing to observe concentration changes of both, oxygenated [oxy-Hb] and deoxygenated hemoglobin [deoxy-Hb]. Arteries deliver fresh blood to the region at which oxygen is needed to keep metabolic demands stilled. Therefore, a neural response should be accompanied by an [oxy-Hb] increase (Buxton, Uludag, Dubowitz, & Liu, 2004). Cells that consumed oxygen release exhausted blood into the vasculature. This is flushed out by the fresh blood. Therefore, mechanical models of the hemodynamic response predict a decrease of [deoxy-Hb], when a hemodynamic response was elicited. However, as the vascular system consists of flexible tubes, despite the described canonical hemodynamic response, a number of alternative blood flow-volume relationships have been proposed (Mandeville et al., 1999). Nevertheless, for the present study the "default"-coupling of the canonical hemodynamic response can be expected. An experimental condition of greater neural activation than another one

should show an [oxy-Hb] increase accompanied by a [deoxy-Hb] decrease (Buxton et al., 2004).

Moreover, theories of the mechanics of the hemodynamic response posit that the [deoxy-Hb] decrease as measured by fNIRS and a blood oxygen level dependent (BOLD) increase as measured by fMRI are explainable by the same neural mechanisms (Buxton et al., 2004, Steinbrink, Villringer, Kempf, Haux, Boden & Obrig, 2006). This gains empirical support from concurrent fNIRS-fMRI studies (e.g., Kleinschmidt et al., 1996). Thus, we expected to observe [deoxy-Hb] decreases accompanied by [oxy-Hb] increases to words in comparison to nonwords in the SFG and the IPG, as well as for low frequency words in comparison to high frequency words in the IFG.

Unlike fMRI, optical imaging itself does not provide information about which brain region was activated. Since this study addressed the neural response of two adjacent regions during language processing (SFG and IFG), an anatomic labeling approach was required. There are three different methods that allow for localizing the NIRS channels (see Dan, Okamoto, Tsuzuki, & Singh, 2007, for an overview):

The first method uses MRI scans of the participants. It is most accurate with respect to the localization, because it provides information with respect to the inter-individual differences of the localizations of the gyri and sulci. This method could not be applied, because MRI scans were not available for the present thesis. The second approach uses a 3D-digitizer to determine the real-world coordinates of the optodes and some reference points. By "overlaying" this information on standard brains the localization of the channels can be obtained. However, a 3D-digitizer was not available, either. Therefore, we conducted the study in collaboration with Ippeita Dan, who helped us to localize the NIRS channels by using the third method: This virtual registration method (Tsuzuki, Jurcak, Singh, Okamoto, Watanabe, & Dan, 2007) attaches a virtual probe set on 1000 virtual heads in the same manner as the real probe set is attached to the real participants. It estimates inter-individual variability of the gyri and sulci of the

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participants by using virtually generated heads and brains of an anatomic database. Thus, spatial standard deviations (SD) of the localizations of the channels are obtained. Once the three-dimensional coordinates of the Montreal Neurological Institute (MNI) are available, anatomic labeling allows for estimating the probabilities of the channels to be localized in the respective brain region. Moreover, this method allows for illustrating the results by using a three-dimensional model of the brain surface, as will be displayed in Figure 8.

Once the methodological obstacles were overcome to make fMRI results and fNIRS results comparable, it was possible to investigate the IFG's function during word recognition. An alternative explanation for a word frequency effect in the IFG would consist of the lexical selection hypothesis. Thompson-Schill, D'Esposito, Aguirre, and Farah (1997) proposed that the IFG's function concerns the selection between several, hypothetically pre-activated semantic word representations. We hypothesized that this process should be elicited by low frequency words, because these are identified more equivocally than high frequency words (cf. Grainger & Jacobs, 1996). Therefore, they may engage greater selection demands.

Conflicting representations, however, were also proposed to result in activation of the anterior cingulate, which is a relatively deep brain structure and thus un-assessable by NIRS (Botvinick, Braver, Barch, Carter, & Cohen, 2001). Therefore, the next model-based study on conflicting representations applied source localization on ERP data to obtain information about the neural regions involved, and the dynamical properties of lexical processing.

Study 3: Modeling electrophysiological responses to conflicting lexical representations

The conflict monitoring theory (CMT; e.g., Botvinick et al., 2001) posits that the anterior cingulate cortex (ACC) and the medial frontal gyrus' function concerns the evaluation of conflicting representations (Ridderinkhof, Van den Wildenberg, Segalowitz, & Carter, 2004). Botvinick et al. (2001) suggest that the so-called Hopfield Energy (Ehopf) is the computational implementation that would predict mediofrontal activation best. It is defined as the sum of the products of all possible representation pairs activated. For example, when "blur", "blue" and "flur" are activated by a stimulus (cf. Figure 2), Ehopf equals the sum of the products of the activations of "blur" and "blue", "blur" and "slur", as well as "blue" and "slur".

To test for the applicability of the CMT to word recognition models, Ehopf was implemented into an MROM including phonological representations (Jacobs et al., 1998). To test whether increased lexical conflict elicits increased RTs and error rates to nonwords, it was manipulated in three conditions of low, medium, and high Ehopf. Yeung, Botvinick, and Cohen (2004) proposed that the second negative deflection of the event-related potential (ERP) – the so-called N2 component – is an electrophysiological equivalent of the ACC's conflict response. Therefore, we expected Ehopf to elicit an increased second negative deflection in the ERP.

To track the time-course of neural information processing, ERPs were calculated from electric potential differences between scalp-electrodes at standardized positions and a so-called reference electrode (Jasper, 1958). The rationale is that there is no activation of interest at the latter site (Lehmann, 1987). Therefore, the reference electrode's site is chosen at a place which shares the same "background" potential – e.g. capturing artifacts resulting from muscle tension – but is shielded from the brain potential of interest. Typically, the relatively thick mastoid bone behind the ear is

chosen. The scalp-electrodes, in contrast, are assumed to record the summed potential changes that result from electric signal transmission in a large amount of neurons (e.g. Kutas, Van Petten, & Kluender, 2004). Negative potentials measured at the scalp can be assumed to reflect apical dendritic signals transmitted from the interior of the brain to the cortex, while cortical potentials transmitted to the interior should elicit a relative positivity (cf. e.g., He & Raichle, 2009). The observed potentials are purged from artifacts, by applying fourier-transfom-based filters extracting the frequency band, which is assumed to contain the event-related activity of interest. Further, the potentials elicited by the eye muscles are mathematically excluded by performing an independent component analyses extinguishing signals apparent across the whole scalp (Onton, Westerfield, Townsend, & Makeig, 2006). These purged potential changes are normalized to a baseline period right before the presentation of the stimulus, and averaged across all trials of an experimental condition for each time-point relative to stimulus presentation. Moreover, for evaluating the model performance in predicting human brain potentials, we averaged the event-related changes also across items (cf. Dambacher, Kliegl, Hofmann, & Jacobs, 2006; Hutzler, Bergmann, Conrad, Kronbichler, Stenneken, & Jacobs, 2004). An sLORETA source localization model served for determining which brain regions most likely produce these potentials (Pascual-Marqui, 2002).

Apart from predicting neural activation in the ACC at a qualitative level of analysis, a successful computational model of word recognition should quantitatively account for a significant portion of item-level variance (Jacobs & Grainger, 1994; Perry et al., 2007, Spieler & Balota, 1997). Therefore, the study tested whether the Ehopf values of the stimuli account for the mean response time (RT), error scores, and N2 amplitudes of the items, when averaged across participants. Additionally, the amount of variance explained allows for quantifiable competition between alternative models. Previous connectionist models of word recognition applied this logic to behavioral data

(cf. Perry et al., 2007, for a review). This study introduced this aspiring model evaluation criterion for psychophysiological data (cf. Rey, Dufau, Massol, & Grainger, 2009).

Study 4: Affective connotation of lexical representations, ERPs, and pupillometry

Not all of the processes, that are critical for the recognition of words, are addressable by the simulation of the cognitive processes in computational models, or by inferring on the processes when examining effects elicited by corpus-analytically defined variables, such as word frequency, for example. Subjective rating data operationalize the affective connotation of a word (Võ, Conrad, Kuchinke, Urton, Hofmann, & Jacobs, 2009). Going back to an early suggestion of Wundt (1896), emotion is commonly subdivided into two orthogonal dimension constituting affective space (Bradley & Lang, 1999). However, most of the previous studies confounded both of these dimensions, *emotional valence* and *arousal*. This typical confound was disentangled in Study 4.

When previous research compared words of negative valence to neutral words, rather inconsistent behavioral results were obtained with respect to its facilitatory or inhibitory influence on the word recognition process. Some studies obtained faster RTs for negative than for emotionally neutral words (e.g., Williamson, Harpur, & Hare, 1991), whereas other studies revealed no effects (e.g., Siegle, Ingram, & Matt, 2002), or even a trend towards slower RTs (e.g., Kuchinke, Jacobs, Grubich, Võ, Conrad, & Herrmann, 2005; Kuchinke, Võ, Hofmann, & Jacobs, 2007). Study 4 was conducted to test the hypothesis that arousal determines whether negative words are responded to faster or slower (Thomas & LaBar, 2005).

In contrast to negative words, positive words consistently yielded faster RTs than neutral words (e.g., Kuchinke et al., 2005). Therefore, positive valence itself may elicit

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the response facilitation. If so, words should be responded to faster, when arousal is controlled for. Since arousal ratings were not available in the original Berlin Affective Word List (BAWL, Võ, Jacobs, & Conrad, 2006), it was necessary to collect these for this study. However, a larger corpus was required for stimulus selection to be able to control for many sub-lexical variables and other potential confounds. Therefore, the BAWL was extended (Võ et al., 2009).

Previous studies investigating whether affective words evoke pupil dilations had provided mixed results. Kuchinke et al. (2007) showed that pupil dilations are not affected by emotional valence during lexical decision. In contrast, Võ et al. (2008) showed that learned high-arousal positive and negative words elicit smaller pupil dilations than low-arousal neutral words during a recognition memory task. Therefore, the experimental manipulation applied in the present study was optimally suitable to discriminate between two complementary interpretations for these divergent findings. The first explanation proposes that the critical difference between Kuchinke et al.'s (2007) and Võ et al.'s (2008) study concerned arousal, which was not considered in Kuchinke et al.'s (2007) study, because arousal ratings were not available at this time. In contrast, Võ et al. (2008) compared high-arousal emotional words with low-arousal neutral words. Thus, low arousal may have been the reason for the absent pupillometric effects in Kuchinke et al. (2007). The second interpretation proposed that pupil dilation effects of affective words are task-specific and only occur during recognition memory tasks. This question also concerned two concurring explanations for the functional locus of pupil dilation effects. Either it can be associated directly with affective processing (Hess, 1965; Janisse, 1974), or the peak pupil dilation correlates with the amount of cognitive load associated with a memory task (Beatty & Kahnemann, 1966; Beatty, 1982). If the pupil dilations were affected by arousal during the LDT presented in Study 4, this would confirm that the affective word features itself evoke the pupil dilations. If no pupil dilation effects were found, it would be likely that diminished cognitive demands to

affective words is the critical process explaining Vo et al.'s (2008) diminished pupil dilations: The behavioral facilitation observed for learned affective words was accompanied by diminished pupil dilations. Non-learned affective word stimuli elicited inhibitory behavioral effects, which were accompanied by greater pupil dilations (Võ et al., 2008) during a study-test recognition memory task. Thus, in old and new stimuli alike, the behavioral findings indicated lower cognitive demands. The lower the cognitive demands were, the smaller was the pupil dilation. The LDT, which only requires the recognition but not the remembering of particular words, would not engage detectable cognitive demands to elicit pupil dilations, whereas Vo et al.'s (2008) memory task would.

Another aim of this study concerned the dynamics of affective word processing. At which time after stimulus presentation are the processes initiated that lead to behavioral facilitation? For answering this question, ERPs were recorded. Sereno and Rayner suggest that the first access to a hypothetical mental lexicon might be underway around 100 ms post stimulus presentation (Sereno & Rayner, 2003). Thus, if affective word features act already during lexical access, at the ERPs of this time frame should respond sensitively to the experimental manipulations of this study.

To test whether the most likely neural generator of the expected ERP effect is in the medial frontal gyrus, source localization was conducted (Pascual-Marqui, 2002). A positive finding in this region could be interpreted as an early attention (e.g., Carretié, Hinojosa, Martìn-Loeches, Mercado, & Tapia, 2004) or decision-related control process (e.g., Botvinick et al., 2001). Alternatively, if the most likely neural generator was the fusiform gyrus, this would support the hypothesis that the functional locus of the affective word processing advantage resides at a lexical-access processing level (Dehaene, Le Clec'H, Poline, Le Bihan, & Cohen, 2002; Kronbichler, Hutzler, Wimmer, Mair, Staffen, & Ladurner, 2004). An increased activation of the medial temporal gyrus to affective word stimuli would suggest a lexico-semantic locus of the ERP effect (e.g.,

Price & Devlin, 2003), which may indicate that much of the variance affective word features account for may be actually explained by semantic cohesion (Maratos et al., 2000; LaBar & Phelps, 1998).

Study 5: Modeling associations between lexical representations and Receiver Operation Characteristics

If semantic representations would indeed account for the variance that was previously ascribed to affective word features (cf. e.g. Võ et al., 2009), the question would remain how semantic cohesion can be captured empirically, and in a computationally concrete theoretical fashion. Maratos and colleagues (2001) explained emotional valence effects by semantic cohesion, because of a remarkable similarity of their ERP observations to those of false memory effects (cf. Johnson, Nolde, Mather, Kounious, Schacter, & Curran, 1997). In false memory experiments, pre-experimentally collected free association performance defines the state of being associated (Deese, 1959; Roediger & McDermott, 1995). A target is presented and participants name the first words coming to their minds. When these associates are learned by the participants of another experiment, the non-learned target is erroneously remembered. This is explainable by associates activating the target's representation (e.g., Kimball et al., 2007). However, such a free association approach cannot take into account all possible associations between all items, because only the strongest associates are considered. Therefore, another study relied on meaning relatedness ratings for respectively two words (Talmi & Moscovitch, 2004). Semantic cohesiveness and affective word features were manipulated separately. The study confirmed the semantic cohesiveness hypothesis: Emotional words are remembered better by virtue of their higher semantic cohesion to other words.

However, massive amounts of meaning relatedness ratings would be required when aiming to extend a model by a semantic-associative layer. An IAM usually contains about 1,000 words (Grainger & Jacobs, 1996; McClelland & Rumelhart, 1981).The number of potential associations between 1,000 items amounts 1,000 * 1,000 = 1,000,000. Therefore, a computational model testable with lexica of about 1,000 words would require ratings for about a million word pairs.

To allow for defining all associations between nearly all words, a word pair can be defined 'associated' due to Hebbian learning (Hebb, 1949; Rapp & Wettler, 1991): Items being repeatedly presented together are likely to be associated. Accordingly, two words were defined 'associated', when they co-occurred significantly often in the sentences of a large corpus (Quasthoff et al., 2006). The corpus used is one of the largest German corpora available. Only google's German corpus is greater, and there is only one another German corpus of comparable size (http://www.ids-mannheim.de/kl/projekte/korpora/archiv.html). This is derived from probably the largest corpus-linguistic project that provides measures comparable across languages. The word frequency and co-occurrence measures of the "Wortschatz" project are available for a constantly growing amount of languages, i.e. 69 at present (www.corpora.uni-leipzig.de/). Moreover, simple co-occurrence statistics had already been shown to predict the free association performance (Rapp & Wettler, 1991).

Both, Maratos et al. (2001) and Talmi and Moscovitch (2004), had investigated "semantic" cohesiveness in tasks at which participants have to explicitly remember words. Thus, in Study 5 a recognition memory task served for testing whether "semantic" cohesiveness can be implemented by co-occurrence statistics. Participants learn words in a study phase. In a test phase, they are required to decide whether a word has been learned ('old' item), or not ('new'). For new and old items, the amount of associated items in the stimulus set varied in two levels. Low co-occurrence target items

had less than 8 associated items in the stimulus set, and high co-occurrence targets at least 8.

Thus, each stimulus selected can serve two purposes. On the one hand, it functions as a target. On the other, it can serve multiple times as an associate that is cueing associated targets, when presented before them.

If associations can be implemented by co-occurrence statistics, more associates should drive erroneous 'yes' responses for non-learned items with many associates in the stimulus set, similar to Roediger and McDermott (1995). Moreover, the amount of associations was hypothesized to drive the correct 'yes' response probabilities for learned items with many associates in the stimulus set. This has previously been observed for recall, but not yet recognition (Kimball et al., 2007). If both of these findings would be observed, this would confirm that co-occurrence statistics can successfully implement associations between the items of an experiment. This, in turn would make co-occurrence statistics a promising way to implement associations into an IAM.

Moreover, the study aimed to separate associative memory signal strength from strategic bias effects, by using a signal detection approach (Green & Swets, 1966). Much as for the signal detection approach to word recognition of the MROM (cf. Figure 3; Jacobs et al., 2003), participants were instructed to judge the confidence with which they recognized a word. In a recognition memory task, this question concerns whether the word has been recognized as having been learned during the study phase, or not. Thus, participants were required to rate their recognition confidence on a six-point scale ranging from 'sure no' ('1') to 'sure yes' ('6'). While simulating the most liberal response bias, which is prone to elicit many 'yes' responses, only '1' responses count as a 'no' response. This is referred to by the criterion C(1). The most conservative bias is simulated, when only '6' responses count as 'yes' response (C(5)). Signal detection theory posits that if a criterion C(i) for i – here ranging from 1 to 5 – is surpassed, a 'yes' response is executed. The obtained criteria C(i) are determined by their empirical 'yes'

response probabilities on a bimodal Gaussian distribution of (memory) signal strength: One Gaussian distribution for the non-learned new items, and another one for the learned old items. The distribution of old items provides greater memory signal strengths on average, which implements mnemonic traces resulting from study-phase presentation. ROCs are generated by opposing the 'yes' probabilities for all criteria on an x-axis for new items (false alarms) to those for old items on a y-axis (hits). When these ROC probabilities are normalized to z-values, the z-ROC typically reveals a slope of less than one during recognition memory tasks. One of the most highly accepted assumptions, that can account for this typical observation, is that the signal strength variance for old items is greater than the variance to new items (Glanzer et al., 1999; but cf. Yonelinas, 1999). This was assumed to result from a single process of memory signal strength increase due to learning (Squire, Wixted, & Clark, 2007). However even when previous signal detection models of memory discuss the memory signal strength of the items (e.g., Glanzer et al., 1999; Yonelinas, 1994), none of these models already took the challenge of likewise predicting the 'yes' response rates of the items by attributing them a particular signal strength value.
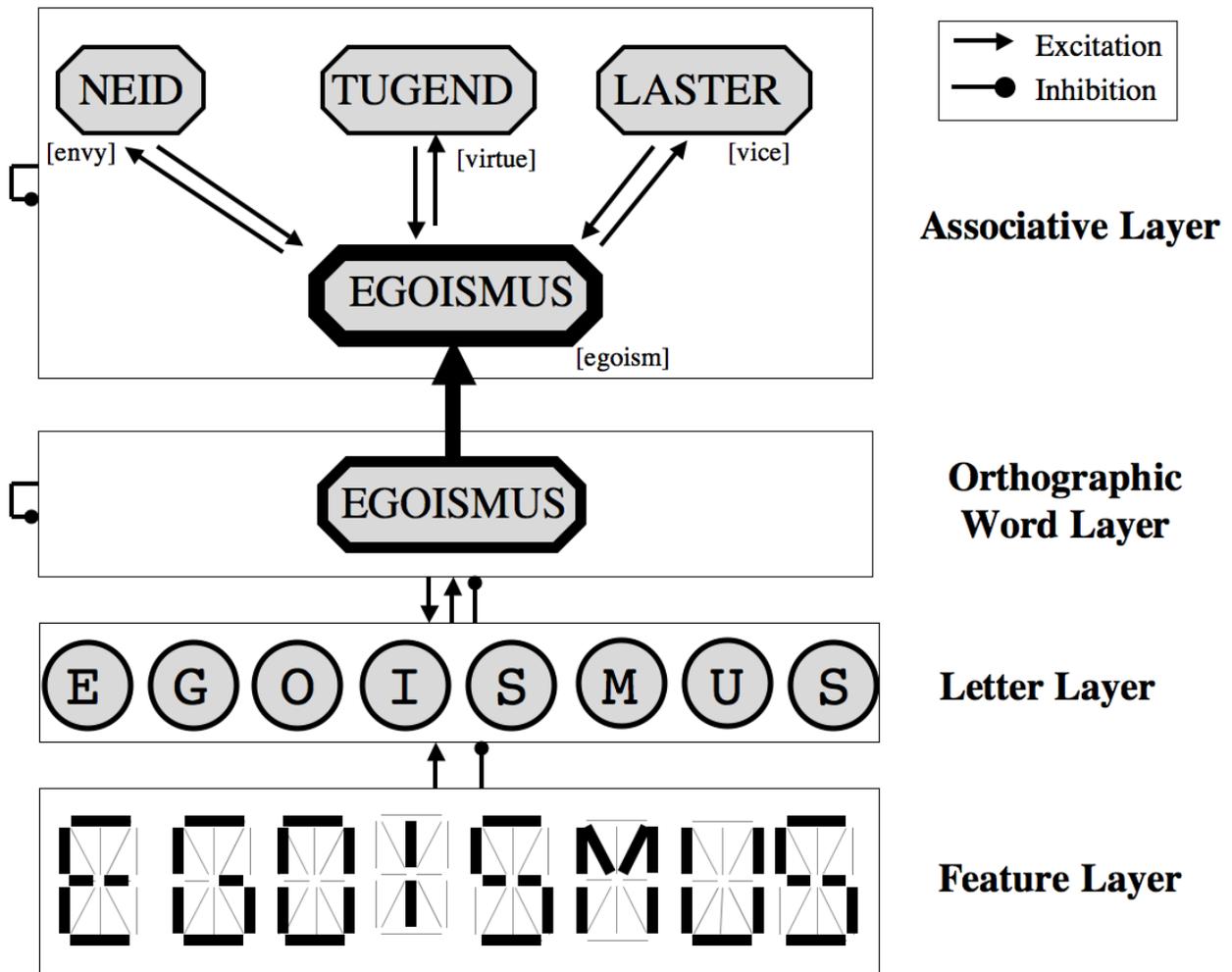
Figure 7 sketches the basic architecture of the AROM: The lower three layers correspond to previous IAMs (Grainger & Jacobs, 1996; McClelland & Rumelhart, 1981). Target stimuli are presented to the feature units, which in turn activate the letter and (orthographic) word layer. The associative layer's unit of the target receives the word identification signal from the orthographic word layer. Moreover, associated item units contained in the stimulus set are activated by the target unit, and activate the target in turn. Thus activations to item units with many associated items are greater, which predicts their higher probability of 'yes' responses. Translations are bracketed.

The aim of this study was to develop an IAM that implements associations between words by co-occurrence statistics. To evaluate the success of the model, two key challenges were set: Predicting z-ROCs and item-level performance.

The MROM accounted for effects resulting from a word's orthographic representation, which can be assumed to affect the identification of a word (cf. Figure 7). Therefore, the MROM was nested into the AROM (Jacobs & Grainger, 1994; Grainger & Jacobs, 1996). The MROM's word identification signal was forwarded to the associative layer, because recognizing a word as having been learned still requires the identification of the word itself. For each word presented in the experiment, an orthographic and an associative word representation was used, while the associative units obtained activation from their orthographic representation. To account for the hypotheses of greater amounts of associates leading to greater amounts of 'yes' responses in new and old items, associative connections were added in the associative layer. Co-occurrence statistics determined whether or not two words are associated.

Thus, the orthographic representation of a presented word activates its associative representation. The associative representation of the stimulus then triggers activation in associated representations, which in turn activate the stimulus representation (cf. Nelson, McKinney, Gee, & Janczura, 1998). This model behavior reflects the following processes during the time course of the test phase of the experiment: When considering that the test phase list is randomized separately for each participant, each of the associated items has a probability to be presented before the target stimulus. Thus, in the data considered across participants, each associate in the stimulus set increases the probability that a target item has been "primed". Thus, the model predicts greater activations for representations with many associates in the stimulus set. In an IAM, activations are interpreted as evidence of the representation being apparent. Accordingly, greater 'yes' response probabilities for items with more associates in the stimulus set can be predicted.

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As this was the first IAM to model explicit memory performance, another assumption was required to implement memory traces resulting from study-phase presentation. As signal detection approaches to recognition memory assume greater signal strengths for learned than for non-learned items (Green & Swets, 1966), old items simply obtained a greater resting level.

Questioning how such a model could account for a z-ROC slope lower one seemed to be another challenge. However, McClelland and Rumelhart (1981) had already implemented a mechanism sufficient for explaining signal detection theory's unequal variance assumption: When a representation receives in sum an inhibitory signal from other representations in an IAM, it is scaled by multiplying the inhibition with the activation of the representation itself. When many memory traces are active, much more inhibitory than excitatory signals arrive at each representation. Therefore, each representation receives a net inhibitory signal. This net inhibition results from the keen competition of many active memory traces being held in memory. As the resting level for old items was defined higher than for new items, scaling the inhibition to obtain the actual change of a representation necessarily leads to greater activation variances for learned old items than for new ones. This increased variance of old items was supposed to be the source of the z-ROC slope lower than one (e.g., Shiffrin & Steyvers, 1997). Thus, the assumption of an increase of memory signal strength by learning may account for the z-ROC slope lower than one in an IAM.

Study 1: Sub-lexical frequency measures for orthographic and phonological units in German

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Abstract

Many recent studies have demonstrated the influence of sub-lexical frequency measures on language processing, or called for controlling sub-lexical measures when selecting stimulus material for psycholinguistic studies (Aichert & Ziegler, 2005). The present study discusses which measures should be controlled for in what kind of study, and presents orthographic and phonological syllable, dual unit (bigram and biphoneme) and single unit (letter and phoneme) type and token frequency measures derived from the lemma and word form corpora of the CELEX lexical database (Baayen et al., 1995).

Additionally, we present the SUBLEX software as an adaptive tool for calculating sub-lexical frequency measures and discuss possible future applications. The measures and the software can be downloaded at http://www.psychonomic.org.

Introduction

Recent studies demonstrate the influence of sub-lexical units on language processing (Nuerk, Rey, Graf, & Jacobs, 2000; Ziegler & Goswami, 2005). Not only behavioral and neurocognitive findings in proficient adult readers, but also findings in subjects with acquired or developmental language disorders indicate the relevance of sub-lexical measures during language recognition and production.

However, to our knowledge, in contrast to word frequency measures (Baayen et al., 1995; Geyken, 2007; http://www.wortschatz.uni-leipzig.de) sub-lexical unit frequency measures are not yet publicly available for the German language. For other languages, at least syllable frequency measures are available (Alameda & Cuetos, 1995, and Davis & Perea, 2005, for Spanish; Stella, & Job, 2001, for Italian; Goslin & Frauenfelder, 2000, New, Pallier, Brysbaert, & Ferrand, 2004, and http://www.lexique.org, for French; and Leung, Law, & Fung, 2004, for Chinese). Inspired by the fact that the grain size of sub-lexical measures is the core topic of a recent developmental theory of skilled reading and dyslexia across languages (Goswami & Ziegler, 2006), we found it useful to calculate sub-lexical frequency measures with a systematic decrease in grain size. This study thus provides orthographic and phonological syllable, dual unit (bigram and biphoneme), and single unit (letter and phoneme) type and token frequency measures, derived from the lemma and word form databases of the German CELEX lexical database (Baayen et al., 1995).

By providing highly comparable measures that were calculated by the same algorithm, we hope to inspire researchers to investigate questions that are difficult to address without these measures. Moreover, we provide further independent and control variables for researchers that investigate language processing. we start with a short overview of the fields of research in which the role of sub-lexical units was recently

investigated, and draw particular attention to connectionist models that can account for these hypothetical levels of representation.

For that purpose we outline empirical and theoretical contributions to the research fields of word recognition and naming in proficient readers, as well as of acquired and developmental language disorders. Since most of the recent studies within those fields investigate syllable frequency effects, we focus on these sub-lexical effects.

Carreiras, Alvarez, and De Vega (1993) showed that syllable frequency plays a significant role during visual word recognition. They found that words with high frequency initial syllables take more time to be processed than words with low frequency syllables. This finding led to the hypothesis that syllables activate competing lexical candidates during lexical access. The processing delay due to syllable frequency was interpreted as interference of other lexical candidates activated by the target's syllabic units. Perea and Carreiras (1998) provided evidence that higher frequency syllabic neighbors are the source of this inhibitory syllable frequency effect. These initial findings from the Spanish language were replicated in French (Conrad, Grainger, & Jacobs, 2007; Mathey & Zagar, 2002) and German (Conrad & Jacobs, 2004).

Whereas the effect of syllable frequency was always inhibitory in tasks requiring lexical access such as lexical decision or perceptual identification (Conrad & Jacobs, 2004), it has been described to be either facilitative (Perea & Carreiras, 1998) or inhibitory (Carreiras et al., 1993; Conrad, Stenneken, & Jacobs, 2006) in the naming task.

Further evidence for the relevance of syllabic processing in naming and word recognition comes from eye movement measures (Carreiras & Perea, 2004; Hutzler, Conrad, & Jacobs, 2005) and electrophysiological findings (Barber, Vergara, & Carreiras, 2004; Hutzler et al., 2004).

The electrophysiological findings shed light on the neurocognitive processes involved in sub-lexical unit processing in proficient readers. It should be noted that

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behavioral findings are also able to contribute to the knowledge about the neuropsychology of sub-lexical word processing. That is, for instance, when acquired impairments of written (Stenneken, Conrad, Hutzler, Braun, & Jacobs, 2005) or spoken (Aichert & Ziegler, 2004; Laganaro, 2005; Stenneken, Bastiaanse, Huber, & Jacobs, 2005; Stenneken, Hofmann, & Jacobs, 2005) language are compared to unimpaired functioning.

Conrad and Jacobs (2004), as well as Hutzler et al. (2004) pointed out that the syllable frequency effect provides a challenge to future computational models of word recognition, as no current model is able to account for these findings, because of the lack of data on syllabic units (Coltheart et al., 2001; Grainger & Jacobs, 1996; Jacobs et al., 2003; Jacobs et al., 1998; Ziegler, Perry, & Coltheart, 2003; Zorzi et al., 1998; but see Ans, Carbonnel, & Valdois, 1998). In contrast, the language production literature has provided one computational model (Levelt, Roelofs, & Meyer, 1999) that could account for syllable frequency effects (Cholin, Levelt, & Schiller, 2006). Levelt et al.'s (1999) model proposed that syllabic processing follows lexical selection that can be associated with lexical access. Thus, it is not fully applicable to the field of word recognition in which sub-lexical processes also precede lexical access (Hutzler et al., 2004).

In contrast to the syllabic level of representation, smaller sized unit frequency effects have been addressed by connectionist models of word recognition and have been discussed as two of the multiple levels of representation (Grainger & Jacobs, 1993,1996; Jacobs et al., 1998; Massaro & Cohen, 1994; Nuerk et al., 2000).

Much as for syllabic processing in proficient readers, there is also no computational model that could provide quantitative predictions concerning impaired syllabic processing. However, there is a pre-quantitative theory that allows for describing the proficient and impaired development of sub-lexical representations in different languages.

Ziegler and Goswami's (2005) grain size theory emphasized the relevance of these multiple levels of sub-lexical unit representations for the research and treatment of dyslexia. One of the core notions of this theory is the problem of granularity. That is, the larger the sub-lexical units are the more of them exist. With regard to reading performance, the most economic strategy with the lowest memory effort would therefore be to link graphemes to phonemes, because for reading acquisition it is necessary to assign a phonological representation to a printed word. In the German language this is a suitable reading strategy, since graphemes usually map to only one phoneme[3] (Goswami, Ziegler, Dalton, & Schneider, 2003; Jacobs, 2002; Jacobs & Graf, 2005).

However, in languages with more inconsistent GPCs larger units may be more suitable for reading acquisition. In some languages such as English this inconsistency consists mainly of the fact that graphemes can be spelled in multiple ways (i.e., feedforward inconsistency; Ziegler, Stone, & Jacobs, 1997). In other languages, such as French, the main source of inconsistency consists of the fact that phonemes can be written in multiple ways (i.e., feedbackward inconsistency; Ziegler, Jacobs, & Stone, 1996).

The development of lexical and sub-lexical representations during language acquisition can be opposed to the most economic reading acquisition strategy, at which the use of the smallest grain size appears to be most suitable. The word level representation is learned first, a syllabic representation develops usually at the age of four to five, and the representation of graphemes and phonemes develops not until reading acquisition (Ziegler & Goswami, 2005).

The differential development of grain size representations during language and reading acquisition, as well as language specific factors that determine the most economic grain size usage strategies suggest that the question "Is there a need to

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[3] There are exceptions such as terminal devoicing and the fact that there is often no orthographic differentiation between short or long spoken vowels.

control for sub-lexical frequencies?" (Aichert & Ziegler, 2005) has to be answered positively.

The measures of the present study could be used to build models that can make quantitative predictions concerning sub-lexical processes during impaired or unimpaired language processing.

Grain sizes, domains, databases, and measures

The multiple grain size theory emphasizes the importance of multiple grain sizes when written words have to be mapped to phonology. The next logical step is to provide the frequencies at different grain size levels - syllables, dual units, and single units - in order to be able to address the question to what degree readers differ with respect to the reliance on different grain size units during language processing.

These three different grain size frequencies can be calculated for different domains (orthographic vs. phonological), different basic databases (word form vs. lemma), and as type and token measures. Earlier studies either were based on a subset of the frequency tables presented in the present study, or provided only incomplete information about these different possibilities to calculate frequency measures. Moreover, when predictive properties of different similar measures have to be assessed, it seems reasonable to calculate all measures in a comparable way by the same algorithm.

The present study demonstrates the diversity of ways to calculate sub-lexical frequency measures. However, when a researcher finally has to choose which of the proposed frequency measures to use, several issues should be considered concerning grain sizes (syllable, dual unit and single unit), processing domains (orthographic or phonological), databases (lemma or word form), and type or token measures.

In the following paragraphs, we describe studies that compared the respective influences of different grain sizes on language processing. In addition, we discuss which database, domain or measure should be used for what type of study. These sections can be used as a guide when decisions for particular frequency tables have to be made.

Grain sizes: Syllable, dual unit, or single unit

A reliable inhibitory effect of the first syllables' frequency on lexical decisions was found reliable when bigram frequency was held constant (Conrad, Carreiras, Tamm, & Jacobs, 2009; Conrad et al., 2007). Given recent evidence that the syllable frequency effect in speech production (Cholin et al., 2006) and lexical decision (Conrad et al., 2007) is based on the phonological syllable, biphoneme frequency might be an interesting control variable for further research. In the orthographic domain, there is evidence for a facilitatory bigram frequency effect during lexical decision (Massaro & Cohen, 1994), even when syllable frequency was controlled for (Conrad et al., 2009). Moreover, Grainger and Jacobs (1993) demonstrated that letter and bigram priming effects during lexical decision are greater when units occurred at the same position within the prime and the target.

In addition to the question of the frequency of sub-lexical units, a controversy in the literature concerns the number of phonemes and syllables, during language production tasks (see Martin, 2004; see Nickels & Howard, 2004a; see Nickels & Howard, 2004b). Nickels and Howard (2004a) obtained no syllable frequency effect in word production accuracy of aphasics that would have been independent of word imageability, word frequency, and the number of phonemes and clusters. Instead, they found evidence that "It's the number of phonemes that counts." They raised the controversial issue that phonemes are the most important units of speech production,

and that effects of the phonological syllable could be attributed to confounding variables.

Aichert and Ziegler's (2004) results neither confirmed nor contradicted this interpretation, because their word repetition experiment reporting syllable frequency effects in patients with apraxia of speech did not control for phoneme frequency. However, they confirmed the prediction of Varley and Whiteside (2001) that at the phonetic encoding level (Levelt et al., 1999) motor programs are provided for high frequency syllables.

Stenneken et al. (2005) reported that the phonemic jargon of an aphasic patient provided a higher correlation with phoneme frequency than with syllable frequency measures. Again, these results neither contradicted nor confirmed Nickels and Howard's (2004a) hypothesis. The grain size theory (Ziegler & Goswami, 2005) presumably suggests that the relative influence exerted by particular grain sizes depends on individual differences.

Laganaro (2005) found evidence for this. First, she found that three out of seven aphasics showed an effect of syllable frequency on substitution errors. In two of them this effect was independent of phoneme frequency. Second, two of the aphasic subjects showed more correct responses for nonwords composed of high frequency syllables than for nonwords composed of low frequency syllables. Third, she investigated the phonemic paraphasias of one aphasic subject and found that syllable frequency influenced error rates.

In accordance with the grain size theory we propose not to neglect any grain size measure, at least when assessing language disorders. When word recognition studies are conducted, at least syllable frequency and bigram frequency may be controlled for, if possible. An independent effect of smaller sub-lexical measures should be evaluated to test the predictions of the grain size theory. This can be done during stimulus generation

by controlling or manipulating variables, or by applying multiple regression methods in a post hoc fashion.

Processing domains: Orthography or phonology

When choosing between the orthographic and phonological domain one could suppose that written language performance can be assessed best by referring to orthographic frequency measures, and spoken language performance by phonological measures. However, particularly with regard to reading, this might be the most interesting and most controversial issue. Whereas Seidenberg (1985) claimed that phonology is not necessary for reading, Van Orden's (1987) article "a rows is a rose" presented strong arguments in favor of the notion that phonological representations are automatically and always activated during silent reading. Today, there seems to be a broad agreement that multiple codes are activated during reading, in particular phonological codes (Ans et al., 1998; Jacobs et al., 1998; Yates, 2005; Ziegler et al., 1997), at different grain size levels (Goswami & Ziegler, 2006; Ziegler & Goswami, 2005). Conrad et al. (2007) suggested that, during word recognition, it is the phonological syllable, not the orthographic syllable that drives the syllable frequency effect. This issue was investigated in a deep orthography with rather inconsistent GPC (Liberman, Liberman, Mattingly, & Shankweiler, 1980), because in shallow orthographies phonological syllable frequency is confounded with orthographic syllable frequency. In this context the question arises whether the primacy of the phonological syllable can be generalized to shallow orthographies like German, too.

This question can be addressed by using regression methods in order to find out which type of syllable frequency is most predictive. Experiments using an orthogonal design, and thus manipulating orthographic and phonological syllable frequency independently, can hardly be realized in a shallow orthography. Today, it is well

accepted that a proficient reader in a language having a deep orthography can hardly avoid phonological processing when exposed to letter strings (e.g., Sumiya & Healy, 2004). When investigating spoken language, the question arises whether highly overlearned orthographic representations of a letter string are also activated (Ziegler & Ferrand, 1998; Ziegler, Ferrand, & Montant, 2004). If one is not interested in addressing this particular question, we suggest that the phonological domain's frequencies are used when investigating spoken language. When dealing with questions concerning reading, this choice is much more difficult. However, the aforementioned findings suggest that using the frequencies of phonological units are as plausible as using the frequencies of orthographic units when conducting word recognition experiments.

Databases: Lemma or word form

CELEX (Baayen et al., 1995) provides a lemma and a word form database. The lemma database provides words in its basic form – that is, nouns are presented in nominative singulars and verbs are presented in infinitives. In contrast, the inflected forms are provided in the word form database. Most psycholinguistic studies use the lemma database. Duyck, Desmet, Verbeke, and Brysbaert (2004) provided "WordGen," a stimulus selection tool for psycholinguistic research. The authors argued (Duyck et al., 2004, p. 490) that they used the lemma database of CELEX, because extensive manual coding and disambiguation made the lemma database more transparent with respect to its records than the word form database. Moreover, they argued that word forms partly activate its corresponding lemma entry in the mental lexicon (Baayen, Dijkstra, & Schreuder, 1997; New et al., 2004). On the one hand, we agree with these arguments, in particular because Levelt et al.'s (1999) influential model proposed the fast and automatic activation of lemmas during word form processing. On the other hand, we suggest that lemma measures systematically over- or underestimate the frequency of

sub-lexical units that occur in inflective morphemes, an issue that will be demonstrated on the basis of the results of this study. Using word form measures not only allows for evaluating language in its natural form, but it is of particular interest when, for example, sentence processing tasks are used. Thus, the choice for a certain database should be based on the task and the theoretical assumptions of a particular study.

Measures: Type or token

The type measure indicates the number of words that contain the specific grain size. For example, the type frequency of the bigram "ba" denotes the number of words that contain this bigram. The token frequency, in contrast, denotes the summed frequencies of the words that contain "ba". Conrad, Carreiras, and Jacobs (2008) showed that it was the token measure of syllable frequency that appears to be responsible for the inhibitory effect of syllable frequency in lexical decision. However, the authors argued that the type measure of syllable frequency led to faster RTs especially when the number of higher frequency syllabic neighbors was controlled for.

Novick and Sherman (2004) provided two reasons for using type measures. They argued that token frequency is confounded to a large degree with word frequency, and found that type bigram frequency was a better predictor for performance in anagram resolution. However, Bailey and Hahn (2001) found that wordlikeness judgments are a function of the token frequency of lexical neighbors. It should be noted that there is a controversial debate about the general impact of type and token measures in the current literature. Many of the contributions to this debate describe sub-lexical, but neither syllabic, nor dual unit or single unit influences on language processing. De Jong, Schreuder, and Baayen (2000) found evidence that it was the type frequency of a word's root morpheme that influences RTs in lexical decision in Dutch.

Eddington (2004) found that type frequency is a better predictor than token frequency while simulating correct outcomes of Spanish stress assignment and English past tense formation. When participants had to produce a past tense ending for pseudoverbs and verbs in Dutch they completed the words with endings of a higher type frequency (Ernestus & Baayen, 2003). In contrast, there was an effect of token frequency in the same paradigm (Ernestus & Baayen, 2001). To resolve the whole controversy, Clahsen (1999) proposed a dual route system that explains type-based analogical effects by a symbolic rule application mechanism, and token-based effects by an associative memory store. Others question the necessity of separate type- and token-sensitive mechanisms by use of connectionist models showing that the differential effects can be reduced to a single token-based mechanism (Moscoso del Prado Martín, Ernestus, & Baayen, 2004; Moscoso del Prado Martín, Kostic, & Baayen, 2004). The decision for one of the measures should be based on previous research working with comparable paradigms.

Useful contributions to this controversy would be to conduct a regression analysis with type and token measures as predictors, to find out which measure is most predictive, or, to manipulate type and token measures independently. In any case, on the basis of empirical studies that compared different grain size units systematically the choice for particular frequency measures should be made. The measures of the present study offer the possibility to unconfound a large amount of variables that potentially pose a problem in interpreting results of recent studies. For example, experiments can be designed that manipulate phoneme frequency while keeping syllable frequency constant. It might help to systematically manipulate the (and only the) variables of interest. Even when investigating whole word effects, for example the emotional valence of words (e.g., Kuchinke et al., 2005), the sub-lexical measures of the present study can be used to rule out the possibility that these effects might be due to the confound between sub-lexical measures and emotional valence.

When a researcher has to choose which of the frequency measures to use, in accordance with the grain size theory (Ziegler & Goswami, 2005) we would suggest neither to neglect the syllabic, nor the dual unit nor the single unit grain size level, if possible. The phonological domain's frequency measures can be used, not only during the assessment of spoken language, but also while assessing written language, as suggested by the multiple code activation hypothesis (Jacobs et al., 1998).

Furthermore, we suggest using word form measures in particular when assessing language as it occurs in its natural inflected form (e.g., in sentences or connected speech). Levelt et al.'s (1999) hypothesis of the automatic activation of lemma entries during word form processing also suggests using frequencies of the lemma database. One reason (see Duyck et al., 2004) to use lemma measures in particular when assessing noninflected language may be the extensive manual coding and disambiguation within the lemma database of the CELEX lexical database (Baayen et al., 1995). When deciding whether to use either the type or the token measures, the decision should be based on prior research working with the same experimental paradigms.

A better solution might be to contribute to the controversy of type vs. token measures by taking into account both of them. This could be helpful, as long as the reduction to a token based mechanism (Moscoso del Prado Martín, Ernestus et al., 2004; Moscoso del Prado Martín, Kostic et al., 2004) has not been broadly accepted.

Method

All measures were calculated using shell scripts, PERL scripts, and the free UNIX programs join, sort and wc. Thus all software used for the present study ran under a free licence. A Macintosh G4 computer was used running a free BSD under Mac Os X

10.3.9, as the native operating system of the SUBLEX-software[4]. However, SUBLEX should run on every UNIX or LINUX shell running with an ISO Latin 9 character set.

Each step of calculation can be adapted flexibly, for example to calculate case-sensitive measures (see README.txt). At this point we will give an overview about all processing steps and provide the results when the program is executed without modifications. The program and the resulting frequency measures can be downloaded at http://www.psychonomic.org.

The sub-lexical measures were derived from the German orthographic lemmas, the German phonological lemmas, the German orthographic word forms, and the German phonological word forms of the CELEX lexical database (Baayen et al., 1995).

Words with acute accents (/#/) were identified as foreign words from the orthographic lemma and word form databases, and excluded from analysis. The phonological transcription of the CELEX[5] was used to exclude words that contained a phoneme occurring only in other languages than German. Words that contained a /ˉ/, an /A/, a /Z/, an /O:/, an /3:/, a /w/, or a /V/ were excluded from analyses. All words that contained a shortly pronounced /e/ or /&/ were excluded from analyses. Additionally, the orthographic and phonological syllable number of each entry was compared. In order to exclude foreign words and errors of the phonological transcription, entries with different orthographic and phonological syllable numbers were excluded from analysis. 51,207 words remained in the lemma database for analysis.

The 363,013 entries of the adjusted word form database consisted of words and phrases (e.g., "bestelltest ab"). Phrases in which the number of words differed in the orthographic and phonological notation were excluded from analysis. The words of a phrase were processed as separate words, with the respective word frequency of the whole phrase. 44,033 phrases consisted of 2 words and 315 phrases consisted of 3 words. After foreign words have been excluded from analysis, 407,676 words remained

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[4] The program is distributed under a free GNU-licence.

[5] The syllabified phonological headwords in the CELEX charset.

in the adjusted word form database. For the calculation of all phonological sub-lexical measures long vowels (/a:/, /E:/, /e:/, /i:/, /o:/, /u:/, /y:/, and /&:/) were treated differently from short vowels (/a/, /E/, /e/, /i/, /o/, /u/, and /y/). When one wants to neglect this distinction, long and short vowel frequencies can be summed post hoc. To calculate the phonological syllable frequencies, ambisyllabic consonants were attributed to both syllables. All uppercase letters were converted to lowercase, to obtain case insensitive frequencies. The resulting type frequency measures indicate the number of times a sub-lexical unit occurs in the respective CELEX database. The token measures refer to the sum of the CELEX's Mannheim frequency of the lexical entries that contained this particular unit. Token frequency measures are given in occurrence per 6 million.

Results

The complete syllable, dual unit (bigram and biphoneme) and single unit (letter and phoneme) type and token frequency measures that were calculated for different domains (orthographic vs. phonological) and different basic databases (word form vs. lemma) are available at http://www.psychonomic.org (see README.txt for the nomenclature of the files). Here, we will illustrate the findings by providing the most frequent sub-lexical units.

For syllable and dual unit frequencies we will additionally provide the number and one example of the most rare sub-lexical units, respectively. For single unit frequencies, we describe the rarest letters and phonemes.

Syllable frequencies of the lemma database

A total of 6,023 different orthographic and 5,679 different phonological syllables were extracted from the 163,099 orthographic and phonological syllables of the lemma database.

The orthographic and phonological syllable with the highest type frequency was "ge" and /g@/. It occurred in 3,076 orthographic and 2,561 phonological words. The derivative affixes "ver" (/fEr/) and "be" (/b@/) were the only other syllables that occurred in more than 2,000 orthographic and phonological words. There were 1,529 orthographic and 1,315 phonological syllables that occurred in only one word (e.g., the free morpheme "auch" or /aux/ was never a syllable of another word than itself).

The orthographic and phonological syllable with the highest token frequency was "der" (/de:r/). The summed frequency of all words that contained this syllable was 703,722 orthographically and 660,055 phonologically.

The only syllables with an orthographic and phonological token frequency larger than 150,000 was "und," while "ge" exceeded this criterion only orthographically. There were 843 orthographic and 724 phonological syllables that occurred only in words with a CELEX word frequency of zero (e.g., "sext" and /zEkst/ occurred only in words like Sextakkord, /zEkstakOrt/).

Syllable frequencies of the word form database

A total of 11,731 orthographic syllables and 10,772 different phonological syllables were derived from the 1,285,294 syllables of the word form database. Again, "ge" and /g@/ were the syllables with the highest type frequency (orthographic: 35,743, phonological: 30,585). The only other phonological syllables that occurred in more than 20,000 words were /t@n/ and /t@/.

Orthographically, "te" reached this criterion and "ten" marginally missed it with a frequency of 19,691. There were 2,231 orthographic and 1,837 phonological syllables that occurred only in one word (e.g., /o:l/ from /Spani:o:l/, Spaniol; "auch" see above).

Again, "der" had the highest orthographic token frequency and /de:r/ had the second highest (orthographic: 269,011, phonological: 219,912). The word with the highest phonological token frequency and the second highest orthographic token frequency was /di:/ ("die") with a summed frequency of 240,694, orthographically, and 249,273 phonologically. There were 4,470 orthographic and 3,841 phonological syllables that occurred only in words with a frequency of zero (e.g., /E:rst/ from /fami:li:E:rst/, familiärst, or "brückst" from "überbrückst").

Dual unit frequencies of the lemma database

A total of 710 different bigrams and 979 different biphonemes were derived from the 453,770 bigrams and 411,358 biphonemes of the lemma database. The bigram with the highest type frequency was "er" (17,315), followed by "en" and "ch" as the only bigrams that occurred in more than 10,000 words. There were only 27 bigrams that occurred in only one word (e.g., "gc" from "Spängchen"). The biphoneme that occurred in the largest number of words (13,756) was /@n/, followed by /@r/ as the only other biphoneme that occurred in more than 9,000 words. There were 47 biphonemes that occurred in only one word (e.g., /zv/ from /SErzvaiz@/, scherzweise).

The bigram with the highest token frequency was "er," too (summed frequency of 1,487,559). "en" was the only other bigram with a token frequency higher than 1,000,000. There were 20 bigrams that occurred only in words with a frequency of zero (e.g., "vl" from "Frevler"). The biphoneme with the highest token frequency (896,914) was /@n/. The only other biphoneme that had a higher token frequency than 80,000

was /e:r/. There were 29 biphonemes that only occurred in words with a frequency of zero (e.g., /E:h/, /zE:hait/, Zäheit).

Dual unit frequencies of the word form database

A total of 721 different bigrams and 993 different biphonemes were derived from the 3,579,388 bigrams and 3,273,332 biphonemes of the word form database. Again, the bigram with the highest type frequency (160,582) was "er." The bigrams "ch," "st," "en," and "te" occurred in more than 100,000 words. Three bigrams occurred only in one word (e.g., "cc" from "staccato"). The biphoneme that occurred in the largest number of words (121,822) was /t@/, followed by /@n/ as the only other biphoneme occurring in more than 100,000 words. 13 biphonemes occurred only in one word (e.g., /io:/, see above).

The bigram with the highest token frequency (1,048,911) was "en." The only other bigram that had a higher token frequency than 1,000,000 was "er," 26 bigrams occurred only in words with a frequency of zero (e.g., "cc," see above). The biphoneme with the highest token frequency (841,141) was /@n/. /ai/ was the only other biphoneme exceeding the 500,000 token frequency threshold. 35 biphonemes occurred only in words with a frequency of zero (e.g., /E:h/, see above).

Single unit frequencies of the lemma database

Thirty different letters and 38 different phonemes were derived from the 505,028 letters and 462,613 phonemes of the lemma database. The letter with the highest type frequency was "e" (69,860). The only other letters that occurred in more words than 40,000 were "n" and "r." The letters "q," "x," "j" and "y" occurred in less than 1,000 words. The phoneme that occurred in the largest amount of words (40,725) was /t/,followed

by /r/, /n/, /@/, and /a/ which exceeded the 30,000 words threshold. The only phonemes that occurred in less than 1,000 words were /j/ and /Q/.

The letter with the highest token frequency was "e" (4,411,788). The only letters that exceeded the token frequency threshold of 2,000,000 were "n" and "r." The letters "q," "x," and "y" had a token frequency below 10,000. The phoneme with the highest token frequency was /n/ (2,545,874). The only other phoneme that exceeded the 2,000,000 threshold was /r/. The phonemes with the lowest token frequency were /&:/ and /Q/, that had a token frequency below 50,000.

Single unit frequencies of the word form database

Again, 30 different letters and 38 different phonemes were derived from the 3,987,164 letters and 3,681,103 phonemes of the word form database.

The letter with the highest type frequency was "e" (663,642). The letters "t," "s," and "r" occurred in more words than 300,000. The only letters that occurred in less words than 10,000 were "q," "j," "x" and "y." The phoneme that occurred in the largest amount (431,585) of words was /@/. The only other phoneme occurring in more words than 400,000 was /t/. The phonemes /j/, /Q/and /&:/ occurred in less than 10,000 words.

Again, the letter with the highest token frequency (4,595,079) was "e." Letters that had a higher token frequency than 2,000,000 were "n," "l," and "r." The only letters that had a token frequency lower than 10,000 were "q,", "x," and "y." The phoneme with the highest token frequency was /n/ (2,504,247). The only other phonemes with a token frequency higher than 2,000,000 were /@/and /t/. The only phonemes with a token frequency lower than 100,000 were /Q/, /&:/, /Y/, /E:/, /y/, and /j/.

In German, most phonemes correspond to one letter. However, there are a few two-letter units (e.g., ch, ck). These frequency counts can be derived from the respective frequency lists at http://www.psychonomic.org. In order to allow for the

assessment of the frequencies of all German graphemes, we also provide the frequency of the only three-letter grapheme here: "sch." The type frequency of "sch" was 7,082 in the lemma corpus, and 54,270 in the word form corpus. The token frequency was 228,422 in the lemma corpus and 228,414 in the word form corpus.

Discussion

Whereas earlier studies assessed sub-lexical frequency effects based on lemma corpora (e.g., Conrad & Jacobs, 2004), or did not specify from which corpus the measures were derived, the present study provides also sub-lexical frequency measures derived from the German word form corpora (Baayen et al., 1995). Hence, sentence-level studies can be conducted avoiding the systematic over- or underestimation of syllable frequencies that determine the inflection of a word that would result from using the lemma database. For example, the word form "wird" contributes to the lemma frequency of the word "werden," and thus the frequency measures of syllables "wer" and "den" are systematically overestimated. On the other hand, underestimations can occur, for example, in syllables that correspond to inflective morphemes. Thus, the syllables "ten" (/t@n/) and "te" (/t@/) that correspond to the German past tense inflective morphemes, are much more frequent in the word form than in the lemma database.

All syllabic level analyses provided more orthographic than phonological syllables. This pattern of results shows that the German language is more feedbackward than feedforward inconsistent (Stone, Vanhoy, & Van Orden, 1997; Ziegler et al., 1996; Ziegler et al., 1997). Phonological syllables necessarily must be written in different ways to generate this number relation. One source of this inconsistency in German is the fact that there is often no orthographic difference

between vowels that are pronounced long or short, e.g., the orthographic syllable "ol" corresponds to one phonological syllable when it is pronounced long (/o:l/), and to 17 words when it is pronounced short (/ol/). The calculation of such inconsistencies is one example of additional measures that can be derived from the CELEX lexical database by making small modifications to the SUBLEX software.

When it comes to smaller sub-lexical units, not only the summed positional bigram measures can be derived from the data of the present study (see Duyck et al., 2004), but also the mean bigram frequency of a word which is not confounded with word length. Additionally, the present study provides the first online database of biphoneme measures.

Once phoneme and syllable frequency measures are available in this way, every study that investigates the processing of word stimuli can, in principle, contribute to Nickels and Howard's (2004a) controversy (see above) that raised the question whether syllable frequency has an influence that is independent of phoneme frequency. This can be done either by controlling for either of both variables, or by evaluating the independence of effects by applying multiple regression methods. All measures are now provided by one study, and were calculated by the same algorithm. Thus, it is now possible to compare the relative influences of each measure in different tasks. It also becomes possible to evaluate which group of subjects is sensitive to what degree to which sub-lexical measure in which task. The present study has provided the basic data to meet Aichert and Ziegler's (2005) call for controlling sub-lexical measures. Systematic comparisons between syllable, dual unit and single unit measures, between the orthographic and the phonological domain, between type and token measures, as well as between measures derived from the lemma and word form database are now possible. It is well known that the larger the grain size, the more units exist (Ziegler & Goswami, 2005). Now, concrete numbers are available for German. The CELEX lexical database (Baayen et al., 1995) consists of 10,722 syllables, 979 biphonemes and 38

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phonemes, derived from the German words of the CELEX word form corpus. According to CELEX, German written texts contain 11,731 syllables, 710 bigrams, and 30 letters.

It should be noted that the present study neglected positional frequency measures (in contrast to Massaro & Cohen's, 1994, approach to bigram frequency, for instance), and concentrated on non-positional measures (as e.g. Duyck et al., 2004). The grain size units were counted irrespective of the position in a word. The question which of both measures reflects the processing of a stimulus best has not yet been answered to our knowledge. Position specificity is a matter of debate in the current literature that has more than these two solutions (see Dehaene, Cohen, Sigman, & Vinkier, 2005; Goswami & Ziegler, 2006; Grainger & Whitney, 2004). For example, relative positions within a word might be another suitable concept (Peressotti & Grainger, 1999). Thus, we decided to neglect position specificity for the present purposes.

To find out how sub-lexical frequency measures can be applied to the diagnosis of language skills, Seidenberg's (1987) principle of orthographic redundancy can be used in a developmental perspective of reading or language abilities in general (Seidenberg & McClelland, 1989). Not all orthographic patterns are equally frequent. Thus, orthographic patterns that occur very rarely are less likely to be recognized than high frequency patterns. we propose that the present studies' frequency measures can be used to determine the relative reliance on particular grain sizes during reading or speaking of an individual. By manipulating each grain size and holding the respective other grain sizes constant, a certain frequency for each grain size and participant can be obtained. Hypothetically, units above these diagnostically relevant frequencies are processed correctly, in contrast to units below that frequency.

By knowing the relative strengths of an impaired reader during the processing of a particular grain size, compensational strategies can be taught to generalize from the

relatively impaired grain sizes to other grain sizes, if proficient reading is correctly characterized by the activation of multiple grain sizes (Ziegler & Goswami, 2005).

Another therapeutic approach deals with the fact that small units are learned by finding the differences between large units (Ziegler & Goswami, 2005). For instance, by naming the common phoneme in the words /pa:t@/ and /kOst/ a reader can gain a cognitive representation of the phoneme /t/. On the basis of the present analysis therapeutic strategies should initially use high frequency phonemes in unskilled readers that can be learned easier than lower frequent phonemes. The calculation algorithms now being available could be used to calculate these measures for other languages provided by the CELEX lexical database (English and Dutch). Such follow-up analyses could easily be performed by a slightly modified SUBLEX software. Since the grain size theory can also contribute to a cross-linguistic perspective (Ziegler & Goswami, 2005), such follow-up studies would allow for comparing the relative influence of different grain sizes across languages. Ziegler and Goswami (2005) already predicted that in languages with more inconsistent GPC (e.g., English) larger grain size units might be more suitable than in languages with more consistent GPC. Such hypotheses can be tested by use of the materials provided by such follow-up studies. we hope that the SUBLEX software will also be applied to newer corpora of the German language, such as the Web-CELEX (see http://www.mpi.nl/world/celex/), the DWDS corpus (Geyken, 2007), or the German Wortschatz-Project (wortschatz.uni-leipzig.de/).

Study 2: Differential activation of frontal and parietal regions during visual word recognition: An optical topography study

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Abstract

The present study examined cortical oxygenation changes during lexical decision on words and PWs using functional Near-Infrared Spectroscopy (fNIRS). Focal hyperoxygenation as an indicator of functional activation was compared over three target areas over the left hemisphere. A 52-channel Hitachi ETG-4000 was used covering the superior frontal gyrus (SFG), the left inferior parietal gyrus (IPG) and the left inferior frontal gyrus (IFG). To allow for anatomical inference a recently developed probabilistic mapping method was used to determine the most likely anatomic locations of the changes in cortical activation (Tsuzuki et al., 2007).

Subjects made lexical decisions on 50 low and 50 high frequency words and 100 PWs. With respect to the lexicality effect, words elicited a larger focal hyperoxygenation in comparison to PWs in two regions identified as the SFG and left IPG. The SFG

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activation difference was interpreted to reflect decision-related mechanisms according to the MROM (Grainger, & Jacobs, 1996). The greater oxygenation response to words in the left IPG suggests that this region connects orthographic, phonological and semantic representations. A decrease of deoxygenated hemoglobin was observed to low frequency in comparison to high frequency words in a region identified as IFG. This region's sensitivity to word frequency suggests its involvement in grapheme-phoneme conversion, or its role during the selection of pre-activated semantic candidates.

Introduction

During the LDT, participants usually react faster to words than to pseudowords (PW). This was termed the lexicality effect. The other effect within the word-category is demonstrated when RTs to high frequency words are compared to RTs to low frequency words. This word frequency effect indicates a faster processing of common words compared to uncommon words and is the probably most robust finding in the word recognition literature (Jacobs & Grainger, 1994). These behavioral findings were investigated by neuroimaging to identify the different brain areas involved in the task.

The key areas for the lexicality effect are the SFG including the medial and middle frontal gyrus, and the IPG including the angular and supramarginal gyrus. Both regions showed a greater response to words than to PWs during a feature detection task in a PET study (see Price, 2000, Figure 10, second row, reanalysis of Brunswick, McCrory, Price, Frith, & Frith, 1999). Also fMRI studies revealed a larger BOLD contrast in SFG and IPG for words compared to PWs. This was demonstrated in visual lexical decision (Binder et al., 2003; Kuchinke et al., 2005), silent articulation and phonological LDTs (Ischebeck et al., 2004). The latter study made subjects decide on whether or not a presented letter string sounds like a word if read aloud.

Functional-anatomical findings can be interpreted in the light of the MROM (Grainger & Jacobs, 1996; Jacobs et al., 1998, 2003), a computational model of word recognition. Briefly, intra-lexical decision criteria of lexical activation generate a "yes"-response to word stimuli while an extra-lexical temporal threshold mechanism generates a "no"-response to PW stimuli. Fiebach et al. (2007) suggested that the putative role of the SFG lies in executive and control functions. More specifically the SFG, an area involved in decision-related processes, can be assumed to respond differently as a function of which of the two response mechanisms postulated by the

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MROM is active: Thus it can be postulated that the "yes" and the "no" reaction will elicit different neural responses in decision-related brain regions such as the SFG (cf. Price, 2000, p. 353). Generally in line with this model, Ischebeck et al. (2004) argued that SFG activation reflects control functions with regard to retrieval of semantic information from posterior areas (for a review, see Binder et al., 1999). Thus words containing semantic information, elicit larger activations than PWs, because the latter are devoid of semantic content.

IPG, particularly the angular gyrus, has an even longer history as a target area in higher order language processing especially at the hinge between reading, writing and overt language production. More than a century ago Déjerine (1891) associated lesions in the IPG with a syndrome later termed "alexia with agraphia". His patient developed an inability to read and write after an IPG-lesion and concluded that IPG is critical for the 'memory' of the visual word form. Later Geschwind (1965) observed that IPG-lesioned patients are not able to understand words when they are spelt. Therefore he concluded that "It is a region which turns written language into spoken language and vice versa" (Geschwind, 1965, p. 278; cf. Damasio & Damasio, 1983).

Beyond lesion studies the analysis of developmental disorders of reading and writing point at the role of the IPG as a pivot between orthographic and phonological representations. Pugh et al. (2000) provided evidence that dyslexia can be conceived as a disorder of relating print to sound and vice versa, which corresponds to a disruption of the projections between the IPG, and occipital as well as temporal cortical areas (Booth, Burman, Meyer, Gitelman, Parrish, & Marsel Mesulam, 2004; Horwitz, Rumsey, Donohue, 1998; but see Kronbichler, Hutzler, Staffen, Mair, Ladurner, & Wimmer, 2006).

To sum up, IPG can be conceived as a hub mediating the transfer between reading, writing, overt language production and semantic processing. Clinically, Price (2000) has pointed out that patients with an IPG lesion not only show impairments in reading and writing, but also perform poorly on semantic tasks (Hart & Gordon, 1990).

With respect to the word frequency effect the IFG plays a major role since it is more activated in response to low than to high frequency words. An early PET study revealed a non-significant trend using a naming task (Fiez, Balota, Raichle, & Petersent, 1999). Consecutive fMRI research rendered the word frequency effect the probably best-replicated finding of fMRI studies on word recognition. Larger BOLD contrasts in the IFG for low frequency words were reported in a silent articulation (Ischebeck et al., 2004; Kronbichler et al., 2004), a visual (Fiebach et al., 2002, 2003; Carreiras et al., 2006), an auditory (Prabhakaran et al., 2006) and a phonological LDT (Carreiras et al., 2006; Ischebeck et al., 2004; Nakic et al., 2006; Prabhakaran et al., 2006).

The finding of a lesser activation for high frequency words was interpreted according to the dual route model (Coltheart et al., 2001; Fiebach et al., 2002). This model assumes that in low frequency words the so-called assembled route generates a phonological representation applying grapheme-phoneme correspondence rules: For each grapheme the corresponding phoneme is retrieved to generate a phonological representation. On the contrary high frequency words will be mainly processed by the addressed route generating a phonological representation by matching the whole word to the phonological representation. Fiebach et al. (2002) suggested that the predominance of generating a phonological representation by computing grapheme-phoneme correspondences for low frequency words elicits the greater IFG activation.

The present study introduces fNIRS into the field of word recognition, a method assessing changes in cortical oxygenation by applying near-infrared light to measure changes in tissue attenuation. The relative transparency of biological tissue to light in the near infrared spectrum allows for optical tissue spectroscopy in a depth of some centimeters. Applied on the intact skull light-attenuation changes can thus be assessed in the cerebral cortex.

Since oxygenated and deoxygenated hemoglobin have differential absorption spectra (i.e., "colors"), focal cortical hyperoxygenation can be reliably detected. The

physiological basis of this measure of cortical activity is the fact that an increase in regional cerebral blood flow (rCBF) is closely coupled both spatially and temporally to neuronal activity. This so-termed neurovascular coupling is the basis of all modern imaging techniques such as BOLD-contrast fMRI and PET (Villringer & Dirnagl, 1995).

Thus fNIRS results are physiologically comparable to fMRI and PET results. However, its spatial resolution is rather coarse (Obrig & Villringer, 2003). Beyond this shortcoming fNIRS combines a number of features extremely attractive for language research. Being compatible with a natural environment and silent, the method's advantage has been proven in a number of previous studies in language research even in earliest infanthood (Fallgatter, Müller, & Strik, 1998; Herrmann, Walter, Ehlis, & Fallgatter, 2006; Homae, Watanabe, Nakano, Asakawa, & Taga, 2006; Horovitz & Gore, 2004; Noguchi, Takeuchi, & Sakai, 2002; Pena et al., 2003; Taga, Asakawa, Hirasawa, & Konishi, 2003; Wartenburger, Steinbrink, Telkemeyer, Friedrich, Friederici, & Obrig, 2007; Watanabe et al., 1998).

Here we challenge the methodology's potential to explore its versatility and reliability to differentiate activation in the three target areas discussed above (SFG/IPG/IFG). To frame the challenge in a more than descriptive way, we apply a recently developed procedure (Tsuzuki et al., 2007), which projects topographical data based on skull landmarks (e.g., 10-20-system) into a 3D reference frame (MNI space). Though the resulting MNI-coordinates are subject to inter-individual error the procedure allows for a probabilistic reference to cortical areas on the brain's surface.

The study is motivated by the perspective to elucidate the neuronal correlates of word processing not only in adult healthy volunteers, but also to extend the research to patients with neuropsychological deficits, and to link imaging results to developmental studies, by allowing to readily examine the emergence of literacy in children. To our knowledge this is the first fNIRS study attempting to disentangle the functional

specificity of two neighboring areas, i.e., the SFG and the IFG. For this purpose, it was necessary to use the probabilistic mapping method.

Methods

Participants

Twelve right-handed healthy native German speaking subjects participated in the experiment (6 female, mean age 26, ranging from 22 to 30). They were neurologically healthy and did not suffer from any language or speech impairment. Subjects were seated in a comfortable chair in a dimly lit room. The distance from eyes to monitor was about 50 cm.

Materials

The 200 experimental stimuli comprised 100 words and 100 PWs. All stimuli were bisyllabic and consisted of 4 to 7 letters. The number of letters was cross-balanced between words and PWs. The 100 PW stimuli were pronounceable and were generated by stringing together legal syllables (taken from Study 1; Hofmann, Stenneken, Conrad, & Jacobs, 2007).

The words used included 50 low frequency and 50 high frequency nouns. Mean word frequency was 2 per million (SD: 1) for low frequency words (e.g., "Reling" [railing], "Sichel" [sickle]), and 229 per million (SD: 141) for high frequency words (e.g., Vater [father], Sache [matter], Baayen et al., 1995). Word frequency differed significantly (t = 11.4, p ≤ 0.001). The number of letters and number of orthographic neighbors was

balanced across categories. The frequency of the highest frequent neighbor did not differ (t = 0.1).

Type and token mean bigram and letter frequencies were taken from the lemma database of Hofmann et al. (2007) and did not differ across cells (ts ≤ 0.1). To assure that all low frequency words were known to a native German speaker, they were tested in a pre-experiment (10 subjects). These participants did not participate in the main experiment and were instructed to mark words that were not well known to them. This led to the replacement of four words from the initial stimulus list.

Experimental procedure

Participants were instructed to decide whether or not a presented letter string was a meaningful word and to respond by pressing one of two buttons using the index of the respective hand. Since motor responses may contaminate the cerebral activations of interest, half of the participants were instructed to press the left button for words and the right button for PWs, and the other half responded vice versa. Accuracy was emphasized over speed.

The 200 experimental trials were presented in two blocks each containing 100 trials, preceded by 10 practice trials. Stimuli were presented in a pseudo-randomized fashion. Maximally three words or PWs were allowed to be presented consecutively. At the beginning of each trial a fixation cross ("+") was presented. After a randomly varied interval of 500 - 1000 ms the stimulus was presented in white uppercase letters on a black background until a response was given. Then five hash marks ("#####") were presented for 3500 ms, followed by a blank screen for 500 ms. There was no feedback on the response.

Data acquisition

Stimulus presentation and behavioral data acquisition relied on Presentation Software (Windows XP). Stimuli were presented on a 17 inch monitor with a screen refresh rate of 70 Hz.

Cerebral oxygenation changes were sampled at 10 Hz by a Hitachi optical topograph (ETG-4000, Hitachi Medical. Co., Kashiwa, Japan). The system is a continuous wave device which measures changes in attenuation at 2 wavelengths (695 and 830 nm, ± 20 nm) and hence allows for the differentiation of two dynamic absorbers ([oxy-Hb] and [deoxy-Hb]). Lock-in technique is used to differentiate between wavelengths. Equipped with 16 light emitting and 17 detector probes, 52 channels can be measured quasi-simultaneously. Concentration changes in [oxy-Hb] and [deoxy-Hb] were calculated based on a modified Beer-Lambert approach (Cope & Delpy, 1988).

Inter-optode distance was 3 cm. The array of 52 measurement positions (yellow circles Figure 8) covered an area of ~6 × 30 cm. As is illustrated in Figure 8 the probe array was positioned on the subject's head with the medial detector of the lowest optode row corresponding to T3 of the 10-20 system while the lower edge of the probe set was fixed 1 cm above the inion (red circles in Figure 8). For the definition of the 10-20 system (Jasper, 1958) the onsets of the zygomatic bones were defined as preauricular points (cf. Jurcak, Tsuzuki, & Dan, 2007, Figure 9D).

Data analysis

For outlier correction of the behavioral data, each RT deviating more than 2 standard deviations from the subject's mean was excluded from further behavioral analysis.

Event related oxygenation changes were analyzed by means of the General Linear Model (GLM), as proposed by Schroeter et al. (2004). To correct for artifacts due to heartbeat, data were low-pass filtered at 0.6 Hz. For each pairwise comparison, a three predictor model was used. The first pairwise comparison was conducted to assess the lexicality effect. The prediction terms consisted of words, PWs, and behavioral errors, respectively. The second pairwise comparison was conducted to assess the word frequency effect. The prediction terms were, low frequency words, high frequency words, and the third predictor consisted of PWs and behavioral errors. The latter predictors were excluded from statistical analyses, respectively. The predictors for the GLM were generated by convolving a Gaussian function with each event (Plichta, Heinzel, Ehlis, Pauli, & Fallgatter, 2007). To estimate the amplitude of the oxygenation response beta-values for each predictor were calculated by a least squares model fitting procedure maximizing model-to-data fitting (Bullmore et al., 1996). The first and second temporal derivative of each prediction term was included to adapt the onset and dispersion of the model functions to the individual's hemodynamic response. To correct for serial autocorrelated errors resulting from baseline drifts, we fitted a first-order autoregressive process to the error term by the Cochrane-Orcutt procedure (Cochrane & Orcutt, 1949). T-statistics were applied for comparison between response amplitudes. Uncorrected t-values were thresholded at $t \geq 2.2$ ($\alpha = 0.05$, two-tailed). we list all channels surviving partial Bonferroni correction in Table 1. For that purpose, the Dubey/Armitage-Parmar alpha boundary was calculated which includes the mean intercorrelation (IC) between the channels (Sankoh, Huque, & Dubey, 1997). The rationale is that correlated channels must not be treated as independent samples.

Beyond the localization of the oxygenation response we examined the time courses of the changes in [oxy-Hb] and [deoxy-Hb] by averaging all responses to each condition respectively. The second before stimulus presentation was used as baseline.

To assess the relative hemodynamic response increase to words in comparison to PWs, and to low frequency words in comparison to high frequency words, we simply subtracted the responses of the respectively less active conditions (PWs, high frequency words) from the activating conditions (words, low frequency words). Examples of the resulting time courses are given in Figure 9. The rationale to select the examples based on the [deoxy-Hb] changes is largely motivated by the physiological link between the changes in [deoxy-Hb] and BOLD contrast. A focal decrease in paramagnetic [deoxy-Hb] is the strongest constituent of a BOLD contrast increase (e.g., Steinbrink et al., 2006). It was thus our intention to link the present work to the fMRI based imaging literature. To estimate correspondence between channels and cortical topography, Tsuzuki et al.'s (2007) virtual registration method was applied. This method uses structural information from an anatomical database (Jurcak, Okamoto, Singh, & Dan, 2005; Okamoto et al., 2004) to provide estimates of the channel positions in a standardized stereotaxic 3D brain atlas (MNI space; cf. Tsuzuki et al., 2007). It also estimates the spatial uncertainty due to inter-subject variability of the channel locations (freeware available under http://brain.job.affrc.go.jp). The estimated locations were anatomically labeled by means of a Matlab function using anatomical labels from Tzourio-Mazoyer et al.'s (2002) brain atlas. Based on this procedure the following labels for the target regions will be used:

SFG (superior frontal gyrus): left and right medial and middle SFG, and the medial and middle frontal gyrus.

IPG (inferior parietal gyrus): left inferior parietal, angular and the supramarginal gyrus.

IFG (inferior frontal gyrus): includes the left triangular and orbital parts of the IFG.

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Channels most probably located in one of those target regions, were indexed from top to bottom and from left to right (cf. Figure 8, upper row and Table 1).

Results

Behavioral results

There was a significant lexicality effect in RTs ($t = 5.2$; $P \le 0.001$) and error rate ($t = 2.8$; $P \le 0.05$) with a mean RT of 737 ms (SD: 257) for words and of 853 ms (SD: 327) for PW. The mean average error rate was 6.5 (SD: 5.0) for words, and 2.5 (SD: 2.2) for PWs.

A significant effect was also found for word frequency in RTs ($t = 4.0$, $P \le 0.001$) and errors ($t = 3.2$; $P \le 0.01$). Mean RT was 802 ms (SD: 310) for low frequency words, and 682 ms (SD: 216) for high frequency words. Corresponding mean error rates were 5.2 (SD: 4.1) for low and 1.3 (SD: 2.0) for high frequency words. In sum the behavioral results are in line with earlier studies examining behavioral effects of lexicality and word frequency (e.g., Fiebach et al., 2002; Jacobs & Grainger, 1994).

Figure 8: The upper row indicates the channels belonging to the target regions and the probe set definition. The optode between the middle channels of the lowest optode row was positioned at T3. The lower edge of the probe set was positioned 1 cm above the inion. Panel A shows the t-values for all channels in the lexicality contrast (words > PWs), separately for [oxy-Hb] (upper row) and [deoxy-Hb] (lower row). The time course of channels SFG-10 and IPG-4 are given in Figures 3.2A and 3.2B, as indicated by the black and green circles, respectively. Panel B shows the t-values for all channels in the word frequency contrast (low > high), separately for [oxy-Hb] (upper row) and [deoxy-Hb] (lower row). The time course of channel IFG-4 is given in Figure 9C, as indicated by the violet circles. Exact t-values of the significant channels can be examined in Table 1.
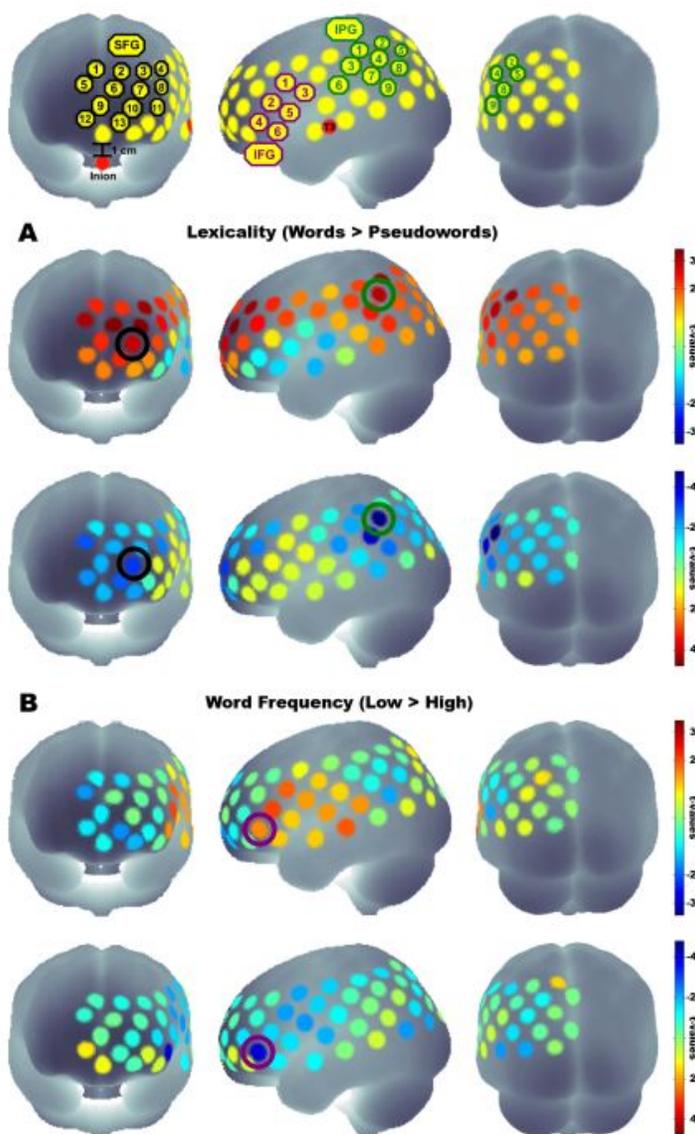
fNIRS (optical topography)

Changes in [oxy-Hb] and [deoxy-Hb] illustrating the effects of lexicality and word frequency, as well as their anatomical location are given in Figure 8 and Table 1.

Concerning the effect of lexicality, eleven channels overlying SFG revealed larger [oxy-Hb] increases to words in comparison to PWs (see Table 1 and Figure 8A). Three of these channels survived the partial Bonferroni correction (ts ≥ 3.2, IC = 0.55). Significant [deoxy-Hb] decreases to words compared to PWs were found in five SFG channels (see Table 1 and Figure 8A).

Four IPG channels revealed a significant [oxy-Hb] increase to words in comparison to PWs. One of these survived partial Bonferroni correction (t ≥ 3.2, IC = 0.55, see Figure 8A and Table 1). Five IPG channels revealed a significant [deoxy-Hb] effect. Two of these survived partial Bonferroni correction (ts ≥ 4.0; IC = 0.20).

Concerning the effect of word frequency, no significant [oxy-Hb] changes were obtained (maximal t = 2.1, P = 0.06 at channel IFG-2, see Table 1 and Figure 8B). Significant [deoxy-Hb] decreases were found in two IFG channels. One of these survived partial Bonferroni correction (t ≥ 4.0, IC = 0.18). Beyond the statistical comparison between conditions we also examined the time course of the oxygenation responses. Figure 9 provides examples for the cortical target regions. For the selection of the example channels we chose those channels in the target regions, which showed the most significant decrease in [deoxy-Hb]. The rationale to select these channels based on [deoxy-Hb] changes is twofold: (i) the signal of the most widely used functional imaging technique, BOLD-contrast fMRI, relies on changes in focal susceptibility elicited by decreases in [deoxy-Hb] (Ogawa, Lee, Nayak, & Glynn, 1990). Thus we consider [deoxy-Hb] changes the best parameter to link the present data to the existing imaging literature (Kleinschmidt et al., 1996; Steinbrink et al., 2006). (ii) The fine-tuned regulation of blood flow velocity and blood volume changes (e.g., Buxton,

Wong, & Frank, 1998) is specific to the cerebral vasculature. This may explain, why [oxy-Hb] changes are more sensitive to extracerebral contamination as has been demonstrated in an experiment using a simple motor paradigm (Boden, Obrig, Koehnke, Benav, Koch, & Steinbrink, 2007).

The time course of the hemodynamic response of channel SFG-10 anatomically corresponding to the left SFG (x/y/z: -23/68/8 in MNI space) is provided by Figure 9A. The differential response (i.e., response to words minus response to PW) demonstrates that the response pattern is in line with previous publications showing a decrease in [deoxy-Hb] accompanied by a larger increase in [oxy-Hb]. A similar difference was seen over the IPG for this comparison (words vs. PWs). Figure 9B illustrates the differential time course in this region (IPG-4; x/y/z: -47/-52/47 in MNI space). Finally, an example for the comparison between low versus high frequency words is given in Figure 9C. Here the response to high frequency words was subtracted from that to low frequency words. Again a stronger increase in [oxy-Hb] and a more pronounced decrease in [deoxy-Hb] is clearly seen to low frequency words in this region corresponding to left IFG (IFG-4; x/y/z: 35/-52/-3 in MNI space). The response pattern seen over all three channels is explicable by an increase in blood volume and a faster washout of [deoxy-Hb], the latter corresponding to an increase in BOLD-contrast (Kleinschmidt et al., 1996). Hence the present findings show greater activations for words (vs. PW) over the left SFG and IPG, while a larger activation over the left IFG is found for low frequency when compared to high frequency words.

Table 1: Channel t-values within the regions of interest

Channel	MNI space correspondence				t-values	
	X	Y	Z	SD	[oxy-Hb]	[deoxy-Hb]
Lexicality (Word >Pseudoword)						
SFG						
1	6	59	37	11	2.4*	− 1.4
2	− 15	59	35	10	2.3*	− 1.6
3	− 33	49	35	9	3.2**	− 1.4
4	− 46	31	38	9	2,4*	− 1.9
5	14	66	25	11	3.1*	− 2.8*
6	− 10	67	22	10	3.4**	− 1.9
7	− 30	61	21	10	3.4**	− 1.8
8	− 46	44	24	9	2.6*	− 2.4*
9	1	70	10	11	2.3*	− 1.9
10	− 23	68	8	9	2.9*	− 3.1*
11	− 43	55	8	8	2.1	0.9
12	13	71	− 1	10	1.7	− 2.2*
13	− 14	70	− 4	8	2.3*	− 2.7*
IPG						
1	− 57	− 38	53	9	2.1	− 2.2*
2	− 46	− 55	58	11	3.2**	− 0.8
3	− 65	− 31	41	9	2.1	− 2.0
4	− 58	− 52	47	10	3.0*	− 4.9**
5	− 42	− 69	51	11	2.1	− 1.8
6	− 65	− 46	34	9	2.4*	− 4.1**
7	− 53	− 67	40	10	2.0	− 2.0
8	− 62	− 60	24	9	2.3*	− 2.5*
Word Frequency (Low >High)						
IFG						
1	− 56	21	28	9	1.9	− 2.0
2	− 55	33	12	8	2.1	− 1.5
3	− 63	6	20	8	1.5	− 2.2*
4	− 52	44	− 3	8	1.6	− 4.0**
5	− 59	18	5	9	1.2	− 1.5
6	− 53	29	11	11	1.2	− 1.3

Channel numbers, MNI coordinates, estimated inter-subject variability (SD) and significant uncorrected t-values (df = 11, Ps ≤ 0.05, two-tailed) are given. Significant channels are marked by * (ts ≥ 2.2). t-values surviving partial Bonferroni correction are marked by ** (ts ≥ 3.2 for [oxy-Hb] and ts ≥ 4.0 for [deoxy-Hb] due to channel intercorrelations). For shaded channels exemplary time courses are given in Figure 9.

A   Lexicality (Words > Pseudowords): SFG

B   Lexicality (Words > Pseudowords): IPG

C   Word Frequency (Low > High): IFG
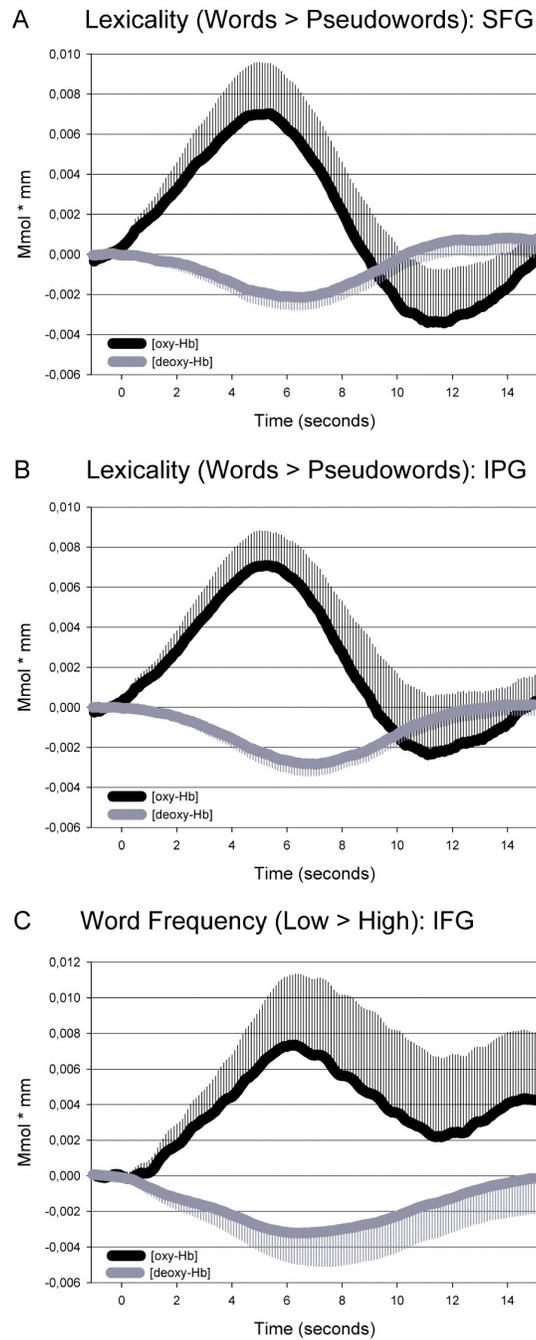
Figure 9: This figure shows the time courses of the hemodynamic responses exemplified on one channel for each target region. Panels A and B show the time course of the word activation relative to PW activation in channel SFG-10 and IPG-4. The time course of the activation of low frequency words relative to high frequency words in channel IFG-4 is given in panel C. Error bars indicate standard errors.

Discussion

The present study shows that neuronal correlates of visual word recognition can be investigated by optical topography. Specifically it was demonstrated that both, lexicality and word-frequency yield differential patterns of cortical activation. The major findings are:

(i) Words elicit a statistically larger activation in the SFG and IPG when compared to PWs (lexicality effect). This is indicated by an increase in [oxy-Hb] and a decrease in [deoxy-Hb].

(ii) Low frequency words elicit a greater activation in the IFG when compared to high frequency words (word frequency effect), as indicated by a decrease of [deoxy-Hb].

Moreover, we demonstrated that more than one target region can be assessed by fNIRS within the same effect, and that the functional specificity of neighboring regions can be assessed by applying the probabilistic mapping method. These findings supply functional neuroimaging support for two models, the MROM (Grainger & Jacobs, 1996) and the DRC (Coltheart et al., 2001), both of which were originally proposed for explaining behavioral data. While the present findings are generally in line with previous imaging studies, the discussion will also focus on the novel methodological approach.

The lexicality effect

We show a statistically larger [oxy-Hb] increase and [deoxy-Hb] decrease to words in comparison to PWs for the channels overlying the SFG. This activation difference of the SFG during visual word recognition is predicted by the MROM (Fiebach et al., 2007; Grainger & Jacobs, 1996; Jacobs et al., 1998) which posits that different decision mechanisms for words and PWs will be activated: A "yes" response is generated by intra-lexical activation criteria while the "no" response is generated by an extra-lexical temporal threshold mechanism (cf. Fiebach et al., 2007). Thus the greater RT for PWs can be explained by the temporal threshold, and the 'no-response' relies on a lesser SFG activation. Previous neuroimaging studies reported similar findings. In a PET study Price (2000) demonstrated an increase in blood volume in the SFG and these findings were confirmed by successive fMRI studies reporting on BOLD-contrast increases in the SFG (Binder et al., 2003; Ischebeck et al., 2004; Kuchinke et al., 2005).

Finally the SFG's role in generating a lexical decision is supported by the finding that word/PW differentiation during silent articulation without overt judgment on lexicality does not activate SFG (Cohen et al., 2003; Kronbichler et al., 2004).

An alternative explanation of the SFG effect observed in the present and the previous imaging studies refers to differences in semantic retrieval. According to this hypothesis the increased SFG activation to words results from control functions with regard to retrieval of semantic information (Binder et al., 1999; 2003).

Principally the present findings might indicate that task difficulty accounts for the SFG effect. Words not only elicited a greater SFG activation than PWs, but also more errors. Error processing has been assumed to rely on the anterior cingulate (Yeung et al., 2004), but also on the mediofrontal gyrus (Ridderinkhof et al., 2004), which is part of the SFG. Though actual errors were excluded from the analyses, Yeung et al. propose that errors may be activated partially, even when a correct response is generated. Thus

items more likely to elicit an error may induce the SFG activation due to partial error activation. To test whether partial error processing is the relevant influence for the decision-related activation in the SFG, we added a fourth predictor in the present GLMs representing the amount of errors per item. If partial error activation was the relevant factor for the differential SFG activation we would expect to eliminate the effect seen in our analysis reported above. On the contrary the present results did not change qualitatively. Still statistically significant differences were obtained in the SFG (cf. Appendix). Thus we conclude that the larger SFG activation found in response to words in comparison to PWs[7] is at least partially independent from error processing. This challenges models of visual word recognition based on behavioral measures alone (Braun, Jacobs, Hahne, Ricker, Hofmann, & Hutzler, 2006; Grainger & Jacobs, 1996; Hofmann et al., 2008).

In the channels overlying the IPG, words also elicited a stronger hyperoxygenation when compared to PWs (Figures 8A and 9B; Table 1).

The role of IPG in lexical decision has been previously reported. A PET study reports blood volume increases to words in comparison to PWs (Price, 2000) while greater BOLD responses in IPG were obtained in response to similar paradigms, though this finding is controversial (Binder et al., 2003; Cohen et al., 2003; Ischebeck et al., 2004; Kuchinke et al., 2005; but see Fiebach et al., 2002). Conceptually Déjerine (1891) was the first to claim this region's role for 'memories' of the visual word form. Nowadays this concept has been further elaborated in the framework of different theories.

Apart from whole word form representations, it was proposed that sub-lexical representations exist even at the level of the syllable (Goswami & Ziegler, 2006). When words are tested against consonant strings (Cohen et al., 2003), an alternate explanation for the IPG effect of lexicality can be discussed. In that case syllabic

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[7] The other main effects also remained unchanged. A larger change in [oxy-Hb] and [deoxy-Hb] over the IPG was observed to words in comparison to PWs. Low frequency words elicited a larger [deoxy-Hb] response than high frequency words. To control for task difficulty, I finally used the RT of each trial to control for activations purely due to varying unspecific task effects. Again, the main results described in our original analysis remained unchanged and statistically significant (cf. Appendix).

representation rather than semantic load may explain the difference in IPG activation (cf. Owen, Borowsky, & Sarty, 2004). Even though we cannot fully exclude the possibility of syllabic representation to drive IPG, we suggest – in line with Binder et al. (1999, 2003) – that the critical difference between words and PWs is the semantic representation exclusive to words, a difference which dominates the differential IPG activation for lexicality. This conclusion receives support from lesion studies of the IPG (cf. Price, 2000, for an overview), and is in line with the concept proposed by BOLD-contrast findings in studies on dyslexia (Booth et al., 2004; Pugh et al., 2000).

In sum the present study provides evidence that the IPG plays a key role in the integration not only of orthographic and phonological information, but actively links these to semantic information.

The word frequency effect

While [oxy-Hb] changes only showed a trend, the word frequency effect elicited significant differences between low and high frequency words for the decrease in [deoxy-Hb] (see Table 1 and Figure 8B). Two channels overlying the IFG showed a larger decrease in [deoxy-Hb] in response to the low frequency words. One of these survived the Bonferroni correction. Note that a decrease in [deoxy-Hb] corresponds to an increase in BOLD-contrast (Kleinschmidt et al., 1996). Hence, the larger decrease in [deoxy-Hb] can be interpreted as an indicator of a stronger underlying neuronal response in analogy to studies relying on BOLD-contrast fMRI (see Figure 9C, and below for the discussion of the NIRS response). The [deoxy-Hb] finding confirms the most established BOLD effect in fMRI research on word recognition (Carreiras et al., 2006; Fiebach et al., 2002, 2003; Ischebeck et al., 2004; Kronbichler et al., 2004; Nakic et al., 2006; Prabhakaran et al., 2006). The established interpretation is that grapheme-phoneme correspondences are being computed in the IFG. An alternative account

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would propose that identification of low frequency words is more equivocal than that of high frequency words. Therefore several semantic candidates are activated, and the left IFG's role is to select between these pre-activated candidates (Thompson-Schill et al., 1997). Although the present results are in line with previous fMRI studies, it should be noted that the present stimulus material was even more rigidly controlled for potentially confounding effects. In order to quantify familiarity with the letter strings in terms of an aggregation of more or less familiar features, Kronbichler et al. (2004) controlled for bigram frequency. The present study used type and token bigram frequencies. Type indicates the amount of words in which a specific bigram occurs, while token denotes the summed frequencies of these words (cf. Study 1). Type measures can be considered to quantify the familiarity of all existing words assuming they are equally activated. Token measures, in contrast, consider the actual likelihood to be activated, because they reflect word frequencies. Therefore, the alternative explanation of a global familiarity with the words as an aggregation of more or less familiar features can be ruled out based on the present study.

Optical topography as a tool to investigate word recognition

Owing to its low constraints on the experimental environment, fNIRS as a silent method is an exquisite tool to investigate language and higher cognition, in which an MRI environment may induce substantial distortion of behavior and speech perception. Like electroencephalography it may also more easily find applications in psychiatric (Fallgatter, Ehlis, Wagener, Michel, & Herrmann, 2004) and neuropsychological patients (Zabel & Chute, 2002) and has already been established as a tool in studying neuropsychological development in neonates and infanthood (Pena et al., 2003; Taga et al., 2003; Wartenburger et al., 2007). However, the appraisal of these advantages must face the fact that NIRS cannot supply the exquisite and ever increasing spatial

resolution of fMRI-based approaches. Like EEG any anatomical inference on the cortical areas relies on external bony landmarks and can thus be referenced to the 10-20 system and its extensions. Recently, a series of publications has addressed this issue and supplied a tool to frame the very rough anatomical differentiation into a probabilistic mapping (Jurcak et al., 2005, 2007; Okamoto et al., 2004). In brief, cortical anatomy was related to landmarks identified by 10-20 system positions (Tsuzuki et al., 2007) in 1000 simulated brains.

The tool therefore supplies a measure of the likelihood of a specific position on the subject's skull to correspond to a specific cortical area and can supply the corresponding MNI space coordinates. we am fully aware of the limitations of such a reference system and its potential source of error, hence without doubt NIRS will always have to respect functional anatomical facts assessed with methods of superior spatial resolution. Nonetheless the present findings demonstrate that the localization procedure yields the very cortical regions previously discussed by functional imaging studies of word recognition. By contrasting the lexicality and the word frequency effect it is apparent that spatially distinct areas are activated (see Figure 8). This we consider a sound basis to address developmental aspects of lexical processing, e.g., in children learning to read.

There is yet another issue which is somewhat controversial concerning the interpretation of fNIRS signals. Accepted models of neuro-vascular coupling posit that the increase in rCBF is disproportional to the increase in oxygen consumption when a cortical area is activated (Buxton et al., 2004; Fox & Raichle, 1986; Huppert, Allen, Benav, Jones, & Boas, 2007). The resulting hyperoxygenation can be measured by NIRS, assessing changes in [oxy-Hb] and [deoxy-Hb]. It is, however, controversial whether an rCBF increase could potentially rely selectively on an increase in blood volume due to arterial dilation without an accelerated flow velocity. Moreover a number of dynamic flow-volume relationships were discussed to explain non-linearities of the

vascular response governing the BOLD contrast (Mandeville et al., 1999). In case of a pure volume increase [deoxy-Hb] might either show no change or even a slight increase due to its production by oxidative metabolism and the fact that even arterial blood contains a quantity of deoxygenated hemoglobin. This may account for the observation, that more [oxy-Hb] channels revealed significant changes than [deoxy-Hb] channels. The channels showing [oxy-Hb] changes but no [deoxy-Hb] changes may be an activation BOLD-contrast fMRI would be 'blind' to, because the decrease in paramagnetic [deoxy-Hb] is the primary source of BOLD-contrast increases (Huppert et al., 2007; Kleinschmidt et al., 1996; Ogawa et al., 1990).

Such observations have regularly led to the additional appraisal as to the superiority of NIRS, assessing oxygenation and volume changes, the latter by summing the changes in both compounds. In the present study we find increases in [oxy-Hb] and decreases in [deoxy-Hb] for the lexicality effect in the SFG and IPG. In contrast, word frequency did not elicit a statistically significant [oxy-Hb] increase in any of the channels. Interestingly an early PET study relying on blood volume changes yielded also only a tendency towards greater blood volume changes for low frequency words (Fiez et al., 1999), whereas successive fMRI studies reliably and reproducibly demonstrated the difference for BOLD-contrast changes. This might be interpreted as an indicator of vascular differences between different cortical areas as has been discussed previously (Blood, Pouratian, & Toga, 2002). However, we favor the alternative explanation that [oxy-Hb] and [deoxy-Hb] changes in NIRS are subject to different signal to noise ratios. The fact that extracerebral, i.e., systemic, hemoglobin changes particularly affect [oxy-Hb] has been stressed recently (Boden et al., 2007). At least for motor tasks increases in heart rate were reported to coincide with the stimulation period (Franceschini, Fantini, Thompson, Culver, & Boas, 2003). In the present study further evidence for the influence of the systemic response specifically on [oxy-Hb] can be derived from the observation that for [oxy-Hb] intercorrelations between channels amount to more than

twice of that observed for [deoxy-Hb]. Moreover, the largest t-values were obtained for [deoxy-Hb]. This may indicate its better signal-to-noise ratio.

In sum, the changes in oxygenation are well in line with the model of neurovascular coupling that is the basis of all vascular based methodologies, most prominently BOLD contrast fMRI.

Though localization of fNIRS is limited, we demonstrate that specific sub-processes can be reliably differentiated by the topographical approach and can be tentatively framed in a common reference system to be compared to fMRI or PET studies. Future studies will have to critically evaluate the versatility of such an approach in the development of literacy in children and its impairment in neuropsychiatric syndromes. Results from work on language perception in adults and language development in infanthood based on spoken language are extremely encouraging with respect to apply the method for this endeavor. It should be noted also that the present study is the first in language research using fNIRS to identify three distinct areas within one hemisphere and to reliably differentiate their respective roles during lexical decision.

Appendix

Table 2: Channel t-values for regions of interest when errors or RTs were held

constant.

Channel	T-values (errors constant)		T-values (RTs constant)	
	[oxy-Hb]	[deoxy-Hb]	[oxy-Hb]	[deoxy-Hb]
Lexicality (Word > Pseudoword)				
SFG				
1	2.2*	− 1.7	1.7	− 1.6
2	1.5	− 1.2	1.3	− 1.1
3	2.7*	− 2.2*	2.4*	− 2.0
4	3.5**	− 1.3	3.3**	− 1.2
5	2.9*	− 2.4*	2.3*	− 2.1
6	3.2**	− 3.5*	2.7*	− 3.7*
7	3.0*	− 1.9	2.7*	− 1.7
8	2.9*	− 1.7	2.3*	− 1.7
9	2.6*	− 3.3*	2.4*	− 3.1*
10	3.6**	− 2.7*	3.2**	− 2.6*
11	2.3*	0.4	1.9	0.9
12	2.8*	− 1.7	2.0	− 1.9
13	3.8**	− 3.2*	3.4**	− 3.4*
IPG				
1	2.1	− 1.8	1.9	− 1.9
2	2.7*	− 3.3*	2.5*	− 3.1*
3	2.1	− 1.7	1.9	− 1.7
4	2.9*	− 3.6*	2.8*	− 3.4*
5	3.9**	− 2.8*	3.2**	− 2.8*
6	2.4*	− 3.0*	2.0	− 2.9*
7	3.9**	− 2.7*	3.4**	− 2.7*
8	3.1*	− 2.2*	2.7*	− 1.8
Word Frequency (Low > High)				
IFG				
1	1.4	− 1.6	1.4	− 1.6
2	1.6	− 1.5	1.5	− 1.5
3	1.0	− 2.0	1.0	− 2.2*
4	0.9	− 3.0*	0.8	− 2.9*
5	0.6	− 1.4	0.6	− 1.4
6	0.6	− 1.1	0.6	− 1.0

Channel numbers and significant uncorrected t-values (df = 11; Ps≤ 0.05. two-tailed) in the target region channels are given (cf. Table 1).

Study 3: Conflict monitoring engages the mediofrontal cortex during nonword processing

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Abstract

The current study investigated the role played by conflict monitoring in a lexical-decision task involving competing word representations, using event-related potentials. We extended the multiple read-out model (Grainger & Jacobs, 1996), a connectionist model of word recognition, to quantify conflict by means of Hopfield Energy, which is defined as the sum of the products of all orthographic word node pair activations within the artificial mental lexicon of this model. With increasing conflict levels in nonwords, a late negativity increased in amplitude (400-600 ms) accompanied by activation of the anterior cingulate cortex and the medial frontal gyrus. The simulated conflict predicted the amplitudes associated with this mediofrontal conflict-monitoring network on an item level, and is consistent with the conflict-monitoring theory.

Introduction

Monitoring of conflicting bits of information is an essential human ability, to respond flexibly to the environment. Many neuroimaging studies associate conflict monitoring with mediofrontal brain areas such as the anterior cingulate cortex (Botvinick et al., 2001) and the medial frontal gyrus (Ridderinkhof et al., 2004). The aim of this study is to demonstrate the role of conflict monitoring during the processing of letter stimuli. we show that a connectionist model of lexical processing can account for behavioral and ERP responses that are related to mediofrontal networks.

The MROM (Grainger & Jacobs, 1996; Jacobs et al., 1998) was used to make predictions about human performance in the lexical decision and related letter-string processing tasks. It basically contains a feature, a letter, and a word level, with the lower levels providing inputs to the higher levels (see Figure 10 and Jacobs et al., 1998, for further details). For example, when the letter F is encoded at the feature level, the letter node F becomes activated to a larger degree than the letter node B, whereas letter nodes that share no feature with F remain inactivated. The same is true for the relationship between the letter and the word levels. The nonword FLUR thus activates the word node BLUR to a larger degree than the word node BLUE, as it shares more letters with this node.

Botvinick et al. (2001; Botvinick, Cohen, & Carter, 2004) reviewed converging evidence that longer RTs, higher error rates, and larger anterior cingulate cortex activations were observed in response to partially activated and conflicting response alternatives in the Eriksen flanker and Stroop tasks. More importantly, Botvinick et al. (2001) used a very similar framework as the MROM (see Figure 10) to make predictions about the extent of conflict during a stem completion task in which participants had to complete a word stem (e.g., BLU_) to form a whole word (e.g., BLUR or BLUE). The

simulated amount of conflict between the word nodes accounted for the finding, such that the so-called strength ratio predicts anterior cingulate cortex activity (Thompson-Schill et al., 1997). This ratio is calculated by dividing the frequency of the most frequent completion by the frequency of the second most frequent completion. The larger the competition that exists between these completions, the larger will be the conflict itself, and thus the anterior cingulate cortex activity. As lexical frequency determines the resting levels of the word nodes in the MROM, it should be capable of accounting for ratio effects, when a measure of conflict between the word nodes is introduced. This is very similar to Grainger and Jacobs' (1996) lexical inhibition hypothesis predicting greater RTs and error rates for nonwords during lexical decision, with an increasing number and relative activations of the word nodes partially activated by a nonword. Botvinick et al. (2001) predicted larger anterior cingulate cortex activations in response to the larger conflict between activated word nodes. The aim of this study was to test the hypothesis, that the keener the competition between these word nodes, the larger will be the anterior cingulate cortex (Botvinick et al., 2001; Yeung et al., 2004) and medial frontal gyrus activity (Ridderinkhof et al., 2004). In ERPs, larger anterior cingulate cortex and medial frontal gyrus activities are often associated with the N2 component being most prominent at frontal sites (Yeung et al., 2004). Therefore, we conducted an ERP study using a lexical-decision task, and applied standardized low-resolution brain electromagnetic tomography (sLORETA) for source localization (Pascual-Marqui, 2002). Botvinick et al. (2001) quantified the extent of conflict by means of the so-called Hopfield Energy (Ehopf), which is the sum of the products of all possible pairs of word node activations. For example (see Figure 10), FLUR activates the word node pairs BLUE and BLUR, BLUE and FOUR, and FOUR and BLUR. We implemented Ehopf into the MROM without changing parameters (version of Jacobs et al., 1998). It includes most of the three-letter to five-letter German monosyllabic words, in all 1025 words. Ehopf was computed from cycles 2-7 (Jacobs et al., 2003) and log transformed

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for normal distribution purposes. Two items were excluded from item analyses because they revealed an Ehopf of zero, resulting in missing values after log transformation.
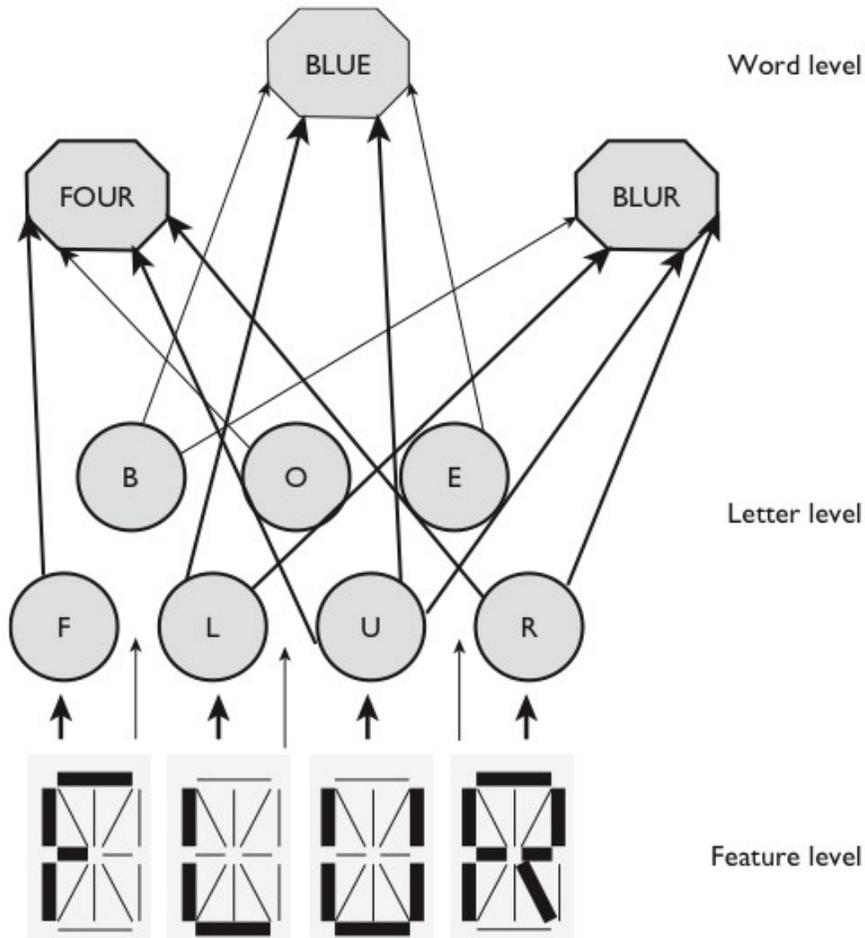
Figure 10: Schematic representation of the basic architecture of the MROM. If more features of a letter are activated, there is greater activation of the respective letter node at the letter level. If more letters of a word node are activated, more activation is fed forward to the respective word nodes. The relative activation of the nodes and the strength of the feed-forward activations are indicated by line thickness.

Methods

Participants

Fourteen right-handed German native speakers (mean age 23 years, range 19-30, seven women) were recruited from the Max-Planck Institute for Human Cognitive and Brain Sciences and were paid for their participation. They had normal or corrected-to-normal vision.

Materials

Stimuli were four-lettered, and consisted of 300 German words and 300 nonwords. Nonwords included a large range of generable nonwords from nonpronounceable consonant strings (e.g., GKNZ) that activate only one word node (GANZ) to pronounceable nonwords (e.g., LUND), which activate many word nodes (e.g., RUND, LAND, and MUND). Three categories, were generated by categorizing the 100 stimuli with the lowest, medium, and the highest Ehopf values into three stimulus categories, respectively.

Procedure

Stimuli were presented as black uppercase letters (courier font, about 4 × 1 cm) on a light grey screen of a 17-inch color monitor (1024 × 768 pixels, 75 Hz). Distance from eye to monitor was about 70 cm. Stimuli were presented by ERTS software (BeriSoft Corp., Frankfurt, Germany) in a pseudorandomized fashion. No more than three words or nonwords were allowed to appear consecutively. After presenting 30

practice trials, stimuli were presented in six blocks of 100 trials. The participants were instructed to respond as fast as possible but not at the expense of accuracy. Half of the participants were instructed to press the right button to words and the left button to nonwords, the other half vice versa. Each trial began with fixation points (':') presented for 500 ms, followed by the stimulus for 100 ms. Thereafter, a mask ('#####') was presented for 300 ms, followed by a blank screen that remained until a response was given (maximally 4 s). After a 1.2-s pause, participants were instructed to press a button to start with the next trial, starting after a 1-sec delay.

Data acquisition

Electroencephalogram data were recorded using ANT Software (ANT Software, B.V., Enschede, The Netherlands), and analyzed by Brain Vision Analyzer software (Brain Products GmbH, Gilching, Germany). The participants were seated in an acoustically shielded chamber. Twenty-six electrodes were attached to an elastic cap (Easy Cap Corp., Herrsching-Breitbrunn, Germany) at 10-20 positions (T7, FT7, FT8, F7, C3, FC3, F3, FP1, FZ, FP2, FC4, F4, AFZ, F8, CP5, P3, P7, O1, PZ, CZ, C4, P4, O2, CP6, T8, and P8) and referenced to the left mastoid. Bipolar electrodes were attached above and below the right eye for the vertical electrooculogram and at the outer canthus of each eye for the horizontal electrooculogram. Impedances for the scalp and mastoid electrodes were kept below 5 kΩ for reference and active electrodes, and below 20 kΩ for eye-movement electrodes. Electroencephalogram data were sampled at 250 Hz and band-pass filtered (0.1-30 Hz).

Data analysis

Incorrect responses and outliers (RTs faster than 300 or slower than 1600 ms) were excluded from the analyses. Muscle artifacts, drifts, amplifier blockings, and eye movements were rejected by visual inspection. Blink artifacts were corrected using independent-component analysis (Onton et al., 2006).

For participant analyses, single participant averages were calculated for the three Ehopf categories separately using segments from 200 ms before the stimulus to 1 s after the stimulus, and baseline corrected (200 ms before stimulus). Grand averages were 8 Hz low-pass filtered for presentation purposes. The ERP morphology (Figure 11) showed a P1 peak at around 150-200 ms. A negativity followed the peaking at around 200-300 ms (N1). The P2 peaked around 300-400 ms and was immediately followed by a negative deflection peaking from 400 to 600 ms (N2). The N2 was most pronounced at the frontal sites, and showed a graded increase in negativity with increasing Ehopf in all electrodes. N2 amplitudes (400-600 ms) were averaged across electrodes for each condition, submitted to repeated-measures analyses of variance, and Greenhouse-Geisser corrected when the sphericity assumption was violated.

Single participant averages of the N2 were subjected to sLORETA (Pascual-Marqui, 2002), and normalized participant-wise. Paired t-tests were conducted on each possible pair of conditions (high vs. low Ehopf, high vs. medium Ehopf, and medium vs. low Ehopf). Statistical testing was performed on average source density. The t-tests were performed using sLORETA randomization procedure to correct for multiple comparisons. Variance smoothing was set to one. Ehopf was used as the predictor for RTs, sum of errors per item, and mean amplitudes over all channels.

Analyses were conducted on all items for which at least 10 observations remained after outlier, error, and artifact rejections. This resulted in 204 items remaining for item analyses.

Results

Behavioral

The participant analyses of behavioral data revealed a significant Ehopf effect in RTs ($F(2,26) = 83.4$, $P \leq 0.001$) and errors ($F(2,26) = 22.1$, $P \leq 0.001$). High, medium, and low Ehopf nonwords revealed a mean RT of 888 (SD: 143), 831 (SD: 136), and 784 ms (SD: 121), and error rates of 13.9 (SD: 9.7), 8.1 (SD: 7.4), and 5.9 (SD: 5.7), respectively. In the item analysis, Ehopf accounted for 28% of the RT and 5% of the error variance (Ps < 0.001).

ERPs

The ERP participant analysis revealed a significant Ehopf effect ($F(1.4,17.9) = 5.3$, $P \leq 0.05$, see Figure 11). High, medium, and low Ehopf nonwords revealed a mean amplitude of 3.1 (SD: 1.2), 3.5 (SD: 1.5), and 3.9 mV (SD: 1.6), respectively. On an item-level of analysis, Ehopf accounted for 12% of the ERP variance (P < 0.001).

sLORETA

sLORETA analysis revealed the largest t-value in the high Ehopf vs. low Ehopf contrast in a medial frontal gyrus voxel ($t = 5.8$, $P \leq 0.005$; MNI x/y/z = -10/40/30, see Figure 12). The significant region extended to the adjacent anterior cingulate cortex ($t = 4.9$, $P \leq 0.05$; x/y/z = -7/36/30). The largest Ehopf high vs. Ehopf medium contrasts were obtained in the medial frontal gyrus ($t = 5.4$, $P \leq 0.005$; x/y/z = -10/40/25) and the anterior cingulate cortex ($t = 4.8$, $P \leq 0.05$; x/y/z = -4/35/22). The largest difference

between the Ehopf medium and the Ehopf low condition was obtained in the left middle frontal gyrus (t = 4.17, P ≤ 0.1; x/y/z = -30/35/45), extending to other nonsignificant differences in the medial frontal gyrus (t = 2.86; x/y/z = -11/31/45).
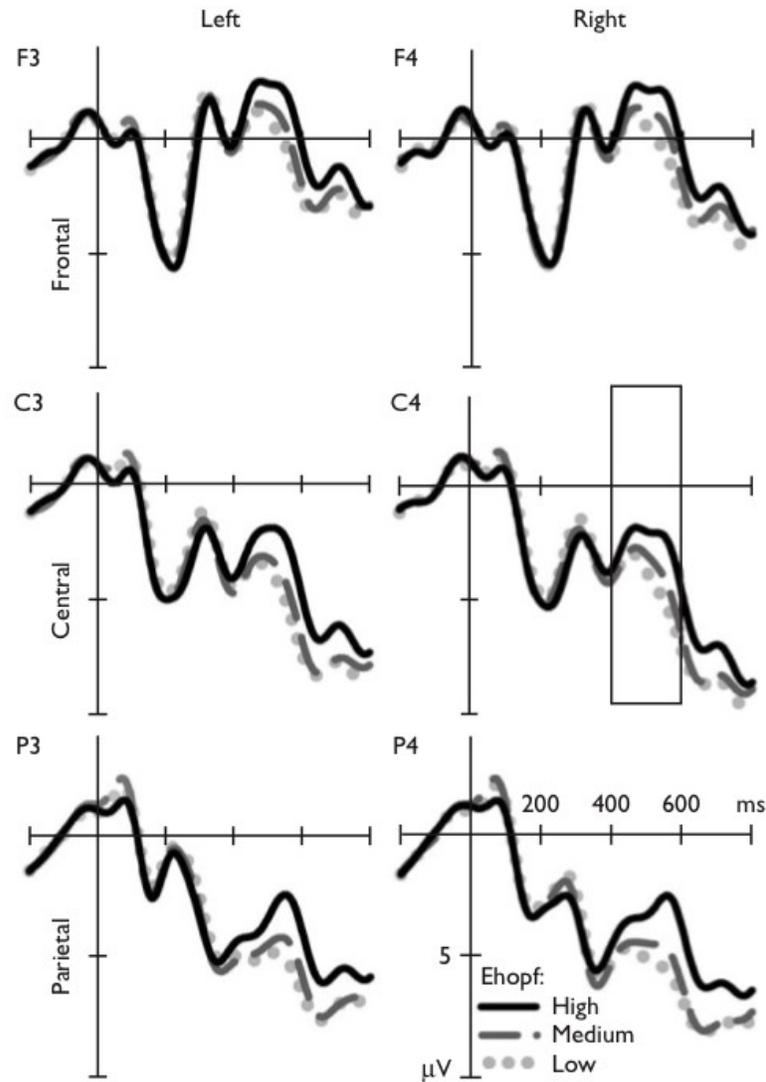
Figure 11: N2 amplitudes increase with increasing levels of Hopfield Energy (Ehopf), as a measure of conflict. This conflict-monitoring effect resulting from nonword processing is indicated at six representative electrodes, and its time frame (400-600 ms) is indicated by the box at the C4 electrode.
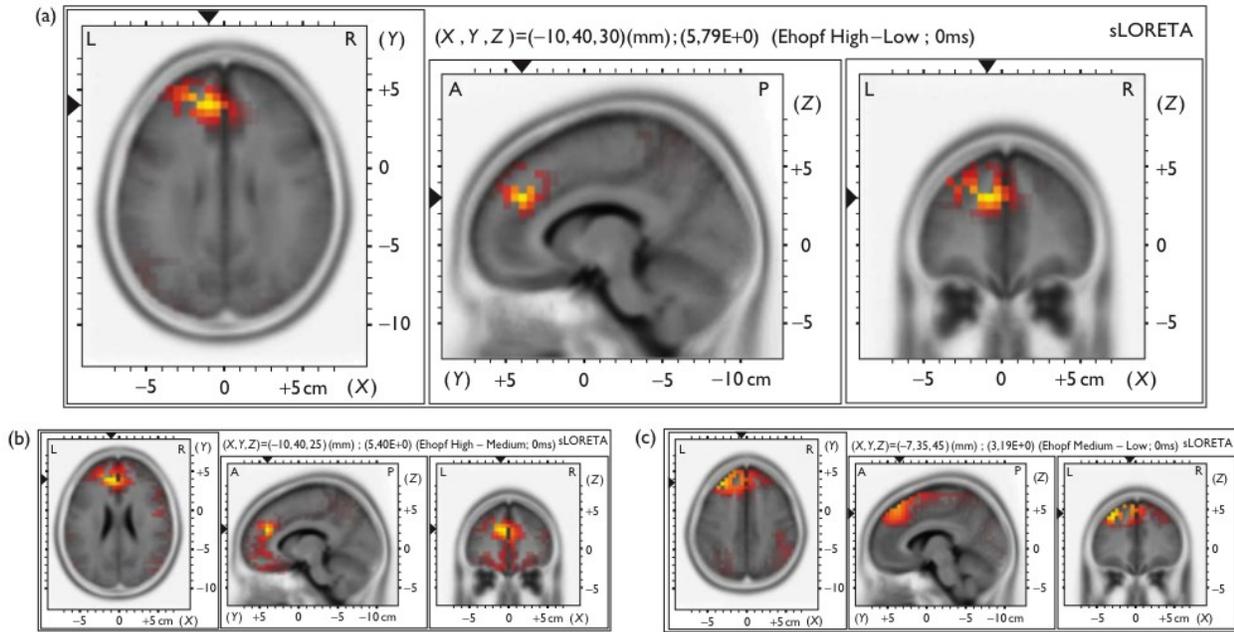
Figure 12: Results of the standardized low-resolution brain electromagnetic tomography (sLORETA) analysis comparing the source density of the N2. Hopfield energy (Ehopf) levels: (a) high-low, (b) high-medium, and (c) medium-low. The X-Y-Z coordinates (MNI space) in each panel correspond to the respective maximum activations in the medial frontal gyrus.

Discussion

The participant analysis of ERP data revealed an ERP effect of Ehopf at all electrodes (see Figure 11). This effect was apparent in the N2, and occurred at a relatively late time frame (400-600 ms) in comparison with other N2 effects. The error-related negativity, however was proposed to be another example for a rather late N2. This was demonstrated by using Ehopf to predict the amount of conflict, and supported by the anterior cingulate cortex being the common source of both effects (Yeung et al., 2004). The error-related negativity occurs after the response, which is usually later than 400 ms after the stimulus. To examine whether the N2 in this study is functionally equivalent to the earlier N2s, we conducted sLORETA source localization. High Ehopf nonwords elicited a larger source density in the anterior cingulate cortex and the medial frontal gyrus than medium and low Ehopf nonwords. Botvinick et al.'s (2001) hypothesis has, thus, been confirmed: greater anterior cingulate cortex activation was observed with increasing levels of conflict. The pivotal role of the medial frontal gyrus was demonstrated as well (Ridderinkhof et al., 2004).

The extent of conflict between lexical representations modeled by Ehopf predicted these source-localization findings: thus this study suggests the functional equivalence of previous N2 findings and the current one.

This proposal is corroborated by the item analysis of the N2. Ehopf accounted for 12% of the ERP variance, which seems to be a good score for item-based ERP analyses (Dambacher et al., 2006; Hutzler et al., 2004). The quantifiable model-to-data fit allows for competition between different models with respect to the variance explained (Jacobs & Grainger, 1994), as previously proposed for behavioral data (Perry et al., 2007). Ehopf accounted for a significant portion of response time ($R^2 = 0.28$) and error variance ($R^2 = 0.05$), suggesting that competing activated word representations

delay the RTs and result in higher error rates. The current N2 time window is largely similar to the time window of N400 (Kutas & Federmeier, 2000). It was demonstrated that with an increasing number of orthographic neighbors, the N400 increases to nonwords (Braun et al., 2006; Holcomb, Grainger, & O'Rourke, 2002). Orthographic neighbors are words that are identical to the stimulus with respect to all but one letter (e.g., rose is an orthographic neighbor of nose). Holcomb et al. (2002) interpreted increased RTs, error rates, and N400s in terms of an increased lexical activation to nonwords with many orthographic neighbors. Grainger and Jacobs' (1996) lexical-inhibition hypothesis suggests that the competition between activated orthographic neighbors can inhibit behavioral responses. To test whether Ehopf can contribute to the N400 discussion of orthographic neighborhood, we confirmed the assumption that the variance of the number of orthographic neighbors is contained in the Ehopf variance (R^2 = 0.52, $P \leq 0.001$). Ehopf, however, accounted for an ERP variance of the N2 (R^2 = 0.12) that was twice the number of orthographic neighbors (R^2 = 0.06, $P \leq 0.001$); therefore, we propose that the competition between activated word representations contributes to the N400. As the MROM simulates word frequency effects by setting the resting levels of the word nodes accordingly, high-frequency word nodes are more strongly activated than low-frequency word nodes. Therefore, Ehopf is larger when high-frequency words compete. This is consistent with previous behavioral (Grainger & Jacobs, 1996) and neurobiological (Botvinick et al., 2001; Thompson-Schill et al., 1997) findings demonstrating the amount of competition to be dependent on the frequency of the word representations, and can account for the variance gain of Ehopf in comparison with the number of orthographic neighbors alone. The current N2 finding is consistent with previous N2 findings in conflict monitoring, and with N400 findings in the psycholinguistic literature. This suggested functional overlap seems to confirm Polich's (1985) notion that both are 'a reflection of the system's overall capability to comprehend complex similarities and relationships among stimulus items' (p. 319).

Conclusion

Response times, errors, the N2, and mediofrontal cortex activity were increased with the simulated extent of conflict between word nodes of the MROM. This is consistent with the conflict-monitoring theory, and might suggest a common functional locus of the N2 and the N400 in lexical processing tasks.

Study 4: Affective processing within 1/10th of a second: High-Arousal is necessary for early facilitative processing of negative but not positive words

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Abstract

In the present study, lexical decisions to high- and low-arousal negative words and to low-arousal neutral and positive words were examined in an event-related potentials (ERP) study. RTs to positive and high-arousal negative words were shorter than those to neutral (low-arousal) words, whereas those to low-arousal negative words were longer. A similar pattern was observed in an early time window of the ERP response: Both positive and high-arousal negative words elicited greater negative potentials in a time frame of 80 to 120 ms after stimulus onset. This result suggests that arousal has a differential impact on early lexical processing of positive and negative words. Source localization in the relevant time frame revealed that the arousal effect in negative words is likely to be localized in a left occipito-temporal region including the

middle temporal and fusiform gyri. The ERP arousal effect appears to result from early lexico-semantic processing in high-arousal negative words.

Introduction

From an evolutionary perspective, deciding appropriately on emotionally significant stimuli is an essential ability that aids survival. Reacting quickly to positive stimuli maximizes the probability of attaining an appetitive state. In contrast with this "first come, first served" principle, two complementary response tendencies can be observed for negative stimuli. Negative arousing stimuli, such as "earthquake" or "alarm," are best dealt with by initiating a fast response. In contrast with this "fight or flight" mechanism, "freezing" can be utilized, for example, to help prey to escape undetected. LeDoux (1996) suggested that ready-made neural pathways of evolutionarily old mechanisms can be activated by newly developed capabilities. Thus, it may be advantageous to respond quickly to symbolic stimuli, such as words, if they signal appetitive or potentially threatening situations. To address this issue, the present study used emotional words in the LDT in which speeded responses were required to decide whether a presented letter string was a word or not.

For words with a negative affective connotation, rather inconsistent behavioral results have been obtained. Some previous studies showed that subjects reacted faster to negative than to neutral words (Williamson et al., 1991; Nakic et al., 2006). In contrast, most studies revealed no difference (Siegle et al., 2002), or even a trend towards slower RTs (Kuchinke et al., 2005; Larsen, Mercer, Balota, & Strube, 2008; MacKay, Shafto, Tayler, Marian, Abrams, & Dyer., 2004). An approach that is as old as psychology itself may account for this divergence in negative-emotion words. Following Wundt's (1896) suggestion, emotion is now commonly subdivided into at least two orthogonal dimensions that constitute the affective space: valence and arousal (Bradley & Lang, 1999; Osgood, Suci, & Tannenbaum, 1957). In the present article, we tested the prediction that high-arousal negative words decrease RTs (Hackley & Valle-Inclán,

1999). We expected no effect or even an RT increase for negative words that were matched for arousal to neutral words (Larsen et al., 2008; Siegle et al., 2002). The German corpus used for stimulus selection revealed a differential arousal distribution for positive and negative words (see Figure 1 in Võ et al., 2009). Therefore, it was impossible to generate high- and low-arousal positive and negative conditions that would have been matched for arousal, particularly while controlling for the most influential variables in word recognition (Graf, Nagler, & Jacobs, 2005). Since positive words consistently decreased lexical decision times (Kuchinke et al., 2005, 2007; Williamson et al., 1991), we tested whether the effect of positive words was due to positive emotional valence independent of arousal. For this purpose, we used a condition of low-arousal positive words. For negative words, in contrast, we tested whether the inconsistent behavioral findings of previous studies can be attributed to arousal by comparing high- and low-arousal negative conditions. Doing this resulted in four stimulus categories that were matched for various potentially confounding variables (Fs < 1; see Table 3). Positive, neutral, and low-arousal negative words were matched for their arousal level. High-arousal negative words were matched with respect to valence to the low-arousal negative words, but were maximized with respect to arousal (see Table 3; for further details; see the Method section).

In addition to testing whether the behavioral facilitation for positive words occurs when arousal is controlled for, and whether arousal modulates the behavioral facilitation in negative words, we targeted the time frame of the processes responsible for the behavioral facilitation. This issue also concerns the interpretation of affective effects as being of lexical or post-lexical origin. Sereno and Rayner (2003) proposed that lexical access is underway already around 100 ms after stimulus presentation (see also Dambacher et al., 2006; Hinojosa, Martin-Loeches, & Rubia, 2001; and Sereno & Rayner, 2003, for reviews). However, Kissler, Herbert, Peyk, and Junghofer (2007) found no ERP correlates of emotional word processing until 200 ms, and concluded that

emotional processing occurs after lexical access (cf. Herbert, Junghofer, & Kissler, 2008). Kissler et al. (2007) used a rapid serial visual presentation paradigm in which no decision was required after word presentation.

However, if affective information processing provides an evolutionary advantage because it allows for making faster decisions, tasks requiring speeded decisions might produce different results. We thus used a LDT in order to test whether emotional information is still processed after lexical access, even when a fast decision is required. Since lexical access is assumed to be underway around 100 ms after stimulus presentation (Sereno & Rayner, 2003), and emotional processing has been found to affect the ERP time course from 80 to 120 ms (Scott, O'Donnell, Leuthold, & Sereno, 2009), the present study targeted this time frame. Scott et al.'s results already challenged Kissler et al.'s proposal of affective information acting after lexical access. This suggests the necessity of specifying conditions for the occurrence of lexical access effects. The participants in the present study were put under severe time pressure. According to the MROM (Grainger & Jacobs, 1996), speeded instructions put an emphasis on an early lexical fast-guess mechanism that might favor early affective effects.

Table 3: Mean Values and Standard Errors of the Control and Manipulation Variables for the Four Stimulus Conditions

| | Stimulus Condition | | | | | | | |
| Control and Manipulation Variables | High-Arousal Negative Words | | Low-Arousal Negative Words | | Neutral Words | | Positive Words | |
	M	SE	M	SE	M	SE	M	SE
Emotional valence	−1.61	0.04	−1.57	0.04	−0.04	0.03	1.55	0.05
Arousal	3.94	0.04	3.15	0.04	3.08	0.06	3.16	0.09
Imageability	4.22	0.18	4.00	0.19	4.23	0.20	4.23	0.17
Number of letters	6.34	0.17	6.40	0.19	6.26	0.15	6.26	0.18
Number of syllables	2.08	0.11	2.14	0.11	2.04	0.06	2.14	0.09
Word frequency	7.00	1.25	5.97	1.56	6.72	1.45	7.94	1.37
Number of orthographic neighbors	0.96	0.25	0.86	0.17	1.04	0.20	1.02	0.23
Mean letter frequency (type)	32,108	959	31,975	706	31,770	1,178	31,062	1,088
Mean letter frequency (token)	1,733,451	70,562	1,708,311	54,517	1,700,929	81,118	1,665,834	75,498
Mean bigram frequency (type)	3,677	252	3,445	234	3,684	297	3,480	301
Mean bigram frequency (token)	210,107	20,734	191,082	18,684	194,017	21,358	204,375	23,441

The ranges of the rating variables are: valence, -3 to +3; imageability, 1 to 7; and arousal, 1 to 5. Word frequency is given as occurrence per 1 million words. Type measures denote the number of words in which the sub-lexical unit occurs in a lemma corpus of 51,207 words. Token measures indicate the summed word frequencies of these words.

To identify the most likely sources of early electrophysiological responses, we conducted sLORETA source localization. We expected the anterior cingulate to emerge as the most likely source, if attention processes were the most likely explanation for response facilitation effects. Carretié et al. (2004) indeed found that an ERP effect in the processing of affective pictures around 100 ms was likely to be localized in the anterior cingulate cortex. Furthermore, Geday, Gjedde, Boldsen, and Kupersa (2003) suggested that the behavioral facilitation found with affective stimuli might result from attentional processes in the medial prefrontal cortex, including the anterior cingulate cortex.

Another region of interest to which LORETA appears to be sensitive is the fusiform gyrus. For example, Pizzagalli, Lehmann, Hendrick, Regard, Pascual-Marqui, and Davidson (2002) found emotional faces to engage the fusiform gyrus (cf. Geday et al., 2003) in an early time frame starting at 120 ms after stimulus presentation.

For word processing, the fusiform gyrus was discussed to act at a visual word form level of processing (Dehaene et al., 2002), or to act as a hub between orthographic and semantic processing (Price & Devlin, 2003). Support for the latter hypothesis would result from activation differences in the medial temporal gyrus, which was suggested to be involved in semantic processing (Price, 2000).

Method

Participants

Twenty native German participants took part in the experiment (16 female, mean age 28 years; 1 was left-handed). They were neurologically healthy and reported no language or speech impairment. Participants received course credits or were paid for their participation.

Materials

The stimulus set consisted of 200 words and 200 nonwords. Word stimuli consisted of four to eight lettered German nouns. We used four stimulus conditions, each comprising 50 stimuli. Positive (e.g., RUHM (fame)), neutral (e.g., BEFUND (finding)), and low-arousal negative words (e.g., APATHIE (apathy)) were matched for arousal.

High-arousal negative words (e.g., ERDBEBEN (earthquake); see Table 3) were matched with respect to valence to the low-arousal negative words, but were maximized with respect to arousal. To control for the undesired influences of other variables that are known to affect lexical decision performance (Graf et al., 2005), nine further variables were matched (all Fs < 1; see Table 3). Estimates for emotional valence and imageability were taken from the Berlin Affective Word List in its revised form (BAWL-R; Võ et al., 2009).

Emotional valence ratings ranged from -3 (very negative) to +3 (very positive), imageability ratings from 1 (low imageability) to 7 (high imageability), and arousal ratings from 1 (low-arousal) to 5 (high-arousal). Word frequency measures are given in

occurrences per million (Baayen et al., 1995). Mean letter and bigram frequencies were taken from the lemma corpus of Study 1. One hundred of the 200 nonwords were generated by replacing the vowel of a non-target word with either another vowel (e.g., erreger->ERREGUR) or a consonant (e.g., mokka->MOKKW).

Procedure

Participants were seated on a comfortable chair in front of a 17-in. color monitor (70 Hz) in a dimly illuminated room. Distance from eye to monitor was about 70 cm. The participants were instructed to respond as fast and as accurately as possible. Experimental stimuli were presented in two blocks, each comprising 200 stimuli. Both blocks contained an equal number of nonwords and words of each stimulus category, and did not differ in any of the control or manipulation variables (see Table 3; Fs < 1). The participants were briefed to press the left index finger for words and the right index finger for nonwords in the first block. This assignment was reversed for the other block. The order of blocks was counterbalanced across participants. Each block was preceded by 10 practice stimuli.

Stimuli were presented in black uppercase letters (Times New Roman font, 20 pt) on a white screen by Presentation 9.0 software (Neurobehavioral Systems, Inc., Albany, Canada) in a pseudorandomized fashion. No more than three words or nonwords were allowed to appear consecutively. Each trial began with a fixation cross (+) presented for 700 ms, followed by the stimulus for 1,000 ms. Participants were instructed to respond before the stimulus offset. After a blank screen appeared for 500 ms, a mask (#####) was presented for 1,500 ms. Participants were instructed to blink only during the masking period.

Data acquisition

EEG data were recorded by a 32-channel amplifier (Brainamp; Brain Products, Germany) using 28 electrodes attached to an elastic cap (EASYCAP, Germany). These recording electrodes were referenced to the right mastoid. Vertical EOG was recorded above and below the right eye, and the horizontal EOG on the outer canthus of each eye. Impedances for the EOG electrodes were kept below 10 kΩ, and all other electrodes were kept below 5 kΩ. EEG data were sampled at 250 Hz. Pupil dilations were concurrently recorded using a videobased IView X Hi-Speed eyetracker (SensoMotoric Instruments, Germany). Pupillometric data were not the primary scope of the present article. Neither emotional valence nor arousal affected the pupillary response. These findings confirmed the results of a prior pupillometric study (Kuchinke et al., 2007), but are not uncontroversial (Võ et al., 2008)[10].

Data analysis

EEG data analysis was conducted using Brain Vision Analyzer software (Brain Products, Germany). Data were band-pass filtered (0.1-20 Hz). Muscle artifacts, drifts, amplifier blockings, and eye movements were rejected by visual inspection. Blink artifacts were corrected using independent component analysis (Onton et al., 2006). ERPs were corrected relative to a 200-ms prestimulus baseline and were averaged per subject and condition. Reactions prior to 300 ms were excluded from analyses. Reactions after a 1-sec poststimulus were not recorded and were counted as errors. Behavioral errors were excluded from electrophysiological and RT analyses. More than 35 trials per subject and condition remained for analyses. In sum, 93% of the trials remained for the analyses of the electrophysiological data.

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[10] For a discussion of these negative findings, please confer the general introduction and disussion of this thesis.

To test for main effects of the stimulus conditions and their potential interactions with topography, we performed a three-factorial ANOVA, comprising the within-subjects factors laterality (left-right), anteriocity (anterior-posterior), and stimulus condition (low-arousal positive, neutral, and negative, and high-arousal negative), followed by planned pairwise comparisons. Positive words were contrasted with neutral words. High- and low-arousal negative words were compared with neutral words, and high- and low-arousal negative words were also contrasted. For ERP analyses, electrodes were averaged for four regions across the critical time frame of 80 to 120 ms: left anterior (FP1, F3, F7, FC5, T7), right anterior (FP2, F3, F8, FC6, T8), left posterior (C3, CP5, P3, P7, O1), and right posterior (C4, CP6, P4, P8, O2).

Apart from the targeted early time frame of 80 to 120 ms, we explored other ERP time frames that were investigated by previous studies of affective word processing (see, e.g., Kissler et al., 2009): the time frame of 140-190 ms, the early posterior negativity (200-250 ms), and the late positive component (450-750 ms).

For estimating the potential neural generators of the early ERP effect, sLORETA analyses (Pascual-Marqui, 2002) were conducted. The averaged ERP data of each subject and condition within the critical time frame (80-120 ms) were submitted to the sLORETA model; thus, images of the electric neuronal activity were derived from the extracranial measurements. These estimated current source densities for each of the 6,430 voxels in MNI space, each representing 5 mm^3 of brain tissue, were time-frame-wise normalized; that is, the average activation of each time frame was normalized to a constant value. Data were baseline-corrected and log-transformed. To correct for multiple comparisons, α was set to $P \leq 0.005$ (two-tailed; $t \geq 3.17$). Maximal t values of the respective areas are reported.

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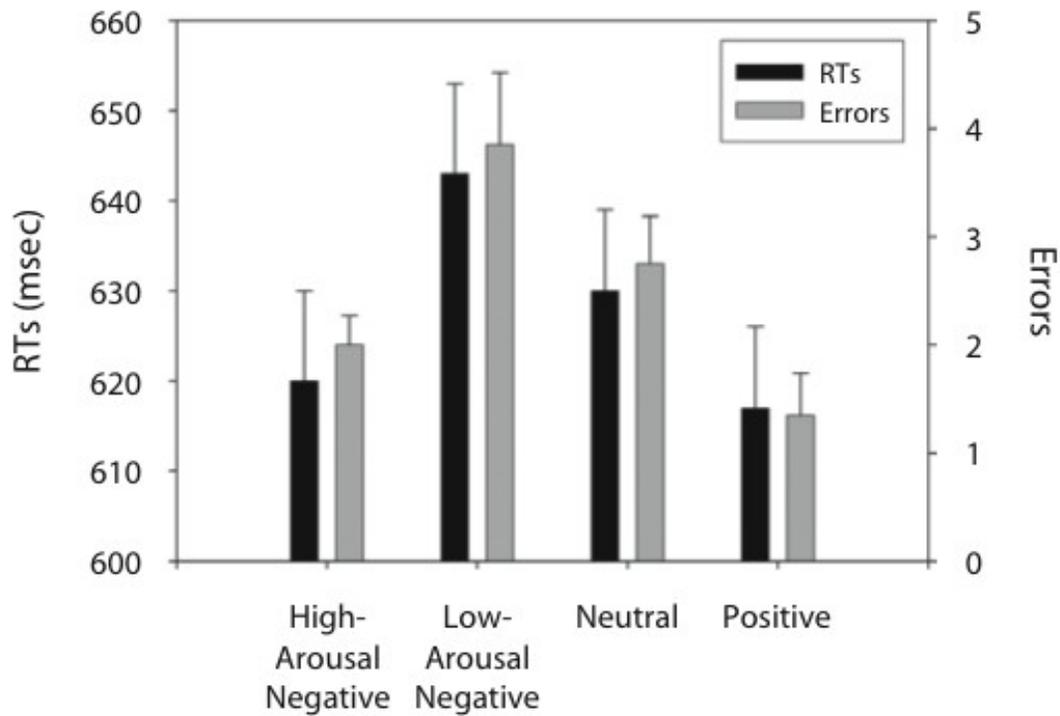
Figure 13: Mean RTs and errors for the four stimulus conditions (N = 20). Error bars indicate standard errors.

Results

Behavioral

In the RT analysis, there was a main effect of stimulus condition ($F(3,57) = 15.78$, $P \leq .01$). Positive words revealed significantly faster RTs than neutral words ($F(1,19) = 9.09$, $P \leq .01$). High-arousal negative words elicited significantly faster RTs than low-arousal negative ($F(1,19) = 27.32$, $P \leq .01$) and neutral ($F(1,19) = 4.36$, $P \leq .05$) words.

Low-arousal negative words revealed slower RTs than neutral words ($F(1,19) = 10.73$, $P \leq .01$). For means and standard errors, see Figure 13 and Table 4. In the error analysis, there was a main effect of stimulus condition ($F(3,57) = 8.82$, $P \leq .01$). Positive words revealed significantly fewer errors than neutral words ($F(1,19) = 10.23$, $P \leq .01$). High-arousal negative words revealed significantly less errors than low-arousal negative words ($F(1,19) = 10.55$, $P \leq .01$), but did not differ significantly from neutral words ($F(1,19) = 2.75$, $P = .11$). Low-arousal negative words only showed a nonsignificant trend to elicit more errors than neutral words ($F(1,19) = 3.23$, $P = .09$). For mean error rates and standard errors, see Figure 13 and Table 4.

ERPs

There was a significant effect of stimulus condition in the early time window of 80 to 120 ms after the stimulus presentation started ($F(3,57) = 4.39$, $P \leq .01$). Positive words revealed a significantly larger negativity than neutral words ($F(1,19) = 7.90$, $P \leq 0.01$). High-arousal negative words were significantly more negative than were low-arousal negative ($F(1,19) = 6.71$, $P \leq .05$) and neutral ($F(1,19) = 4.40$, $P \leq .05$) words. Low-arousal words did not differ significantly from neutral words ($F < 1$). In all of these

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analyses, there were no significant interactions of frontality and/or anteriocity with the experimental conditions (all Fs ≤ 1.4). Only in the analysis comparing high versus low-arousal negative words the interaction with laterality provided a nonsignificant trend (F(1,19) = 3.38, P = .07). See Figure 14 for the ERPs of exemplary electrodes. For means and standard errors, see Table 4.

Neither the time frame of 140-190 ms nor the early posterior negativity (200-250 ms) provided any significant main effects or topography interactions with the experimental conditions (Fs ≤ 1.5, Ps ≥ .22). The late positive component (450-750 ms) showed a significant three-way interaction of laterality, anteriocity, and experimental conditions (F(3,57) = 2.8, P ≤ .05). Paired comparisons revealed that only high-arousal negative words provided a significantly greater positivity than neutral words in the left- and right-posterior electrode clusters (ts(19) ≥ 2.8, Ps ≤ .01). This in part replicates the results of previous studies, which found that high-arousal negative words elicit a greater late positivity than do neutral words (see Kissler, Herbert, Winkler, Junghofer, 2009, Scott et al., 2009), but this result may also be explained by the saliency of the relatively rarely occurring arousing stimuli (Donchin & Coles, 1988).

sLORETA

Positive words did not reveal any significantly greater activation than neutral words. High-arousal negative words elicited significantly greater activation than low-arousal negative words in a left occipito-temporal region, including the left fusiform (t = 3.46; x, y, z = -46, -54, -17) and middle temporal gyri (t = 4.18; x/y/z = -60/-50/0; see Figure 15). Contrasting high-arousal negative words with neutral words confirmed this activation difference (left fusiform, t = 4.45; x/y/z = -48/-58/-17; left middle temporal gyrus, t = 4.85; x/y/z = -56/-59/-3; see Figure 15).
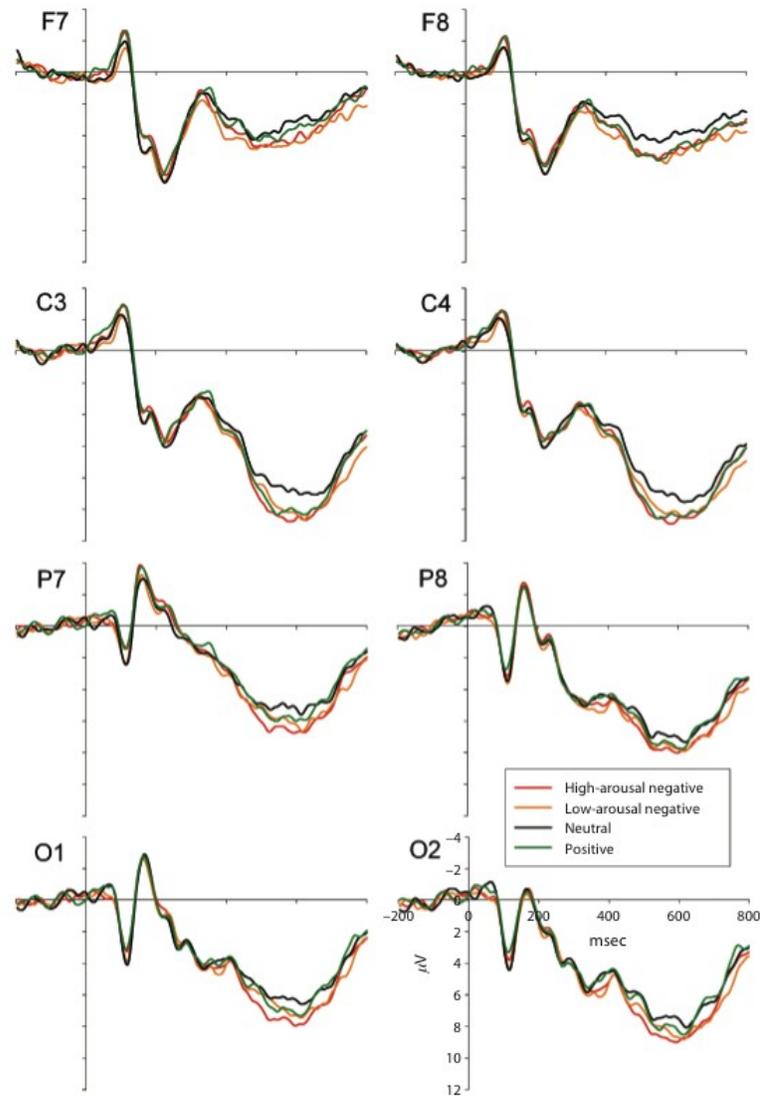
Figure 14: The event-related potentials for the four stimulus conditions at eight exemplary electrodes

Table 4: Means and Standard Errors for the Behavioral Measures and the Targeted Early Time Frame

| Dependent Variable | RT (msec) | | Errors | | Amplitudes (80–120 msec, μV) | | | | | | | |
| | | | | | Left Anterior | | Right Anterior | | Left Posterior | | Right Posterior | |
Condition	M	SE	M	SE	M	SE	M	SE	M	SE	M	SE
High-arousal negative	619	10	2.0	0.3	−2.2	0.3	−1.9	0.3	−0.7	0.4	−0.1	0.4
Low-arousal negative	643	10	3.9	0.7	−1.2	0.3	−1.3	0.3	−0.1	0.3	0.2	0.3
Neutral	630	9	2.8	0.4	−1.5	0.4	−1.4	0.3	−0.2	0.4	0.2	0.3
Positive	617	9	1.4	0.4	−2.3	0.4	−2.0	0.3	−0.9	0.4	−0.4	0.3
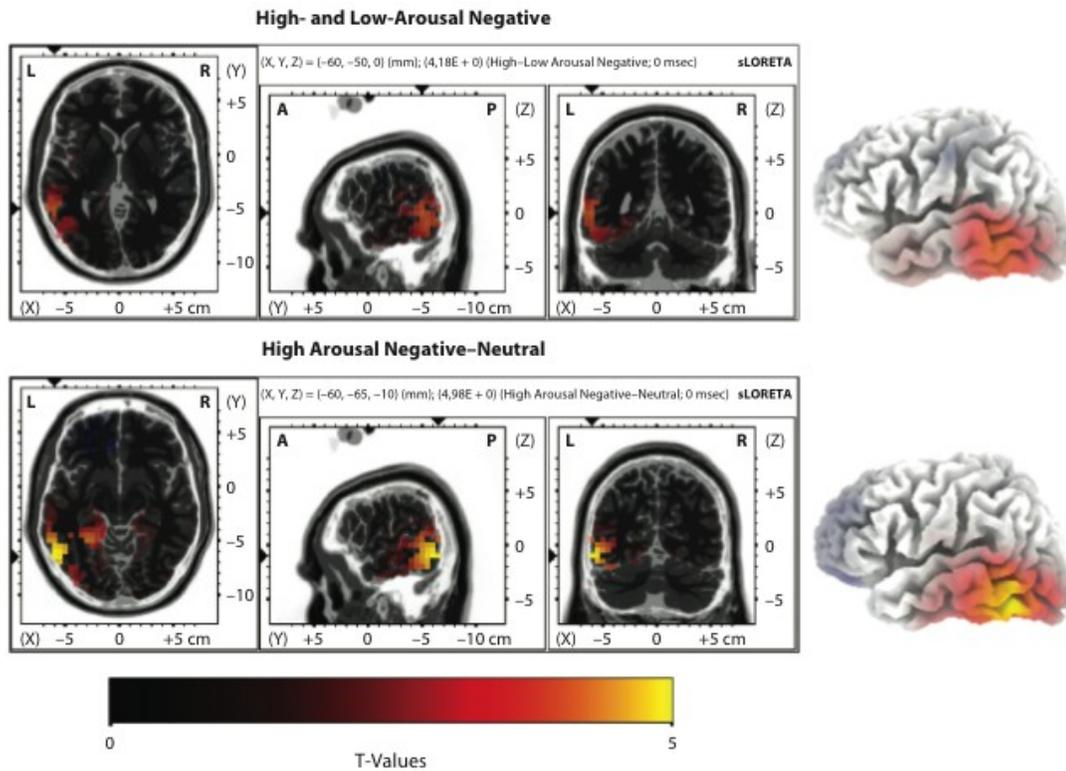
Figure 15: The maximum contrasts of high- and low-arousal negative words (upper panels), and high-arousal negative and neutral words (lower panels). Significant activation differences were observed in the occipito-temporal gyrus, including the fusiform gyrus. The X-Y-Z coordinates (MNI space) in the left panels show the activation maxima in the middle temporal gyrus.

Discussion

Whereas the behavioral facilitation to positive words was observed regardless of their arousal level, as was reflected by faster RTs and fewer errors, arousal seems to modulate behavioral responses to negative words. Thus, differences in arousal might explain the inconsistent findings of previous studies using negative words. These studies showed a speed-up (Nakic et al., 2006; Williamson et al., 1991), no influence of (Siegle et al., 2002), or even a trend towards slowing during lexical decision (Kuchinke et al., 2005; MacKay et al., 2004). Most interestingly, another recent study (Larsen et al., 2008) mathematically disentangled the influence of arousal on negative words, while canceling out the variance accounted for by various lexical variables. The authors observed longer RTs for emotionally negative words when arousal and other lexical variables were controlled for. The findings of the present study converge with this result, suggesting that emotional information can interfere with a decision that is theoretically based on cognitive information only (Siegle et al., 2002). In addition to Larsen et al.'s (2008) finding, the present study showed that high-arousal negative words elicited faster RTs and fewer errors than neutral or low-arousal negative words. Thus, it appears that the inhibitory role of negative valence on word recognition could be overruled by an arousal mechanism, which allows for fast and less error-prone reactions. The observed shortening of RTs for high-arousal negative words is in line with previous studies' finding of a similar speed-up during lexical decision. Nakic et al. (2006) observed this RT decrease for highly negative but not for moderately negative words. The authors, however, did not control for arousal. Nevertheless, it is likely that the highly negative words were also of high-arousal (Bradley & Lang, 1999; Võ et al., 2009). Moreover, Thomas and LaBar (2005) showed that priming effects during lexical decision are enhanced for high-arousal taboo words as compared with neutral words, whereas low-

arousal negative words showed no such enhancement of priming effects. This result has already indicated the influential role of arousal on negative words. The present study goes beyond this finding by showing that arousal also facilitates unprimed word recognition in negative words.

Apart from Thomas and LaBar's (2005) study, most other previous experiments taking arousal into concern manipulated arousal and emotional valence simultaneously. They presented high-arousal positive and negative words, and contrasted them with low-arousal neutral words (see Kissler et al., 2007). Although controlling for many influential variables in word recognition necessitated less extreme valence manipulations than in previous studies, the present study shows that positive emotional valence still exerted its facilitatory influence when arousal was controlled for. Moreover, arousal determined whether the effect of negative words was facilitatory (high-arousal negative words) or inhibitory (low-arousal negative words), in comparison with that of neutral words. This indicates that low-arousal positive and negative words are processed differently. The experimental conditions revealing the fastest responses -that is, positive and high-arousal negative words- elicited a greater ERP negativity than did the slower responses to neutral and low-arousal negative words in the time window of 80 to 120 ms. This may be taken as evidence that the behavioral facilitation observed for low-arousal positive and high-arousal negative words stems at least partially from early effects. As such, the present results replicate and extend the findings of Scott et al. (2009), who found high-arousal negative words to elicit a greater negativity than did low-arousal neutral words in the same time frame. However, this result was obtained only for high-frequency words. In contrast, the present study found the same early ERP arousal effect using low-frequency words (see Table 3). Moreover, Scott et al. (2009) did not observe the early ERP effect in positive words. This discrepancy might be due to differences in the task and the control variables used in these studies.

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The participants of the present study were instructed to respond within 1 sec after the stimulus presentation. We suggest that this time pressure may have resulted in an augmented usage of a lexical fast-guess mechanism, as implemented in the MROM (Grainger & Jacobs, 1996), which puts an emphasis on early processing. In addition to the control variables of length, word frequency, and valence used by Scott et al. (2009), we also controlled for imageability, number of syllables, number of orthographic neighbors, and mean type and token letter and bigram frequency (see Table 3). The application of these additional control variables may have resulted in a more consistent early processing across items, which might have increased the probability to observe early ERP effects in low-frequency positive and high-arousal negative words. In sum, the present results indicate that for negative words, it is the level of arousal and not the negative valence per se that affects the early processing.

Supporting the idea that lexical access for neutral words can be underway around a 100-ms poststimulus (Sereno & Rayner, 2003), the present data suggest that lexical access is speeded in positive and in high-arousal negative words. Thus, the time frame of the present ERP effects (80-120 ms) might capture the initial moments of lexical access in these affective stimuli. Similar to the present findings, those of Ortigue, Michel, Murray, Mohr, Carbonnel, & Landis (2004) showed occipital source localization differences that were the result of laterally presented emotional words around a 100-ms poststimulus (see also Bernat, Bunce, & Shevrin, 2001). Moreover, since Scott et al.'s (2009) early effect seemed to be modulated by word frequency, and word frequency effects were argued to constitute an upper limit for the time frame of lexical access (e.g., Dambacher et al., 2006; Hauk & Pulvermüller, 2004), the notion of an early lexical locus of the present ERP effects gains support.

This idea contrasts with Kissler et al.'s (2007) conclusion that emotional processing occurs only after lexical access. We suggest that the evolutionary advantage of emotional information processing in part results from its attribute to speed up

decisions, particularly when fast decisions are important. Since no such decisions were required in Kissler et al.'s study, the earliest emotional activation might not have been strong enough to be detected in the ERPs.

Such a lexical interpretation might also imply that semantic information can be activated in this early time frame. Since emotional words seem to trigger more associations than do neutral words, much of the effects of emotional valence may be accounted for by semantic cohesion (Maratos et al., 2000; Talmi & Moscovitch, 2004; but see McNeely, Dywan, & Segalowitz, 2004). Another study suggesting a semantic and thus lexical locus of the present effect comes from Skrandies (1998). He found that the semantic dimensions of words affect word processing as early as 80 ms after the stimulus presentation. Slightly later, semantically integrative effects during sentence processing have been observed (Penolazzi, Hauk, & Pulvermüller, 2007).

The early ERP time frame showed the same increased negativity to positive and high-arousal negative words, which may suggest a similar process in both conditions. However, sLORETA could not narrow the most likely neural source for the early ERP effect to positive words, which contrasts with a left occipito-temporal region emerging as the most likely neural source for the early arousal effects for negative words. This divergence points towards the early facilitation processes for low-arousal positive and high-arousal negative words to be based on different neural mechanisms. Within the left occipito-temporal region's showing a stronger activation to high-arousal negative than to low-arousal negative and neutral words, one subregion was the fusiform gyrus. This region was proposed to act as an interface between visual word form and higher order stimulus properties (Devlin, Jamison, Gonnermann, & Matthews, 2006; Price & Devlin, 2003; but see, e.g., Dehaene et al., 2002; McCandliss, Cohen, & Dehaene, 2003). Moreover, the largest activation differences were obtained in voxels located in the left medial temporal gyrus, which has been associated with semantic processing (Price, 2000). We thus suggest that the co-activation of the left fusiform and the medial

temporal gyrus supports Price and Devlin's (2003) suggestion of the fusiform gyrus operating as a hub mediating between visual word form and higher order stimulus properties, such as semantics. It is intriguing that the present ERP effect ascribed to arousal in negative words was localized in about the same brain region as was Kissler et al.'s (2007) localization of affective word processing. Their finding, however, was observed in a slightly later time frame. Like in the present study, Kissler and colleagues concluded that this effect reflects semantic processing. We propose that all of the early time frames prior to 300 ms contribute to semantic affective processing. This suggestion is corroborated by Hinojosa, Carretié, Valcarel, Mendez-Bertolo, and Pozo (2009). When the task is likely to be performed without semantic information, by identifying letter strings in contrast with nonletter stimuli, none of the early time frames is sensitive to the affective features of words. However, which of the early ERP time frames are more or less sensitive to semantic processing appears to be modulated by the application of a fast-guess mechanism. Computational models of word recognition (Grainger & Jacobs, 1996) can account for such differences in the processing dynamics by modeling differential task demands. Moreover, a computational model of affective word processing proposing that affective features take effect during an initial access to a hypothetical mental lexicon would account for the present results (Kuchinke, 2007). However, its assumption of arousal affecting positive and negative valence equally requires revision in the light of the present findings.

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Study 5: Remembering words in context as predicted by an Associative Read-Out Model

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Abstract

The present study extends the Multiple Read-Out Model of word recognition (MROM, Grainger & Jacobs, 1996) by an associative layer, using co-occurrence statistics. The predictions of this Associative Read-Out Model (AROM) were tested in a study-test recognition memory task (N = 30). According to Hebbian learning, two words were defined as being 'associated' if they occurred significantly often together in the sentences of a large corpus. The AROM correctly predicted an increased amount of 'yes' responses to both, learned and non-learned target words with more associated items in the stimulus set.

In the AROM, episodic memory traces are implemented in accordance with signal detection theory by larger initial activation signal strengths for learned than for non-learned words. As a consequence, old target items exhibit greater signal strength variance within the Interactive Activation Model (IAM) architecture, because the item's initial activation scales inhibitory activation changes (McClelland & Rumelhart, 1981).

This explains the typical recognition memory finding of a slope lower one of the z-transformed Receiver Operation Characteristics (z-ROCs). When fitting the model to the empirical z-ROCs, the AROM predicted item-level performance, i.e. which word is recognized with which probability given an experimental context of more or less associated items. AROM thus unifies processing models of implicit and explicit memory. Since many of the strongest associates reflect semantic relations to a target item (e.g., synonymy), this deterministic, localist connectionist model merges form-based aspects of meaning representations with meaning relations between words.

Introduction

IAMs have been used successfully to predict human word recognition performance, when the task implicitly requires retrieval of orthographic or phonological word forms from memory, such as perceptual identification, naming, lexical decision, or word stem completion (e.g., Grainger & Jacobs, 1996; McClelland & Rumelhart, 1981; Klonek, Tamm, Hofmann, & Jacobs 2009; Perry et al., 2007). However, IAMs have not yet been applied to model performance in explicit memory tasks, such as the recognition of a set of studied words. Since Berry, Shanks, and Henson (2008) propose that the same signals are detected in implicit and explicit memory, in this paper we explored the versatility of IAMs to predict explicit memory performance. This seemed like a natural extension, given that in an implicit memory task the MROM; Grainger & Jacobs, 1996) already successfully predicted ROCs (Jacobs et al., 2003), which are crucial for the development of formal memory theories (cf. Malmberg, 2008, for a recent overview).

A distinctive strength of IAMs is that they allow item-level predictions for various dependent variables, such as 'yes' response rates, mean response times, or mean amplitudes in electrophysiological responses (e.g., Hofmann et al., 2008; Perry et al., 2007; Rey, Dufau, et al., 2009; Spieler & Balota, 1997). IAMs are currently able to simulate effects resulting from lexical whole word representations or from smaller, sub-lexical representations during word recognition (e.g., Conrad et al., 2009; Perry et al., 2007; cf. Ziegler & Goswami, 2005). So far, however, they neglect the fact that words are embedded into an experimental context of other meaningful words that potentially share a common learning history with the target word. Contextual between-word associations like the semantic relation of 'lung' to its hypernym 'organ' were discussed as extension possibilities for connectionist models (e.g., Coltheart et al., 2001;

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Rumelhart & McClelland, 1982; Seidenberg & McClelland, 1989), but never used for quantitative performance predictions. Such inter-item associations are better understood in the explicit memory literature (e.g., Kimball et al., 2007; Nelson et al., 1998; Roediger & McDermott, 1995), while item-level predictions of recognition memory performance are still lacking. Therefore, the present study aimed to keep the IAMs' quantitative strengths of z-ROC and item-level predictions, while seeking to overcome an important weakness: predicting the impact of associative relations between words in an explicit recognition memory task.

Does associative spreading activate 'false memories'?

The probably best-known associative memory phenomenon is the so-called "false memory effect" (Deese, 1959; Roediger & McDermott, 1995): Learning associated items (e.g., "table", "sit", "legs") to a non-learned target item (e.g., "chair") favors its erroneous recall or recognition. Moreover, when learning "chair" in the company of such associates, its "veridical recall" is more likely (Kimball et al., 2007). These experiments rely on tediously collected free association performance to define associations in subjective terms: A target is presented and participants name the first associates coming to their minds. Learning all of the most strongly associated items increases the target's retrieval probability in a later memory experiment. However, such an experimental design takes only a small subset of the possible associations between the items of an experiment into account (Ratcliff & McKoon, 1994). The present study tested a simple co-occurrence approach allowing to consider all associations between all items (cf. Andrews et al., 2009; Bullinaria & Levy, 2007; Griffiths et al., 2007; Landauer & Dumais, 1995): Two words were defined as being 'associated' when they occurred significantly more often together than alone in a sample of 43 million sentences (Quasthoff et al., 2006; http://corpora.uni-leipzig.de/). Hebbian learning is the

only assumption required for this definition: Stimuli being repeatedly presented together are likely to be associated (Hebb, 1949; Rapp & Wettler, 1991).

Roediger and McDermott (1995) compared targets of which all of the most strongly associated items were learned, to targets of which no (freely) associated item occurred in the experimental context. Here, we hypothesized that the more associates occurred to a non-learned (new) target in the stimulus set, the greater is the amount of erroneous 'yes' responses. Similarly, learning the most strongly associated items of a target word should increase the tendency to freely recall it (Kimball et al., 2007). This led to the hypothesis that learned (old) targets, which have more associates in the stimulus set, produce greater recognition rates. We tested these hypotheses in a study-test paradigm with the experimental factors old/new and co-occurrence level (low/high): low co-occurrence target items had less than 8 significantly co-occurring items in the stimulus set, and high co-occurrence words had at least 8.

To implement these hypotheses, we extended the MROM by an associative layer (Grainger & Jacobs, 1996). The MROM consists of three layers of interacting processing units (Figure 16): The visual features of the target stimuli serve as input variables for the model's feature layer. Feature units activate letter units, which in turn excite units of the orthographic word layer (McClelland & Rumelhart, 1981). In the Associative Read-Out Model (AROM), an associative unit for each item presented in the experiment was added. Since the process of word identification is necessary for recognizing it as learned, the association unit obtained an excitatory word identification signal from the corresponding orthographic word unit. The co-occurrence statistics implemented excitatory associative connections between the units in the associative layer. These linkages are assumed to reflect the pre-wired associative structure of human long-term memory, which matured by experience with words (Hebb, 1949). When the target item is presented to the model, its association unit activates all associated item units, which in turn activate the target unit. Thus, the greater the

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amount of associations of a word to the other items of the stimulus set (Anderson, 1983; Collins & Loftus, 1975), the greater is the activation 'echo' from associated units that spreads back to the target item's unit (Nelson et al., 1998). Since greater activation signals of IAMs typically predict a greater amount of 'yes' responses (e.g., Grainger & Jacobs, 1996; Hofmann et al., 2008), the AROM allows the following hypothesis: The more associated items a target has, the larger its associative activation. This should result in a greater amount of 'yes' responses for both, new and old high co-occurrence target items. Apart from this qualitative, condition-wise prediction, we fitted the AROM to (cross-condition) ROCs, and tested whether the obtained signal strengths accounted for item-level variances.
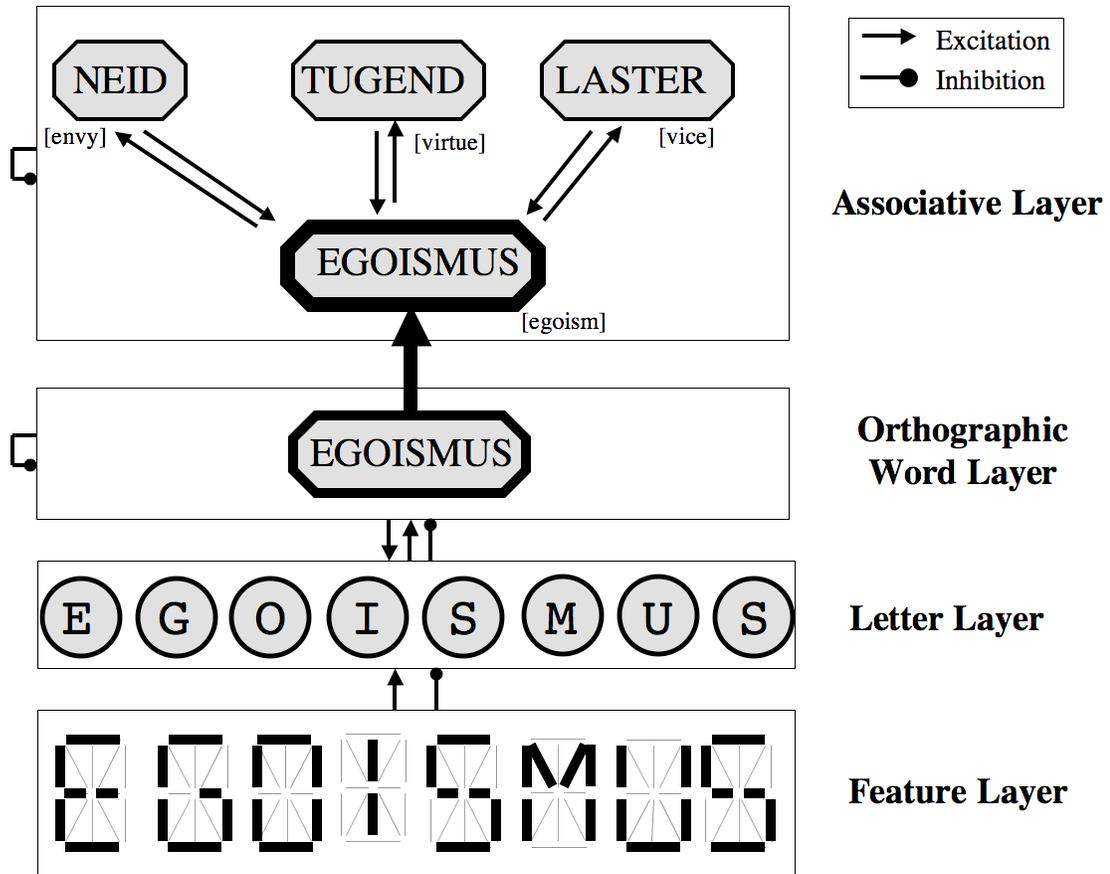
Figure 16 sketches the basic architecture of the AROM: The lower three layers correspond to previous IAMs (Grainger & Jacobs, 1996; McClelland & Rumelhart, 1981). Target stimuli are presented to the feature units, which in turn activate the letter and (orthographic) word layer. The associative layer's unit of the target receives the word identification signal from the orthographic word layer. Moreover, associated item units contained in the stimulus set are activated by the target unit, and activate the target in turn. Thus activations to item units with many associated items are greater, which predicts their higher probability of 'yes' responses. Translations are bracketed. This Figure corresponds to Figure 7 and is reprinted here for convenience.

Can each item's signal be detected in an explicit memory task?

To allow for signal detection analyses, participants in the experimental study were instructed to rate their recognition confidence on a six-point scale ranging from 'sure no' ('1') to 'sure yes' ('6'). For all but the ROC analyses, '4' ('unsure yes') to '6' counted as 'yes' response. Based on these confidence ratings, the signal detection approach (Green & Swets, 1966) allows for simulating performance from the most liberal response bias by the criterion C(1) to the most conservative bias: C(5) is prone to elicit the fewest 'yes' responses by counting all '1' to '5' responses as 'no'. The criteria C(i) are assumed to reflect empirical 'yes' response probabilities on a bimodal Gaussian distribution of (memory) signal strength of the items: One distribution for the new target items, and another one for the old ones (cf. Figure 17, upper panels). Signal detection theory describes episodic memory traces resulting from study-phase presentation by the ad-hoc assumption of greater mean memory signal strength for old than for new items. To generate ROCs, the 'yes' probabilities for all criteria (Figure 17, middle panels) are plotted for new items on the x-axis, those to old items on the y-axis. When z-normalizing these ROC probabilities (cf. Figure 18, lower panels), the so-called z-ROCs typically reveal a slope of less than one during recognition memory tasks (e.g., Glanzer et al., 1999; Ratcliff, Sheu, & Gronlund, 1992). Single-process signal detection models describe this by a second ad-hoc assumption: The signal strength variance is greater for old than for new items (Green & Swets, 1966). However, such an unequal variance model does not provide an answer to the question of why the variances are greater to old items (Glanzer et al., 1999). In contrast, Yonelinas' (1994) dual-process model gives a simple account of the z-ROC's tilt-down: Recollection, i.e. the detailed recognition of a particular item, is a memory process only apparent for old items. One aim of the present study was to provide an explanation relying on a single signal strength variable: (associative memory) signal strength.

Jacobs et al. (2003) equated model activations with signal strength to predict z-ROCs from the MROM's activations. To adopt signal detection theory's assumption of greater signal strengths in old items (Green & Swets, 1966), the initial activation values were increased for association units representing learned items, in comparison to non-learned ones: This resting level represents every memory trace which has been potentially activated before the presentation of the present test-phase trial, and will be indicated as cycle 0 (Figure 19). Learned item units are given greater pre-activation values than non-learned ones, because they have been presented before in any case. In randomized stimulus sets, non-learned associates of a target item were exposed previous to that target with an average probability of 50%. Therefore, the resting level of non-studied item units is defined to be lower than that of learned ones. Both resting levels were initialized above the activation threshold (of zero), so that all associative units can excite and inhibit each other in cycle 0. Due to excitation, new and old associates can take an active role in contextually cueing the present item (Gillund & Shiffrin, 1984). Since only about 5% of the possible unit pairs are associatively connected in an excitatory fashion (cf. Simulation Methods), the net sum of inhibition is greater than the excitation in cycle 0. When the activation change of the target item's association unit is calculated from this net inhibition in an IAM, it is weighted by its present activation (McClelland & Rumelhart, 1981). As the resting level was defined to be greater for old than for new item units, greater inhibitions result for old item units. Therefore, the target unit's activation variability in cycle 1 is necessarily greater for old than for new items. As a consequence, the second ad-hoc assumption of unequal variance follows logically from the first assumption, when implementing it into an IAM: a greater signal strength variability for old targets items, which monotonically increases with the memory signal strength difference between old and new items.

To predict human performance, Jacobs et al. (2003) defined signal strength as the mean activation across the first seven cycles (see also Grainger & Jacobs, 1996;

Hofmann et al., 2008). Accordingly, in the AROM a target unit's mean associative activation in cycles 1-7 is taken as its signal strength in the associative layer, henceforth called Associative Memory Signal Strength (AMSS). For cycle 1, the first assumption of signal detection theory of greater old item variances transforms into the prediction of larger old items' variances as compared to new items in an IAM. For AMSS, however, this prediction has to be tested within the AROM architecture across the whole parameter space, i.e. irrespective of the choice of the five free parameters: the scaling of excitation from the orthographic identification signal to the association units, the scaling of excitation and inhibition in the association layer (Figure 16), and the resting levels of old and new item units.

For obtaining signal strength distributions, the resulting AMSS values were transformed to functional forms for all four experimental conditions, i.e. the new and old low and high co-occurrence conditions. Since AMSS is conceptualized as the signal strength of the items, an additional source of variability of the items' fixed signal strengths was required. Therefore, smoothed kernel density functions were applied for the transformation to functional forms, and the smoothing kernel factor κ was the only free parameter required for z-ROC generation. κ reflects the variability of the deterministic AMSS values of the items. The empirically obtained 'yes' response probabilities were used as C(i) (cf. Figure 17, second row). The parameters were optimized by fitting the model-generated z-ROCs to the empirical z-ROCs by minimizing the sum of the least squared errors of the slopes and intercepts of the low and high co-occurrence conditions (cf. Figure 17, third row). We then tested whether the z-ROC slopes of the participants deviated from those predicted by the model. These model tests were run for low and high co-occurrence conditions, separately.

Once the parameters were fixed, the AROM was challenged to account for item-level variance. Previous signal-detection-capable models of recognition memory (Malmberg, 2008) targeted the signal strengths of the items, but did not specify which

particular word stimulus provides which signal strength (e.g., Glanzer, Adams, Iverson, & Kim, 1993; McClelland & Chappell, 1998; Murdock, 1997; Shiffrin & Steyvers, 1997). Instead of representing items by random variables, the AROM relies on local representation units (Page, 2000). That is, visual features and letters define a particular word form (Grainger & Jacobs, 1996; McClelland & Rumelhart, 1981). In contrast to its direct precursors, the AROM additionally defines the meaning of a word by the company it kept during its learning history, i.e. co-occurrences (Andrews et al., 2009; Firth, 1957; Hebb, 1949). Localist representations are particularly suitable for testing whether the words associated by the model display intuitively valid associations, and whether the AROM can integrate semantic representations into a processing model of recognition memory (Steyvers et al., 2006).

Simulation methods: The AROM and its predictions

The feature, letter, and word layers remained largely[12] unaltered compared to the AROM's predecessors (Grainger & Jacobs, 1996; McClelland & Rumelhart, 1981). The word and associative layer lexica of the model contained one unit for each of the 160 items presented in the experiment. The added associative layer in general reflects the basic architecture of each layer of an IAM architecture, which is described more thoroughly elsewhere (Grainger & Jacobs, 1996; McClelland & Rumelhart, 1981). Only modifications of these, as well as assumptions critical for the present findings will be described in the following.

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[12] Since the original IAM was designed for four-letter stimuli (McClelland and Rumelhart, 1981), and the present stimulus set contained three- to eight-letter stimuli, the **e**xcitatory **a**ctivation forwarded from the letter to the orthographic word layer was **norm**alized by word **l**ength (ea$_{norm}$ = l * ea/4; cf. Conrad, Tamm, Carreiras, and Jacobs, 2010). The rationale is that attention is uniformly distributed across all letters, but remains the same as in the original IAM for four-letter stimuli. Inverted frequency class measures of the Leipzig Corpus were used for setting the resting levels in the orthographic word layer (cf. Corpus).

Word identification signals from the orthographic word layer activated the associative units (cf. Figure 16). Each **A**ssociative word unit **x** in cycle **c** obtained input activation $A_x(c)$ by excitatory connections from the corresponding **O**rthographic word unit activation of the last cycle [$O_x(c-1)$]. Please note that only if the activation $O_x(c-1)$ crosses the activation threshold (of zero), excitation or inhibition take place, i.e. if ($O_x(c-1) > 0$) its logical value is 1, otherwise it is 0. The excitation from the **o**rthographic to the **a**ssociative layer was scaled by the free excitatory parameter α_{oa} [$A_x(c) = (O_x(c-1) > 0) * O_x(c-1) * \alpha_{oa}$]. If a word **y** was significantly co-occurring to the word x [i.e., **x^y**], an excitatory associative connection was added. It was quantified by log10-transformed χ^2 values of within-sentence co-occurrence statistics crossing the significance threshold of $\chi^2 = 6.63$ (P < 0.05; Dunning, 1993; Quasthoff et al., 2006), and scaled by a free parameter α_{aa}. Thus, the associative excitation function can be written $A_x(c) = A_x(c-1) + (A_y(c-1) > 0) * A_y(c-1) * log10\chi^2_{x^y} * \alpha_{aa}$. Moreover, all activated words [e.g., $A_y(c-1)$] inhibited each other word [e.g., $A_x(c-1)$] by an amount scaled by a free parameter γ_{aa} [$A_x(c) = A_x(c-1) - (A_y(c-1) > 0) * A_y(c-1) * \gamma_{aa}$]. According to this architecture, the AROM predicts greater activations, and thus a greater amount of 'yes' responses for target items with a greater amount of associated items in the stimulus set. Thus, the summed **n**et change $n_x(c)$ of each association unit is a function of the amount of **e** excitatory units (i.e. the number of significantly co-occurring items), and a function of all **N** neighbor units (N = 159) potentially inhibiting the respective unit, i.e. $n_x(c) = (O_x(c-1) > 0) * O_x(c-1) * \alpha_{oa} + \sum_{y=1}^{e} ((A_y(c-1) > 0) * A_y(c-1) * log10\chi^2_{x^y} * \alpha_{aa}) - \sum_{y=1}^{N} ((A_y(c-1) > 0) * A_y(c-1) * \gamma_{aa})$.

For simulating episodic memory traces, the resting levels ρ were constrained to be larger for **old** [ρ_{old}] than for **new** items [ρ_{new}, i.e. $\rho_{old} > \rho_{new}$]. Resting levels are referred to by cycle c = 0, i.e. $A_x(0) = \rho_{old}$ for all old items, and $A_x(0) = \rho_{new}$ for all new units. All units cross the activation threshold at resting level, and thus inhibit and excite other units. As each unit can be connected to each other unit, but the association of a unit to itself is set to zero, 25,440 associations between the units are possible ($160^2 -$

160 items). 1,402 of these associations (i.e., significant co-occurrences) were apparent. Most of the connections are inhibitory and thus a negative net inhibition $n_x(0)$ follows from cycle 0. To obtain nonlinear dynamics, with a minimum activation **m** = -1, a net inhibitory change is weighted by the associative activation of the unit $A_x(c-1)$ itself, thus finally giving: $A_x(c) = A_x(c-1) - n_x(c-1) * (A_x(c-1) - m)$ (cf. McClelland & Rumelhart, 1981, p. 381, formula 3 and 4 while decay is zero in this case). Even when the net changes would be of equal variance across $n_{old}(0)$ and $n_{new}(0)$, $A_{old}(1) = \rho_{old} - n_{old}(0) * (\rho_{old} - m)$ will produce a greater variance across all old target item units than $A_{new}(1) = \rho_{new} - n_{new}(0) * (\rho_{new} - m)$, for all new items (see Appendix for a Matlab script providing a logical demonstration based on random equal variance net inputs).

Formally, the memory signal strength of the **t**arget item's unit is defined as **AMSS** $= (\Sigma_{c=1}^{7} (A_t(c))) / 7$ (cf. Introduction). We tested whether the old item units reveal a greater variance across these first seven cycles (AMSS) than new item units in the following parameter space, using step-sizes of 0.01: α_{oa} from 0.04 to 0.09, α_{aa} from 0.03 to 0.08, γ_{aa} from 0.03 to 0.08, ρ_{new} from 0.01 to 0.05, and ρ_{old} from 0.06 to 0.1. This resulted in 5400 parameter sets.

To fit the simulated to the empirical z-ROCs, we transformed the AMSSs of the four experimental conditions into smoothed kernel density functions (Figure 17, first row), using the smoothing kernel factor κ as free parameter. When these functions are transformed to cumulative 'yes' response probabilities, the empirical 'yes' response probabilities of new items were used as signal detection criteria C(i) of the model (Figure 17, second row). κ was fitted iteratively from 0 to 30 using step sizes of 0.01, while minimizing the root mean squared differences between the modeled and the empirical z-ROC slopes and intercepts for the low and high co-occurrence conditions (Figure 17, third row). Finally, we tested whether the AMSS values of the fixed parameter set can account for a significant portion of item-level variance in new and old items.

Experimental methods: Testing the AROM's predictions

Participants

The participants were 30 native German speakers (17 female, mean age: 29.5, SE: 2.39, range: 16-60) without known reading disorders. They had normal or corrected-to-normal sight, and were paid for participation or received course credits.

Corpus

Word frequency and co-occurrence measures were taken from the German corpus of the "Wortschatz" project (status: December 2006, http://corpora.informatik.uni-leipzig.de/; Quasthoff et al., 2006). They are based on 800 million tokens and 43 million sentences. The corpus is largely composed of online newspapers (1992-2006). To allow the AROM's testability in 69 languages, corpus-size independent word frequency class measures of this cross-linguistic project were used. These relate the frequency of each word to the most frequent word, i.e. "der" is 2^{class} more frequent than the given word. Thus the lower the frequency class, the higher is the word frequency. Further, two words were defined associated if they co-occurred significantly more often within the same sentence than predicted from their single frequencies by the log-likelihood test ($P \leq 0.01$, $\chi^2 \geq 6.63$; Dunning, 1993).

Stimuli

Each cell in the 2x2 design (factors: old/new and co-occurrence) contained 40 nouns. Stimuli of the high co-occurrence conditions had at least 8 significantly co-occurring neighbors in the stimulus set, and low co-occurrence stimuli less than 8. To rule out biased effects due to confounding variables (all Fs < 0.5, cf. Table 5), we controlled for emotional valence, arousal, imageability, number of orthographic

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neighbors and letters (Võ et al., 2009), as well as word frequency, and token bigram frequency. Token bigram frequencies were calculated by the SUBLEX software (Hofmann et al., 2007), using the frequency counts of the Leipzig Wortschatz project cleaned by all word forms not contained in the CELEX lexical database (Baayen et al., 1995).

Table 5 displays the means (SDs) of the manipulated and controlled variables of the target stimuli in the four experimental conditions. Emotional valence ranges from -3 to +3. Imageability and arousal range from 0 to 5.

Factors:				
Old/new:	New	New	Old	Old
Co-occurrence:	Low	High	Low	High
Number of stimuli	40	40	40	40
Number of significantly co-occur-ring items in the stimulus set	3.85 (1.70)	13.90 (4.73)	3.80 (1.70)	13.85 (4.04)
Emotional valence	0.11 (1.31)	0.03 (1.23)	0.03 (1.09)	0.00 (1.34)
Imageability	3.89 (1.22)	3.96 (1.29)	3.94 (1.20)	4.01 (1.43)
Arousal	2.95 (0.53)	2.90 (0.58)	2.87 (0.54)	2.98 (0.64)
Word frequency class	11.65 (0.70)	11.65 (0.70)	11.68 (0.47)	11.57 (0.71)
Number of orthographic neighbors	1.57 (2.26)	1.32 (1.81)	1.57 (2.14)	1.70 (2.29)
Bigram Frequency	17520 (106001)	17556 (9263)	16489 (9149)	16648 (8546)
Number of Letters	6.08 (1.07)	6.12 (1.14)	6.22 (1.10)	5.97 (1.35)

Procedure

80 old words were presented in the study phase and all 160 words in the test phase. Participants were instructed to judge how confident they are that a presented target stimulus was presented in the previous study phase ('yes'), or not ('no'). Participants were informed that they receive feedback about their error scores after the test phase. Performance data were acquired using a computer mouse. Stimuli were presented by Presentation 9.9 software (Neurobehavioral Systems Inc., Canada). To familiarize the participants with the task, five practice items were presented each before the study phase and before the test phase.

Study phase. Each trial began with a fixation cross remaining on the screen for 500 ms followed by a stimulus presented for 1500 ms. Five hashmarks ('#####') appeared until a mouse button was pressed. To avoid primacy and recency effects, three filler items were presented before and after the critical stimuli.

Test phase. A fixation cross was presented for 500 ms. Target stimuli were presented for 1500 ms, followed by a blank screen of 1500 ms. A rating scale appeared on the screen, and the participants judged their recognition-confidence via mouse clicks on a 6-point scale ranging from '1' ('sure no') to '6' ('sure yes'). For a random number of participants, this assignment was reversed during the experiment, but not for the analyses. Participants were instructed to use all confidence judgments approximately equally often. A blank screen of 500 ms was presented before the next trial started with a new fixation cross. None of the filler and practice items had any significantly co-occurring item in the critical stimulus set.

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Experimental and modeling results

A 2x2 repeated measures ANOVA on the percentage of 'yes' responses revealed a significant old/new effect ($F(1,29) = 167.77$, $P < 0.001$, $\eta_p^2 = 0.85$). Old items produced more 'yes' responses. Moreover, a significant effect of co-occurrence was obtained ($F(1,29) = 21.91$, $P < 0.001$, $\eta_p^2 = 0.43$), but no significant interaction ($F < 1$). The planned comparison revealed that high co-occurrence new stimuli produced a greater 'yes' response rate ($M = 0.2$; $SE = 0.02$) than low co-occurrence new stimuli ($M = 0.13$; $SE = 0.02$; $t(29) = 3.80$, $P < 0.001$). High co-occurrence old stimuli ($M = 0.76$; $SE = 0.04$) produced more 'yes' responses than low co-occurrence old stimuli ($M = 0.69$; $SE = 0.03$; $t(29) = 3.02$, $P < 0.005$). Averaged across participants, the z-ROC slopes were 0.66 in the low co-occurrence condition and 0.70 in the high co-occurrence condition. Figure 17 displays the empirical z-ROCs with slopes smaller than 1.

All 5400 parameter sets used for optimal parameter estimation revealed a greater AMSS variance for old than for new target items (Figure 18). The least squared differences between the modeled and the empirically obtained z-ROCs for low and high co-occurrence items were obtained for the parameters of $\alpha_{oa} = 0.09$, $\alpha_{aa} = 0.03$, $\gamma_{aa} = 0.04$, $\rho_{new} = 0.05$, $\rho_{old} = 0.07$, and $\kappa = 10.09$. The parameters were fixed at these values. Simulated z-ROC slopes were 0.75 and 0.77 for the low and high co-occurrence conditions, respectively. For both co-occurrence conditions, the modeled z-scores for the five criteria of the new and old items, respectively, were tested for their capability to predict the ten z-scores empirically obtained (cf. Jacobs et al., 2003): The model's z-scores accounted for 99.61% of the variance of the low co-occurrence data ($F(1,9) = 2044.85$; $P < 0.001$; RMSD = 0.07), and 99.05% of the high co-occurrence z-scores ($F(1,9) = 834.45$, $P < 0.001$, RMSD = 0.10). The behaviorally obtained z-ROC slopes of the low and high co-occurrence conditions for the individual participants did not differ significantly from the z-ROC slopes predicted by the model ($t(29) = 0.17$; $t(29) = 1.55$;

Ps > 0.1)[13]. The new target items AMSS scores accounted for 14.32% of the variance of the 'yes' response probabilities (F(1,79) = 13.04), and the old targets for 10.45% (F(1,79) = 9.10; Ps < 0.001; RMSDs = 0.08).

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[13] Zero 'yes' responses were treated as one 'yes' response, and only 'yes' responses were treated as all but one 'yes' responses, to allow for z-transformation.
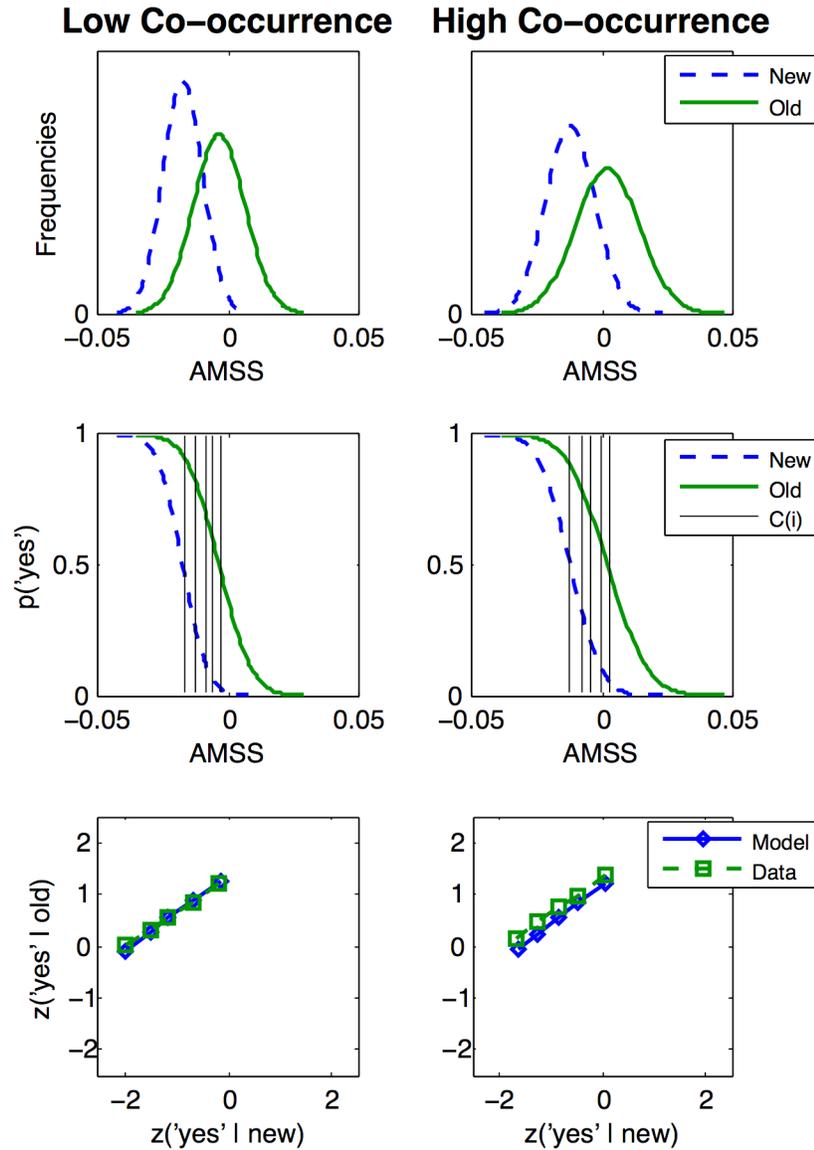
Figure 17 shows the distributions of the associative activations and the resulting z-ROCs for the low (left panels) and high co-occurrence (right panels) conditions: The first row displays the associative memory signal strength (AMSS) distributions transformed to smoothed probability density functions for the four experimental conditions. The second row depicts these functions transformed into cumulative 'yes'-response probabilities and the five response criteria $C(i)$ for $i = 1$ to 5. The third row shows the empirical and modeled z-ROCs.
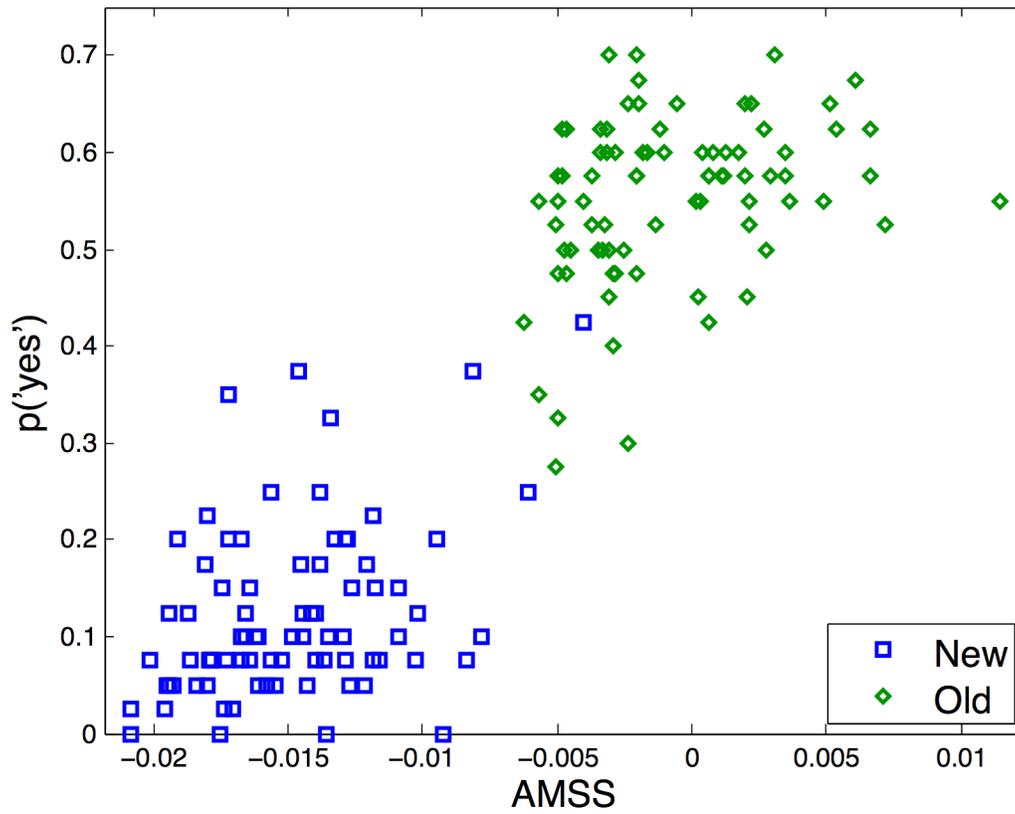
Figure 18 shows the AMSSs of the word units predicting the 'yes' response probabilities for new and old items.

Discussion

The present study provides two novel IAM features: Relying on Hebb's (1949) notion of stimuli that are repeatedly presented together as being 'associated', we correctly predicted that a higher amount of associations in the stimulus set lead to higher proportions of 'yes' responses to non-learned and learned items in recognition memory for words. Second, we extended a localist connectionist word recognition model by an associative layer, and showed that this AROM predicts recognition memory performance from the core cross-condition level of ROCs down to the fine-grained item level.

The effect in non-learned items is related to the false memory effect but goes beyond Roediger and McDermott's (1995) seminal work: 'False memories' consisted of the comparison of target items from which either all of the most strongly associated, or no (freely) associated items were learned. The present study observed similar effects in a recognition memory task. However, defining associations by co-occurrence statistics allowed for taking all associations between all items of the stimulus set into account. Still, when a target item contained more associations in the stimulus set, a significant effect of co-occurrence indicated more 'yes' responses for new words.

For learned target items, we discovered that many associations boost recognition memory performance, as indicated by a co-occurrence effect for old words. Since the present stimulus set was carefully controlled for all kinds of psycholinguistic single-word features, we suggest that both, the co-occurrence effects to new and old items, can be attributed to the manipulation of the amount of associations of a target item.

To account for both of these findings, the co-occurrence statistics were embedded into an associative activation-spreading network (Collins & Loftus, 1975) that was added to an IAM-architecture (cf. McClelland & Rumelhart, 1981; cf. Figure 16):

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The MROM (Grainger & Jacobs, 1996) can account for human performance in a variety of tasks that rely on implicit mnemonic processes. As no top-down modulations from the associative to the lower layers were implemented (cf. Figure 16), the AROM in its simplest form contains an unchanged MROM. Therefore, the AROM can still account for all of its predecessor's effects and thus has a higher level of generality than the MROM (e.g., Grainger & Jacobs, 1996).

For extending the scope of IAM's to explicit memory processing, we implemented memory traces from the study-phase presentation according to signal detection theory (Berry et al. 2007). It assumes greater signal strengths for old than for new items (Green & Swets, 1966). Thus, the units of learned items obtained greater resting level activations in the associative layer than non-learned ones. Unequal variance analysis models require a second assumption to describe the z-ROCs tilt-down, i.e. a greater signal variance to learned items (Green & Swets, 1996; cf. DeCarlo, 2002). The present study shows that implementing the first assumption of the old items' greater memory strength into an IAM makes the second ad-hoc assumption of unequal variances redundant. An IAM explains a slope of the z-ROC smaller one based on its antecedent conditions (cf. Jacobs & Grainger, 1994): An increased signal variance for old items – critical for the z-ROC's slope smaller than one during recognition memory – can be explained by the necessity of nonlinear activation dynamics, which are an element of all neurobiologically plausible connectionist models (cf. O'Reilly, 1998; McClelland, 1993): A modeling unit – mirroring a neuron or a cluster of neurons in the brain – can receive one to nearly an infinite amount of excitatory or inhibitory signals from other neurons. To avoid catastrophic cascades of neural activation bursts that could potentially damage neurons, this activation is bounded to a maximum. As the firing rate of a neuron cannot be negative, a further assumption of minimum activation is required (e.g., Bogacz, Usher, Zhang, & McClelland, 2007). Such biological constraints necessitate the activation of modeling units to be a nonlinear (sigmoid) function of the amount of net

input (Grossberg, 1978; McClelland, 1993). Therefore, the activation change of a unit is scaled by its current activation in an IAM (McClelland & Rumelhart, 1981). Resulting from the activation-scaling by a unit's resting level, which is higher for old items, incoming inhibitory signals affect the old target item units to a greater degree than units representing new items of lower resting level activation. Therefore, the variability of the signal is greater in the old items' units starting from cycle 1. The assumption of greater activation variance of old items was also confirmed to be true across the first seven cycles. The AMSSs are greater for old than for new items, irrespective of the choice of the free parameters explored. Accordingly, the AROM correctly predicted z-ROC slopes smaller than one, which are typically observed in the recognition memory task (Glanzer et al., 1999; Ratcliff et al., 1992).

Apart from these proof-of-concept explanations, the present study aimed at fitting the actual z-ROCs to low and high co-occurrence words by the AROM. Predicting z-ROCs from the AMSS of the items involves a modeling challenge well-known in recognition memory research (Gillund & Shiffrin, 1984, p. 16). The overlap between the old and new item signal distributions was too low (cf. AMSS values in Figure 18). A previous MROM-based simulation study solved this by adding noise to the criteria (Jacobs et al., 2003). In contrast, the present AMSS values were transformed into smoothed kernel density functions to obtain an estimate of the (random) signal variability of the otherwise deterministic AMSS values. Thus even 'noise' was conceptualized in a fashion allowing the model to remain fully deterministic. Moreover, instead of three free parameters required for z-ROC generation in the MROM (Jacobs et al., 2003), the present study cut this number down to one, the Gaussian smoothing kernel factor κ.

In addition to the z-ROC parameter, two free parameters were necessary for the (old and new item units') resting levels, and three scaled the excitation from the orthographic word to the associative layer, as well as excitation and inhibition within the

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associative layer. After fitting these free parameters, the empirically obtained z-ROC slopes and z-scores did not deviate from those predicted by the model (Figure 17).

The unequal variance signal detection model just begged the answer to the question of why the z-ROC slope is smaller than one, by assuming greater signal strength variances of old items (Glanzer et al., 1999; Green & Swets, 1966; cf. DeCarlo, 2002). The dual-process model may, in contrast, provide an answer by conceiving of recollection as a phenomenally and neurally distinguishable process (Yonelinas, 1994; Yonelinas, Otten, Shaw, & Rugg, 2005; Wixted, 2007; cf. Malmberg, 2008). The AROM's architecture complements previous unequal-variance based models by an answer to the question of why the z-ROC slopes are smaller than one during recognition memory: These are a logical consequence of the episodic memory traces built at study itself. When many traces actively compete in memory, each representation unit obtains net inhibitory signals. As the resulting activation changes are scaled in an IAM-architecture by the unit's activation, larger resting levels of old items lead to their greater signal strength variances (Squire et al., 2007).

Although the earliest associative activation-spreading models did not discuss false and veridical recognition, they would likely predict these effects (Anderson, 1983; Collins & Loftus, 1975; Quillian, 1967). A contemporary modeling approach can account for the build-up of associations, but not yet for effects of the pre-wired associative paths in long-term memory (e.g., Danker, Gunn, & Anderson, 2008). Though Ratcliff and McKoon (e.g., 1994) envisioned the predictive power of co-occurrence statistics early, Nelson et al. (1998) used free association performance to propose a pre-quantitative model, which accounted for effects of the number of associates in a stimulus set during recognition memory (cf. Andrews et al., 2009; Thompson-Schill & Botvinick, 2006). Kimball et al. (2007) recently proposed a computational model that can quantitatively account for false and veridical recall.

The AROM is novel in that it provides quantitative associative-spreading predictions for recognition memory performance. Neither any spreading-activation model, nor any recognition memory model simulates word recognition with the same depth as the AROM: It predicts which word is recognized with which probability depending on the amount of its associates. The more associated items are in the stimulus set for a non-learned or learned target item, the larger is the probability to classify it as old. Thereby, the false memory logic is elevated to a level capable of making item-level predictions. For veridical memory of old items, the AROM's item-level performance is somewhat lower than for the false memories in new items (see also Figure 17, lower right panel). This potentially results from the need to consider a second source of information for the prediction of old items (e.g., Yonelinas, 1994; DeCarlo, 2002). Moreover, we are fully aware that the AROM's 'horizontal' generality is limited (Jacobs & Grainger, 1994): Other recognition memory models account for a much broader range of explicit memory phenomena (e.g., Glanzer et al., 1993; Malmberg, 2008; McClelland & Chappell, 1998; Shiffrin & Steyvers, 1997; but cf. Grainger & Jacobs, 1996, for implicit memory). In turn, the present approach 'vertically' generalizes across different instances of the same data, i.e. cross-condition z-ROCs, condition-wise associative effects in new and old items, and last but not least, the AROM is the first signal-detection model of recognition memory that assigns signal strength to each particular word stimulus. This allows for predicting the percentage of participants recognizing this particular orthographic word form in the distinct associative context of other words, which extends signal detection theory to an item-level.
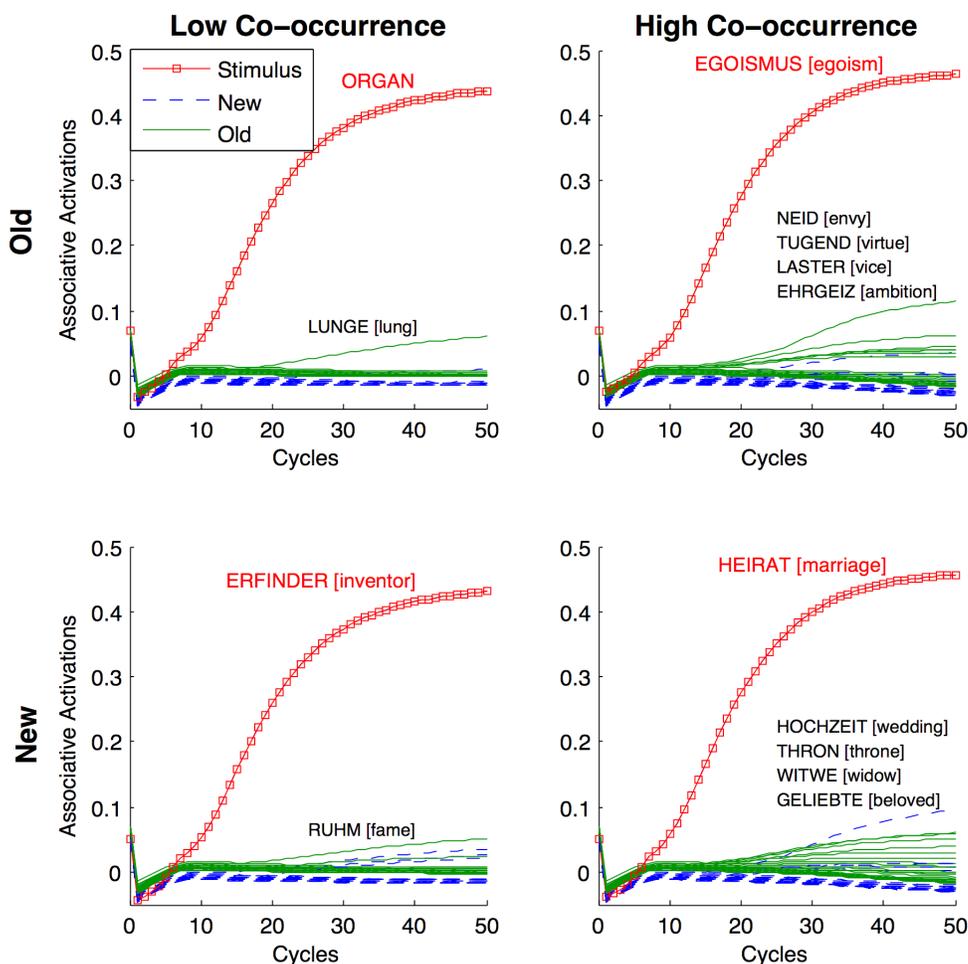
Figure 19 presents exemplary association functions for one target of the four stimulus conditions. Upper panels represent old target items and the lower depict new ones. Left and right panels display low and high co-occurrence stimuli, respectively. The y-axes indicate the associative layer activations. The x-axes indicate simulation cycles. Cycle 0 activations depict resting levels for learned ($\rho_{old} = 0.07$) and non-learned stimuli ($\rho_{new} = 0.05$), implementing all events before the present trial. When associative excitation and inhibition generated the cycle 1 activations, these define the state of the cognitive system when a test-trial starts. The target items (and their association functions) are shown in (boxed) red (lines), old associates in green (solid lines), and the new associates in blue (dashed lines). Though the AMSSs as predictor variable in Figures 2 and 3 reflect mean activations across cycles 1-7, the strongest associates at cycle 50 are shown for face validity purposes (activations > ρ_{new}).

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The item-level variances were predicted by associative cross-trial excitation from the associative context of the experiment to the target items. The more associated items are presented before the target, the larger is its unit's activation in cycle 1. Moreover, learned items still have a larger activation than new items at this cycle. Starting at cycle 4 the visual input of the feature layer reaches the associative layer, and the identification of the stimulus begins to cue the associative memory layer (Gillund & Shiffrin, 1984; cf. Hofmann, Kuchinke, Tamm, Võ, & Jacobs, 2009). Although we did not deviate from the tradition to predict item- and ROC-performance by the mean activation of the cycles 1-7 (Hofmann et al., 2008; Jacobs et al., 2003), the face validity of the model was demonstrated at cycle 50, at which the most strongly associated items emerged.

As is evident from Figure 19, the associates to a target item reflect intuitively valid associations. Moreover the AROM can simulate semantic relations in the narrowest sense of the term, as e.g. the associate [lung] is a hyponym of the target [organ]; [vice] can be considered as a hypernym of [egoism]; [virtue] is the antonym of [vice]; and [wedding] and [marriage] are (partial) synonyms. As the associative layer receives input from the orthographic layer, the unique identity of a word is not only defined by its associations, but also by its orthographic form-properties. As the orthographic layer also activates orthographically similar words (Grainger & Jacobs, 1996), and semantic-relation- and form-properties were both proposed to be crucial for morpheme representations (e.g., Devlin et al., 2004), future studies will have to show whether the AROM can account for morphemic effects.

Form-constituents of meaning have been modeled using distributed representations (e.g., Harm & Seidenberg, 2004; Plaut et al., 1996). Rumelhart and Todd (1993) assume that (hidden) units shape associations between words, because of the repeated co-exposure of *words* in sentences like 'a *robin* is a *bird'* (cf. Collins & Quillian, 1969; Rogers & McClelland, 2008). We suggest that the AROM's associations – implemented as two *words* significantly co-occurring within sentences – correspond to

the associations of the (hidden) learning units in a mature cognitive architecture. Thus, the AROM can be considered as a first step towards a fully localist connectionist model containing an implemented semantic layer. This has been theoretically postulated for some time, but it resisted a computational implementation so far (e.g., Coltheart et al., 2001; Rumelhart & McClelland, 1982). Finally, we suggest that Rumelhart and Todd's model (1993) and the AROM complement each other in a seamless theoretical symbiosis. The first accounts for the maturing of associations, and the AROM predicts human performance from the outlearned associative structure of human long-term memory.

Conclusions

This study introduces the AROM as a model capturing explicit memory performance for IAMs. Associative spreading activation inserted into the MROM can account for cross-condition z-ROCs, condition-wise effects of associations in new and old items, and item-level performance. Given that many words most strongly associated by the model reflect semantic relations (e.g., hyponomy), the AROM should be a convenient tool for future investigations of semantic effects in word recognition, particularly also for the tasks IAMs were originally designed for: implicit memory tasks.

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Appendix

```matlab
function stdproof

%Copyright by Hofmann, M.J., Kuchinke, L., Biemann, C., Tamm, S., & Jacobs, %A.M.

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%

%Distribution of random-numbers: negative net input to a unit, which

%represents a stimulus:

n=-rand(80,1);

% A larger resting-level for old than for new items...

[oldrest,newrest]=oldgreaternew;

%... is scaled like in McClelland & Rumelhart (1981).

oldvals=netscale(n,oldrest);

newvals=netscale(n,newrest);

% This necessarily leads to a lower standard deviation for new than for old

% items:

stdratio=std(newvals)/std(oldvals);

%If n would be normally distributed with equal variance net inputs,

%the nonlinear transformations scaling the net input

%provides greater variances for old items.

%The following conditions will never be fulfilled:

if (oldrest>newrest) && (std(newvals)>std(oldvals))

disp('Impossible!');

else

disp('Quod erat demonstrandum.');

end
```

```matlab
end

function [oldrest,newrest]=oldgreaternew

%Generates random old and new resting levels constrained to be greater for

%old than for new items.

oldrest=rand(1,1);

newrest=rand(1,1);

if newrest >= oldrest

[oldrest,newrest]=oldgreaternew;

end

end

function val=netscale(n,acti)

%The IAM-function that transforms negative net-input into activation-change:

%Cf. McClelland & Rumelhart (1981, p. 381, formulas 3 and 4).

%Decay does not apply because there is a change of the node-activation.

m=-1;

val=acti+n*(acti-m);

end
```

General Discussion: Summary and outlook

In sum, IAMs provide a powerful theoretical framework that simulate all basic processes of word recognition, and thus account for many effects. As they also predict effects resulting from sub-lexical representation levels, experimental control of sub-lexical frequency measures helped to rule out that the psycholinguistic variables investigated in this thesis are explainable by confounds at a sub-lexical representation level. Thus, word frequency effects cannot be explained by confounds at a sub-lexical representation level. Most likely, the IFG has a role in the selection between competing lexico-semantic representations. Moreover, this thesis also shows how conflicts between orthographic representations can be modeled. IAM simulations can be used for fine-grained quantitative predictions of the brain responses to each particular letter string. Whether the affective processes itself boost lexical activation, or whether affective words simply engage larger associative networks is an issue for future research.

Sub-lexical frequencies

Sub-lexical frequency measures constrained the interpretation of effects!

By controlling for bigram and letter frequencies with the measures provided in Study 1, the behavioral and neurocognitive effects observed in the Studies 2 and 4 were constrained to result from the manipulation of the variables investigated, and did not result from confounded manipulations on a sub-lexical level.

Previous research showed that RTs can be affected by bigram (Massaro & Cohen, 1994; Rice & Robinson, 1997) or letter frequency during lexical decision (Grainger & Jacobs, 1993; Lupker, Perea, & Davis, 2008; cf. Stenneken, Hofmann, & Jacobs, 2005, 2008). The low and high frequency words in Study 2 did not differ with respect to these sub-lexical frequencies. Therefore, the behavioral word frequency effects in Study 2 can be assumed to result from whole word frequency, rather than from the frequency of its constituents. Moreover, the effects elicited by affective word features in Study 4 cannot be accounted for by confounded manipulations of the sub-lexical frequency measures. These were controlled.

Moreover, experimental control was also beneficial to constrain the functional loci of the brain regions investigated in this thesis. ERPs were recorded in Study 4 to target an early time frame of about 100 ms after stimulus presentation. Hauk and colleagues found words consisting of higher frequency sub-lexical units to elicit more negative ERP deflections in this time window (Hauk, Patterson, Woollams, Watling, Pulvermüller, & Rogers, 2006; cf. Hauk, Davis, Ford, Pulvermüller, & Marslen-Wilson, 2006). Therefore, if high-arousal negative and low-arousal positive words would have provided higher sub-lexical frequencies than low-arousal negative and neutral words, the early ERP effects would have been fully explainable by a confounded manipulation of sub-lexical

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frequencies, but not affective word features. As they were rigidly controlled, this potential concern can be rejected.

Moreover, the fusiform gyrus was one of the most likely neural generators of the ERP arousal effect. Some researchers attribute this region a function at a pre-lexical and thus sub-lexical analysis level (Dehaene et al., 2002; Schurz, Sturm, Richlan, Kronbichler, Ladurner, & Wimmer, 2010). Thus, if sub-lexical features would not have been controlled, this effect would have been easily interpretable as resulting from a sub-lexical confound.

As a consequence, the fusiform finding in Study 4 can be interpreted in line with Kronbichler et al. (2004). They suggested that the fusiform gyrus acts at a lexical level of processing, which potentially interfaces to higher-order representations such as semantics (Price & Devlin, 2003). This is supported by co-activation of the middle temporal gyrus in this time frame, which was associated with semantic processing (Price, 2000).

Can the matching of global features be replaced by specific ones?

Why does the control of sub-lexical frequency measures constrain the recognition memory effects observed in Study 5?

Two of the leading models in this research field propose that a critical process of recognition memory is the matching of the features of words (McClelland and Chappel, 1998; Steyvers & Shiffrin, 1997). For instance, they account for the word frequency effects in recognition memory by assuming that high frequency words consist of high-frequency features, and low frequency words are composed of low-frequency features. A basic assumption is that rarely occurring word features are more diagnostic in determining whether a learned word is correctly recognized (cf. Steyvers et al., 2006). Thus, the low frequency features of a learned low frequency word are unlikely to be

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confused with any learned word features. This accounts for the finding that learned low frequency words provide more correct 'yes' responses than high frequency words in a recognition memory task. For non-learned items, in contrast, the high frequency features of a high frequency word are very likely to be confused with the features of the learned words. Therefore, non-learned high frequency words elicit more erroneous 'yes' responses (McClelland & Chappel, 1998; Shiffrin & Steyvers, 1997; cf. Malmberg, 2008). However, these models leave open the question which word features are more diagnostic, and thus are critical for the effects. Do they result from sub-lexical word features?

Thus, controlling for bigram frequency ruled out that learned words have been recognized better, because the more unusual a (low frequency) bigrams is, the more likely its resulting saliency would elicit successful recognition (cf. McClelland & Chappel, 1998). Moreover, a word that consists of high frequency bigrams would be more likely to be confused with a learned word, because these are relatively likely to be contained in learned words. Therefore, the sub-lexical feature of a bigram is unlikely to contribute to the effects obtained in Study 5.

On a more general theory level, the manipulation and control of psycholinguistic variables, and their theoretical counterpart of local representation variables can help to answer the question which orthographic, phonological, or semantic-associative word features are crucial for recognition memory (McClelland & Chappel, 1998; cf. Shiffrin & Steyvers, 1997). This may help to identify the most critical features that determine successful memory performance.

Word frequency and optical imaging

Optical imaging revealed greater "neural activations" to low frequency words!

Low frequency words elicited a greater [deoxy-Hb] response than high frequency words in a region identified as the IFG. This can be interpreted as a stronger neural activation to low frequency words (Buxton et al., 2004). Therefore, the results confirm previous fMRI studies of word recognition (e.g., Fiebach et al., 2002). However, the stimulus set was even more rigidly controlled for confounding variables than in previous fMRI studies. For instance, this effect was shown to result from whole-word, lexical frequency by controlling for bigram and letter frequency. Moreover, greater activation in the SFG and the IPG to words in comparison to nonwords demonstrated that fNIRS provides comparable results to fMRI studies (cf. Ischebeck et al., 2004). These effects were interpreted to follow from decision-related processes in the SFG (e.g., Fiebach et al., 2007), and the integration of orthographic, phonological, and semantic representations in the IPG (e.g., Binder et al., 1999).

Thus providing cross-validated evidence, these results confirm balloon models of the hemodynamic response (Buxton et al., 1998, 2004), that offer a theoretical base for making fMRI and fNIRS studies comparable.

Because sound representations influence word recognition (e.g., Coltheart et al., 2001; Van Orden, 1987), it was questionable whether the relatively loud scanner environment affected the word recognition process. As the relatively quiet fNIRS method provides results similar to those of fMRI studies, this concern can be rejected. This is particularly crucial for a dual route interpretation of the neurocognitive word frequency effect on IFG activation (Coltheart et al., 2001; Fiebach et al., 2002; Perry et al., 2007):

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It explains greater IFG activation to low frequency words by the assembled route, which processes sound-based, sub-lexical word features (Fiebach et al., 2002).

However, please note that there is an alternative interpretation for the IFG's major function. Its activation may reflect the competition between semantic representations (Thompson-Schill et al., 1997). Particular attention will be drawn at this theoretical perspective below. Before we turn on the psychological mechanisms that determine the competition, scrutinizing how one can infer "neural activation" from the measured (de-)oxyhemoglobin changes seems worthwhile.

What is "neural activation" in the IFG?

The ability of NIRS to assess more than one hemodynamic response parameter synchronously complements our knowledge by intriguing mechanical features of the hemodynamic response (Buxton et al., 2004; Steinbrink et al., 2006). A relatively high temporal resolution allows optical imaging to particularly enlighten the dynamic interplay between different parameters. The canonical hemodynamic response due to the balloon model posits that a neural response triggers the expenditure of oxygen (Buxton et al., 2004). Usually, enough oxygen is contained in the blood of the adjacent vessels, which are then drained from its oxygen. After the blood fulfilled its metabolic "work", the exhausted blood flows back into the vessel (Raichle & Mintun, 2006). This results in a temporary increase of [deoxy.Hb], which is called the initial dip (Buxton, 2001). According to models of the hemodynamic response (Buxton et al., 1998, 2004), the fMRI-BOLD response and [deoxy-Hb] changes as measured by NIRS relate to each other in an inverted fashion, and correspond to the same neural process (Buxton et al., 2004; Kleinschmidt et al., 1996). Both reflect the amount of deoxygenated hemoglobin. Another hemodynamic NIRS-parameter closely related to [deoxy-Hb] is cytochrome oxidase (Heekeren et al., 1999; Obrig et al., 2000). It allows for inferring on the amount

of metabolized oxygen. As soon as the blood is drained from its oxygen, the hemodynamic system is fast in its adaptability. The vascular system delivers fresh blood to the activation site. Thus, a few seconds later, fresh, un-exhausted oxygenated hemoglobin arrives at the region where the neural response occurred. This need is suited either due to the redirection from neighboring regions (cf. Pfurtscheller, Bauernfeind, Wriessnegger, & Neuper, 2010) or by an increase in heart rate (Franceschini et al., 2003). Other observables are blood volume and blood flow, i.e. blood volume per time (i.e., rCBF). Both of these parameters usually increase synchronously with the increase of oxygenated hemoglobin, because the most part of the blood volume consists of oxygenated hemoglobin. As an indicator of these processes, some NIRS studies also rely on the total amount of hemoglobin as an indicator of blood volume (e.g., Plichta et al., 2006; Steinbrink et al., 2006), i.e. the sum of oxygenated and deoxygenated hemoglobin. As soon as the fresh oxygenated blood is delivered to the region that was activated, deoxygenated hemoglobin is flushed out. Therefore, during neural activation [deoxy-Hb] decreases and the BOLD response increases for the largest part of the time of a hemodynamic response.

The effects of lexicality in the SFG and IPG were generally in line with this default coupling mechanism of the hemodynamic response: Words elicited a decrease of deoxygenated hemoglobin which was accompanied by an increase of oxygenated hemoglobin (Buxton et al., 2004; Steinbrink et al., 2006).

For the word frequency effect in the IFG, the highly significant [deoxy-Hb] decrease was not accompanied by a significant increase of oxygenated hemoglobin. This most likely follows from [oxy-Hb] being more prone to be influenced by artifacts, which result from extra-cerebral tissue oxygenation (Boden et al., 2007). Proposing non-'default' hemodynamic response mechanics (cf. Mandeville et al., 1999) to account for the missing oxygenated hemoglobin finding would be premature, although a PET study supported the finding of no increase of oxygenated hemoglobin. Fiez et al. (1999)

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found no IFG blood flow effect of word frequency. This may cast doubt on the explanation of extra-cerebral artifacts, because PET is not influenced by this particular artifact source. However, conclusions proposing new couplings of the hemodynamic parameters would require a baseline for which no neural response should hypothetically occur (Gusnard & Raichle, 2001).

Consider for instance, that participants may think verbally during the resting periods (cf. Raichle, MacLeod, Snyder, Powers, Gusnard, & Shulman, 2001). This may cause that so much oxygenated blood is delivered to the IFG during the whole experiment, that a ceiling effect of blood flow is observed, and thus no increased flush-out of deoxygenated hemoglobin could occur. Only an extended initial dip would be observable, which is consistent with the finding of no increase of oxygenated hemoglobin. In this case, the greater BOLD response to low frequency words would correspond to a weaker neural response (oxygen demand) than that to high frequency words in terms of balloon models (Buxton et al., 2004). Of course, this would be the reverse conclusion than the one presented in Study 2, which was based on the default coupling assumptions. The author of this thesis suggests, however, that any firm conclusion would be premature. Apart from a potential ceiling effect of blood flow or extracerebral artifacts, that particularly add noise to oxygenated hemoglobin (Boden et al., 2007), there is at least a third possible explanation. In differential sub-portions of the IFG, Yamamoto and Kato (2002) found positive and negative correlations between deoxygenated hemoglobin as measured by fNIRS and the fMRI-BOLD signal. They suggest that BOLD-contrasts are particularly sensitive to measuring deoxygenated hemoglobin in the large vessels. If the laser light particularly penetrates large vessels, deoxygenated hemoglobin decreases while the BOLD response increases. However, when the laser light particularly penetrates tiny capillary vessels, the amount measured [deoxy-Hb] may increase during neural activation, because the much more flexible tiny vessel can more easily dilate, and a dilated vessel can contain the delivered and

consumed oxygen at a time. Thus, a flush-out is not necessary or can be postponed (Yamamoto & Kato, 2002).

In sum, if the [deoxy-Hb] IFG finding of Study 2 could indeed be attributed to a capillary effect, neural activation would be higher to high frequency words. However, though not significant, [oxy-Hb] likewise tended to increase. In Yamamoto and Kato's (2002) model, an increase in [oxy-Hb] would indicate an increase in neural activation. However, further research is required to gain a deeper understanding of the relationship between the physically observable brain processes, and the mental phenomena likely eliciting these physical phenomena, and/or vice versa?

To the author's opinion, only computational models integrating physical and psychological processes could satisfactorily answer questions about these relationships. For both sides of the same coin, i.e. the mind and the brain, computational models exist. Not until the integration of these models, one can really understand how the brain gives rise to the psyche, and the psyche shapes its material counterpart in the brain.

Lexical conflicts

Lexical conflicts predicted behavioral data and ACC activation!

To provide a quantitative definition of a cognitive process resulting from lexical activation, Study 3 relied on the MROM (Grainger & Jacobs, 1996; Jacobs et al; 1998). Ehopf implemented the amount of conflict between the lexical wordform units of the MROM (Botvinick et al., 2001). Consistent with the CMT (Botvinick et al., 2001) and its ERP extension (Yeung et al., 2004), this conflict measure predicted RTs, error rates, ERP amplitudes, and the neural sites from which the ERPs' electric current differences

most likely resulted (Pascual-Marqui, 2002). The greater the conflict was, the greater were the RTs and error rates. Moreover, keener conflict led to more negative N2 deflections, that were localized in the ACC and the mediofrontal gyrus (Botvinick et al., 2001; Ridderinkhof et al., 2004).

Most notably, this was the first study that evaluated an IAM's capability to make item-level predictions using neurophysiological data (cf. Perry et al., 2007; Spieler & Balota, 1997). Ehopf predicted which particular nonword elicits which mean ERP amplitudes (cf. Rey, Dufau et al., 2009). The inhibitory processes – as quantified by the conflict monitoring theory (Botvinick et al., 2001; Yeung et al., 2004) – accounted for a fine-grained, gradual N2 increases with a frontal maximum. Since the time frame of the N2 corresponded to previous N400 findings, speculations about a common functional locus of the N400 and the N2 in language tasks were substantiated (cf. Polich, 1985).

Our subsequent research (Briesemeister et al., 2009; Klonek et al., 2009), however, either casted doubt on Yeung et al.'s (2004) N2 prediction in terms of the conflict monitoring theory (cf. Masaki et al., 2007). Klonek et al. (2009) used a task in which a word's initial three letters had to be completed to a whole word. A larger amount of possible completions, i.e. lexical competitors, revealed a lower negativity in an N2/N400 time frame. Thus, when taking Yeung et al.'s (2004) proposal of the N2 to indicate the ACC's conflict response for granted, a prediction of Botvinick et al.'s (2001) model was falsified. Another study provided evidence for a less negative N2/N400 for nonwords that elicit another conflict. If the orthographic representation indicates 'nonword', but the phonological representation corresponds to a word (e.g. brane), phonology may activate a semantic representation. Thus, orthography leads to a tendency to respond 'no', and phonology may activate a 'yes' response during lexical decision. These incompatible response tendencies did not elicit a greater negativity as predictable by the CMT (Yeung et al., 2004). Rather, these so-called pseudomophones elicit a lower negativity in the N2/N400 time frame than nonwords that do not elicit this

type of conflict (Briesemeister et al., 2009). On the other hand, the obtained error rates, RTs, response confidence ratings, and pupil dilation effects can be well explained by the conflict monitoring theory (Briesemeister et al., 2009; cf. Braun et al., 2009). Thus, Yeung et al.'s (2004) ERP extension of this theory might be rejected rather than the whole conflict monitoring theory itself (Masaki et al., 2007). Alternatively, Study 3 might have assessed a particular type of conflict, in which the extended conflict monitory theory can be fully applied.

Please note that Study 3 reported no Ehopf effects in word stimuli, because they did not elicit any significant effects. Like for pseudohomophones and stem completion (Briesemeister et al., 2009; Klonek et al., 2009), words can be assumed to trigger activation in semantic representations. In contrast, nonwords do not activate 'semantics', and the conflict stays at the level of competing lexical wordform representations. In nonwords, Ehopf accounts for a significant portion of ERP variance (cf. also Braun et al., 2006). Thus, there appears to be a single critical difference between the conditions at which lexical conflict effects are predictable, or not. This critical difference lies in whether or not a letter string elicits a semantic representation. When a model ignores semantic representations, for those stimuli that elicit 'semantics' the N2/N400 becomes unpredictable.

When the competition includes 'semantic' representations, the monitoring demands associated with ACC activation may have become unpredictable, because another competition process came into play. This process is probably also hosted by another brain region, that governs the selection between competing semantic representations (Thompson-Schill & Botvinick, 2006).

Does associative-semantic competition predict IFG activation?

Thompson-Schill et al.'s (1997) lexical selection hypothesis suggested that the IFG's primary function concerns the selection of an appropriate semantic representation from multiple, pre-activated representations. The more representations are active, the larger is the selection demand and thus IFG activation. This verbal explanation can account for the effect of word frequency in the IFG in Study 2. Low frequency words are identified more equivocally. Thus, selection demands would be higher, when many units are active and in competition. Study 3 showed that Ehopf can predict behavioral and neural responses for nonword stimuli, but not for words, which elicit a semantic representation. This led to the suggestion that Ehopf, which predicted neural responses to nonword stimuli, might not have worked in word stimuli and any other stimulus that elicits 'semantics' (Briesemeister et al., 2009; Klonek et al., 2009), because semantics was the critical information missing in these IAMs (Grainger & Jacobs, 1996; Jacobs et al., 1998).

However, Thompson-Schill and Botvinick (2006) exemplarily demonstrated how semantic competition might be modeled. A presented stimulus triggers activation in associated representations, which are in competition (cf. Thompson-Schill & Botvinick, 2006, Figure 2). The previous lack of an operational definition for "semantic" representations and their pre-wired associations so far has prevented full-scale, quantitative modeling approaches to semantic competition (but cf. Danker et al., 2008, for an approach to experimentally induced associations). As the AROM can represent the meaning of a word by the company it keeps (Firth, 1957), calculating Ehopf across the associative-semantic layer to predict IFG activation, is a next logical step predictable by Thompson-Schill and Botvinick's (2006) proposal. They suggested that only more explicit computational approaches could potentially further our understanding of the IFG's function.

Affective word features

Affective lexical features elicited behavioral and ERP, but no pupil dilation effects!

Not all the variables that are known to affect word recognition can be defined by corpus-analytically defined psycholinguistic variables, or by computational models. Affective word features are typically addressed by manipulating subjective rating variables. The most frequently investigated affective word features are emotional valence and arousal.

Study 4 showed that lexical decisions to high-arousal negative and low-arousal positive words were faster than those to low-arousal neutral and negative words. One explanation for this result pattern can be provided by LeDoux (1996). As the appropriate response to negative arousing stimuli like "earthquake" or "alarm" would be "fight or flight", they elicit fast responses. Positive words like "fame" might be associated with an appetitive state, which also facilitates behavioral responses. Moreover, negative low-arousal words were even responded to slower than neutral words. This may correspond to an evolutionarily old "freezing" mechanism, that helps prey to escape undetected (LeDoux, 1996).

The manipulation of these affective word features showed no significant effects on pupil dilations, however. This confirmed a previous study, which revealed that the manipulation of emotional valence did not elicit any effect on pupil dilations during lexical decision (Kuchinke et al., 2007). In contrast, a previous recognition memory task showed a decrease in pupil dilation due to the conjoined manipulation of arousal and emotional valence (Võ et al., 2008). The present replication of Kuchinke et al.'s (2007) zero-findings render the explanation unlikely that their zero-finding was due to the

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failure to control for arousal, because Study 4 carefully controlled and manipulated arousal. The occurrence of pupil dilation effects in recognition memory, in the absence of such effects during lexical decision, suggests that affective processing does not influence pupillary responses per se (Hess, 1965; Janisse, 1974). In contrast, less cognitive demands during memory retrieval of affective words may be the better explanation (Beatty & Kahneman, 1966). Võ et al.'s (2008) pupil dilations are proportional to the error rates in the six experimental conditions, crossing three levels of emotional valence (negative, neutral, positive), with study-phase presentation (old/new). The greater the error rates, the larger were the pupil dilations. The proposal that cognitive demands are the most critical factors driving the pupil response receives support from more recent studies (Briesemeister et al., 2009).

The faster RTs to positive and high-arousal negative words were accompanied by an increased early ERP negativity between 80 and 120 ms, supporting the notion of an impact of affective word features on early lexical processing (Sereno & Rayner, 2003). This conclusion was corroborated by the source localizations of the early arousal effect. It was attributed not only to the left fusiform gyrus' function (Dehaene et al., 2002; Kronbichler et al., 2004), but also to the medial temporal lobe (Price, 2000). This supports the hypothesis of the fusiform gyrus' role as a hub to semantic processing (Price & Devlin, 2003). The role of the fusiform gyrus for early lexical processing was corroborated by a recent virtual lesion study (Duncan, Pattamadilok, & Devlin, 2010): If repetitive transcranial magnetic pulses disrupted the functionality of the occipito-temporal gyrus including the fusiform gyrus, the time frame of 80-120 ms was the first to influence behavioral effects during lexical decision. Since the medial temporal gyrus was co-active during this time frame in Study 4, these affective effects could have resulted from early semantic processing (Price, 2000).

Can semantic cohesiveness account for affective effects?

The temporal gyrus finding of Study 4 may be seen as evidence for a semantic locus for the influence of affective word features during word recognition. Maratos and colleagues (2000, cf. LaBar & Phelps, 1998) proposed that much of the behavioral and neurophysiological variance, that affective word features account for, can actually be explained by the word's higher semantic-associative cohesion. Therefore, the AROM was proposed in Study 5. A word presented to the AROM often elicited the strongest co-activation in word representations that are in a semantic relationship with the stimulus (cf. Figure 19). Therefore, the AROM can be considered as the first localist connectionist model of word recognition with an implemented "semantic" layer. Thus, semantic cohesiveness is addressable by the AROM. In the author's ongoing work, some experiments have already been conducted to explore the role of "semantic cohesiveness" during the recognition of affectively loaded words (e.g., Maratos et al., 2000):

When implementing co-occurrence as in Study 5, and additionally comparing words of positive valence to neutral words, our preliminary findings showed that the amount of associations, but not positive valence drives the false alarm rate (Hofmann, Kuchinke, Biemann, Tamm, & Jacobs, 2008). Thus, the semantic cohesiveness hypothesis was straightforwardly confirmed (Maratos et al., 2001; Talmi & Moscovitch, 2004). The stronger the associative-semantic connectivity to the other words of the experiment, the more likely is the erroneous recognition of a word as having been learned. The false alarm rate did not further increase as a function of positive emotional valence.

Another more recent experiment addressed emotional valence and associative-semantic connectivity. This time, negative and neutral words were compared. It revealed that both, valence and the amount of associated items, affect recognition memory. The

preliminary results show that negative valence and "semantics" interact. In old words, negative valence reverses the effect of the amount of associates, when compared to Study 5. Negative words with less associative connections to the rest of the stimulus set elicit more 'yes' responses. These results appear to be puzzling at present. Therefore, further evidence would be needed before firm conclusions can be drawn. However, a new working hypothesis emerged:

Affective word features may shape the development of the associative wiredness of the semantic-associative long-term memory structure. The basic idea of this new hypothesis is that affective systems are older than semantic systems in an evolutionary sense (cf. Panksepp, 2004). The development of a semantic system is thus based on an already established affective system. Thus, if useful from an evolutionary perspective (LeDoux, 1996), semantic nets that mean appetitive states 'by tradition' act in a facilitatory way, e.g. to increase the probability of attaining the positive outcome. If negative non-arousing meaning is activated, however, the semantic activation triggers a process inhibiting behavioral responses, because "freezing" is an evolutionary old mechanism aiding survival (cf. Bower, 1981).

This working hypothesis is also testable by recent extensions of the "Berlin Affective Word List" databases (Briesemeister, Kuchinke, & Jacobs, 2011; Briesemeister, Hofmann, Kuchinke, & Jacobs, 2011). If correct, the recognition of words representing the affective states that require 'fight or flight' – i.e. anger and disgust– or appetitive emotions – i.e. happiness – may be facilitated by associations to other words. In contrast, affective states corresponding to 'freezing' might have shaped 'semantic' sub-networks that act in an inhibitory manner, e.g. sadness. Because fear can either lead to fighting or freezing, no concrete prediction can be made for words loading high on this emotional dimension.

This perspective on affective-semantic sub-nets for each of the five basic emotions (Briesemeister, Kuchinke et al., 2011), would be most easily reconciled with

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one of the most recent computational approaches to semantics (Andrews et al., 2009). On the one hand, this approach calculates the 'latent factors' that determine the co-occurrence of words. On the other hand, the authors calculate the latent factors that determine (free) association performance. Finally, they integrate both analyses into latent factors that determine both, the experienced subjective-associative and the co-occurrence variance. These integrated factors account best for performance. Thus, a five-dimensional 'semantic' space – with each dimension representing a latent factor – that determine both, co-occurrence and the basic-emotion ratings, might be a theoretical perspective worthwhile to be investigated in the future (Andrews et al., 2009).

Given the preliminary findings in recognition memory as well as the results of Study 4, it appears that every approach, that is more differentiated than comparing high-arousal valenced to low arousal neutral words is not fully explainable by the initial semantic cohesiveness hypothesis. If low arousal negative words still would provide a higher 'semantic' cohesion, it is questionable why only this class of affective words should have inhibited behavior in Study 4. The preliminary results comparing negative valence with 'semantic cohesion' in recognition memory support the idea that a more differentiated semantic cohesiveness hypothesis of emotional word processing is required.

Depending on the particular affective quality of a word, its semantic cohesiveness might act in an inhibitory or excitatory fashion. Therefore, the a-priori role of affect may shape the development of a semantic system rather than affective effects being fully explainable by semantic cohesiveness. The semantic system is based on evolutionarily old emotional processes, and thus emotion regulates the semantic system (cf. Panksepp, 2004).

Associative-semantic representations

Modeling associations between the word stimuli of an experiment predicted false and veridical memories!

Preliminary recognition memory evidence led to the speculations about a more differentiated semantic cohesiveness hypothesis of affective word processing. This experiment included two experimental manipulations. On the one hand, negative low-arousal words were compared to neutral words. On the other hand, 'semantic cohesiveness' was implemented as in Study 5. The amount of associated items in the stimulus set implemented 'semantic cohesion'. How did we come to the hypothesis that simple associations can mimic 'semantic' effects?

Roediger and McDermott's (1995) seminal work relied on free associations, in which participants freely generate associates to given target word. In a later false memory experiment, other participants learned (free) associates to a given non-learned target-item. These associates elicited the target's false recognition. A theoretical account of these findings would propose that associative activation spreads from the learned associates to the target word (e.g., Collins & Loftus, 1975; Kimball, Muntean, & Smith, 2010). The false recognition of this target is driven by associations.

Study 5 was theoretically based on Hebbian learning (Hebb,1949). Items occurring often together are likely to be associated. Accordingly, co-occurrence statistics implemented associations between words. The more associated items a given stimulus had in the stimulus set, the larger was the expected associative activation (Collins & Loftus, 1975). A greater false alarm rate resulted for the stimuli with a greater amount of associated items in the stimulus set. Moreover, associations drove the correct recognition of learned words. When many associated items were in the stimulus set, the

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correct retrieval of learned words was facilitated. This effect has previously been observed in a free recall task (Kimball et al., 2007). To the best of the author's knowledge, Study 5 provided the first evidence that the effect is also apparent in a study-test recognition memory task. This was to be expected, because recall and recognition can be assumed to share common retrieval processes (cf. Gillund & Shiffrin, 1984).

Apart from the increased amount of 'yes' responses to new and old stimuli, the main effect of co-occurrence in the absence of a significant interaction suggests that associations implemented via co-occurrence statistics affected the amount of 'yes' responses to new and old items likewise. In general, the obtained main effect of co-occurrence supports the notion that associations can successfully be estimated using co-occurrence statistics. This has already been suggested by Rapp and Wettler's (1991) early observation that co-occurrence statistics can predict free association performance.

However, apart from staying within a verbal-theoretical framework of associative activation (Collins & Loftus, 1975), we aimed at capturing associations in a computational model (cf. Anderson, 1983). Therefore, the AROM was developed to extend the false memory logic to a novel, more fine-grained level of analysis that takes into account all associations between all items in the stimulus set. The increase of 'yes' responses, which was elicited by the associated items, can be simulated by the AROM. Excitatory associative connections from other items of the stimulus set drive the activation of the presented target stimulus. Generally in line with the logic of IAMs, the target's larger activation predicts an increased amount of 'yes' responses (e.g., Grainger & Jacobs, 1996). However, the AROM is the first of these models implementing the spreading of activation along pre-wired associative connections (cf. Anderson, 1983; Collins & Loftus, 1975). This associative structure of human long-term memory can be assumed to result from the learning history of the subjects, i.e. words that occurred often together in the past are likely to be associated (Hebb, 1949). The activation that

spreads along these long-term memory paths can be assumed to represent temporarily activated memory traces during the experiment.

To extend an IAM to be able to simulate study-test recognition memory performance, only a single new assumption was required. The associative representation's resting level activation was assumed to reflect stronger memory traces for old items. These stronger traces result from learning during the study-phase presentation (cf. Reder, Nhouyvanisvong, Schunn, Ayers, Angstadt, & Kazuo, 2000). When modeling the test phase, this ad-hoc assumption describes the old/new effect, i.e. the increase of 'yes' responses to old items (cf. Võ et al., 2008). Taken together with already established architectural features of IAMs, the assumption moreover explained why the variances of old items should be higher than those of new items:

For each word presented in the experiment, an associative representation was contained in the AROM's associative layer. As stimulus sets are randomized for each subject, each associated word has a probability to be presented earlier than the target. Therefore, an associate can cue the presented target stimulus. To give each associate the chance to cue the target in the model, all associative representations were initialized in an active state: These activations greater than zero are necessary for associative excitation.

However, many active representations also lead to a great amount of inhibition in the associative layer – there is competition between the active memory representations. Each learned item "wants" to be remembered. By virtue of the active competition of many memory traces for being held in memory, each associative representation obtains a net inhibitory signal, in sum. To obtain the activation change of an IAM's representation, the net inhibition is scaled by multiplying it with the activation of the representation itself. As the activation of an old item was assumed to be greater than that for new items, the activation variability for old items necessarily becomes greater than that for new items. This is because old items obtained a greater resting level

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activation. Thereby, the present modeling architecture explained signal detection theory's ad-hoc assumption of unequal variances (Green & Swets, 1966). This assumption typically accounted for the old items greater signal strength variances and the resulting z-ROC slope lower one, which is usually observed during recognition memory (e.g., Glanzer et al., 1999; Ratcliff et al., 1992).

Once the five free parameters were adopted to account for the empirically obtained z-ROCs, the AROM's associative memory signal strengths also accounted for a significant portion of variance of the 'yes' response probability of the items. Thus signal detection was elevated to an item-level.

Apart from leveling recognition memory processing models to a quantitative item-level of predictions, the AROM also provides qualitative face validity (cf. Figure 19). The most strongly associated items often reflected a semantic-taxonomic relations to a presented target stimulus. Therefore, the AROM can address semantic cohesiveness not only during affective word processing, but also in another theoretical framework of recognition memory. The available orthographic familiarity processes (Jacobs et al., 2003) can potentially be complemented by a recollection-processes, which was associated with semantics (Yonelinas, 2002).

Going beyond measurement models of familiarity and recollection?

The first signal detection approach in an IAM used the summed lexical activations of the orthographic word layer to define (orthographic) familiarity (Jacobs et al., 2003; cf. Figure 3). When the participants conducted lexical decisions under limited exposure conditions, the decisions can be based on familiarity, solely. Consistent with mere familiarity in a dual-process architecture, linear z-ROCs with a slope of one were obtained (cf. Jacobs et al. 2003; Yonelinas, 1994). However, Jacobs et al. (2003)

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predicted more recollection-shaped z-ROC's, when an identification mechanism is additionally active.

Study 5 showed IAM mechanisms that can elicit z-ROC slopes lower one. As discussed by Jacobs et al. (2003), this 'recollection' mechanism was based on an IAM's identification information: The identification signal of the MROM was forwarded to the associative layer of the AROM. Thus, the recollection information – here based on the AROM's associative activations – can tilt the z-ROC down (Yonelinas, 1994).

It remains to be discussed whether the AROM could be used as model relying on two types of information (cf. Yonelinas, 1994), and how it would compare to other dual-process models. The AROM contains a largely unchanged MROM. Thus, the author would propose that (orthographic) familiarity reflects the summed orthographic representations (Jacobs et al., 2003). Recollection would reflect the AROM's associative identification information.

Such an extended AROM would share some assumptions with even the earliest dual process models. Yonelinas (2002) nicely summarizes Atkinson and colleagues's earliest dual-process-model as "Familiarity and recollection (…) support memory for perceptual and semantic (or meaning-based) information, respectively" (Yonelinas, 2002; p. 444). This closely reflects the AROM, at which familiarity would be defined in an orthographic-perceptual fashion, and recollection would reflect contextual meaning properties of the words (cf. Dennis & Humphreys, 2001; p. 452).

When Yonelinas (2002) reviewed later approaches, he noted that "familiarity is assumed to support not only recognition memory performance, but also performance on implicit memory tasks such as word stem completion. (…) In contrast, recollection is assumed to reflect a search process that supports both recognition and recall" (Yonelinas, 2002; p. 445). The MROM's recent approaches to lexical decision and word stem completion were primarily based on its familiarity mechanism (Braun et al., 2006; Jacobs et al., 2003; Klonek et al., 2009). This seems to reflect the notion of familiarity

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being the main mechanism responsible for implicit memory performance (Grainger & Jacobs, 1996). When it comes to tasks at which memory is explicitly required, the AROM's associative mechanisms should be able to mirror the effects elicited by an extensive search process, which is apparent for recall (Gillund & Shiffrin, 1984; Kimball et al., 2007).

Similar to the AROM, the search of associative memory model (Gillund & Shiffrin, 1984) contains two sources of information that determine memory performance. One source reflects the summed activations of the representations – like the MROM's familiarity mechanism –, and the other source reflects the single representations' activation – like the AROM's associative identification mechanism. The first one was termed 'familiarity'. It was introduced to account for recognition. The second 'search'-process primarily accounted for recall. However, Gillund and Shiffrin (1984, pp. 55) pointed out that it remains an open question whether there is a search component in recognition.

Thus, the theoretical perspective of integrating single-representation and summed-representation information to predict recognition memory performance would follow an old theoretical notion. Study 5 provided a necessary precondition for this enterprise. It showed how an IAM's identification mechanism can account for z-ROCs (cf. Jacobs et al., 2003; Grainger & Jacobs, 1996). As associations were proposed to engage recollection, using the associative representation as recollection seemed straightforward (Yonelinas, 1997). Moreover, the recent replications of the behavioral findings of Study 5 seems to support that notion. The amount of associated items in the stimulus set engages the hippocampus relatively selectively (Fritzemeier, 2010; Fritzemeier, Hofmann, Kuchinke, & Jacobs, in prep.). As the latest research seems to converge on the idea that the hippocampus hosts recollection (e.g., Wixted & Squire, 2011), future studies will have to show whether the AROM can quantitatively predict brain activations (cf. Jacobs & Hofmann, subm.; cf. Study 3).

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Previous dual-process models were implemented as analytic measurement models that evaluate given data in a post-hoc fashion (cf. Malmberg, 2008, Yonelinas, 1994). If realized at the level of a processing model, they did not allow for quantitative item-level predictions or the evaluation of the face validity of semantic-associative relations between words (Malmberg, 2008; Reder et al., 2000; Wixted, 2007; cf. Figure 19).

If the challenge of integrating both sources of information would be taken, the AROM could help to decide between the appropriateness of single or dual-process approaches to recognition memory. Does an AROM relying on two sources of information account for a significantly greater portion of item-level variance than the present 'single-process' AROM? Addressing this question will hopefully help to further our understanding of the processes engaged in recognition memory.

The rebirth of a mental lexicon: How to answer the challenge of fixing the structure of time?

The AROM's long-term memory associations seem to indispensably rely on the theoretical notion of a mental lexicon. Jeff Elman (2004) has called into question whether such a theoretical treatment of language processing is appropriate. He particularly criticized that the 'mental lexicon' cannot be regarded as a dictionary that relies on a passive data structure. This structure would reside in long-term memory and would contain semantic, syntactic and phonological information. Rather than retrieving a presented word from that lexicon, he emphasizes the theoretical perspective that words are stimuli that act on mental states. Thus, words don't have a meaning that could be retrieved. Rather, words provide "clues to meaning" (Rumelhart, 1979, cited from Elman, 2004).

A passive lexicon does not allow to constrain the meaning of a presented word by the clues that were provided by other words in the language context (Elman, 2004). Concerning that part of the criticism, I suggest that the AROM's treatment of lexical-associative interactions between words can in part reject Elman's (2004) concern. Clearly, the effects predicted by the AROM's associative layer do not result from single, passive entries in a "dictionary". The activation of a "semantic" representation results from the interaction of the context of the other words in the experiment, and the target stimulus.

Elman (1990) exemplifies how context can change meaning by two senses of the term 'bake'. I will use this example but will apply other meaning-implications of these sentences (cf. Elman, 1990, pp. 304). What's the meaning of 'bake' in 'Ray baked a potato', vs. in 'Ray baked a cake'. In the first sentence it means 'make hot'. In the second sentence 'bake' also includes putting butter, meal, sugar, eggs etc. together, and then making it hot. So, 'bake' can either have meaning A (make hot), or meaning A (make hot) and B (putting meal, butter etc. together). A passive dictionary could take this meaning-differentiation into account by enumerating different meanings, at the most. It cannot differentiate between the meanings, when retrieving the meaning of a single word from a passive dictionary.

In Elman's so-called simple recurrent networks, meaning-differentiation "happens for free", because meaning is defined by context (Elman, 2004; p. 305). The same is true for the AROM. The associated items occurring in the experimental context contribute to the definition of the meaning of a word. 'Bake' might be associated with 'sugar', and 'cake' might be associated with 'sugar'. Therefore, an associate activated in this language context could be 'sugar'. Thus, the AROM's association functions would likely co-activate 'sugar', when 'bake' is presented, and 'cake' was another contextual item (cf. Figure 19). The activation of 'sugar' would point at the activation of meaning B, i.e. putting a cake's ingredients together. In contrast, 'potato' is not associated with

'sugar'. Therefore, 'sugar' would less likely be co-activated in the context of 'potato' and 'bake' than in the context of 'cake' and 'bake'.

In sum, when assuming that 'bake' is presented two times to the AROM, one time with 'potato', and another time with 'cake' as a contextual representation, the network states of the AROM would differ. The co-activated associates would reflect that meaning differentiation. I suggest that meaning differentiation can be reflected by the AROM, much like in Elman's simple recurrent networks. The activation triggered by a word stimulus is not any more reflecting the retrieval from a passive storage.

What is the AROM's 'associative lexicon' then, if it is no passive dictionary? When compared to Elman's definition, this term might be considered as a technical one, here. The associative layer contains one representation for every word that was activated at least for one time in the experimental context. So, that part of the long-term memory, which becomes likely activated by the experiment, is represented in the associative layer's 'lexicon'. The common learning history of these words is reflected in the associative layer. Thereby the influence of the common past of the words that are 'old pals' helps to better quantify recognition performance. Therefore, I suggest that the term 'mental lexicon' in the sense of 'associative layer' can be usefully employed: In this sense, the term misses the passive dictionary-nature, that was criticized by Elman (2004).

His criticism was based on so-called simple recurrent networks (Elman, 1990, 2004). Therefore, let's have a look what a simple recurrent network is, what it does, and what the AROM still cannot.

Elman (1990) had 'found the structure of time': He used a (recurrent) connectionist network with representations that link back to themselves. Thus, there can be representations that only become active when particular sequences of events co-occur. So, one representation might predominantly mean 'bake' with 'potato'. Another representation, might indicate 'bake' in the context of 'cake'. This network expects

certain representations to occur in the future by simple mechanisms that learn statistical regularities of occurrence. The more often 'bake' and 'potato' has occurred previously, the more dominant this meaning would become. Elman (1990) showed also that this type of network can account for 'syntactic' effects. When many simple recurrent representations expect the occurrence of a noun, statistically shaped structural properties of sentences evolve. This might be functionally equivalent to what classical linguistics calls 'syntax' (Chomsky, 2002). But rather than being separate from semantics, this is simply another feature of the recurrent representations. In contrast to Elman's (1990) approach, however, the AROM does not yet consider the actual sequence of events.

Network properties that allow to predict which word occurs when, or even which word class occurs at which time or position, surely are a limitation of the AROM (Dambacher et al., 2006; Friston, 2009). At present, AROM modeling takes a 'blocked' perspective to 'semantics' (cf. Abdel Rahman & Melinger, 2007, 2011). It considers which words occur in the context, but it does not consider the actual sequence of the words. In our ongoing work, we already started to address sequential relations empirically (Kuchinke, Hofmann, Jacobs, Früholz, Tamm, & Herrmann, 2011). In a word recognition task like lexical decision, this surely also includes decision-related strategic processes. Though only these were addressed initially (Kuchinke, et al., 2011), more recent work revealed that sequential-associative relations can be easily addressed by the co-occurrence statistics used in the AROM. When a word is preceded by an associate, it is recognized faster (Brockhaus, Hofmann, Jacobs, & Kuchinke, 2010). Neuroimaging will further help to disentangle strategic effects (Kuchinke et al., 2011) from associative-mnemonic ones.

In sum, recurrent networks and the AROM share a theoretical notion: Recurrent networks learn statistical co-occurrence patterns of language. The AROM uses

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statistical co-occurrence properties of words to predict performance. Thus, the author suggests that both of these models are two different implementations of the same basic theoretical notion.

It is questionable, whether all aspects of Elman's (1990) distributed representations approach could be 'translated' into a localist, deterministic modeling perspective. To generate 'syntactic' expectancies of particular word classes, other co-occurrence statistics than the ones used in the AROM could prove useful. The AROM relied on words occurring together in sentences. Co-occurrence statistics that determine whether a word does significantly often occur one, two, or three words later than another one might be used to generate more syntax-like expectancies. Such position-sensitive associations might be capable of pre-activating predictable words to mimic 'syntactic' predictability effects (cf. Dambacher et al., 2006). It is questionable if and how these statistical properties can be used to predict performance. I believe that a deterministic modeling perspective could 'fix' the structure of time to predict performance quantitatively, even in the sentence context.

Does the mind construct semantic taxonomies from associations?

From a network based on statistical-associative co-occurrence probabilities, semantic-taxonomic relations popped out as the most strongly associated words (cf. Figure 19). Here, I like to speculate about the reason for this by proposing closer definitions of the terms "semantic" and "associative" originating from language philosophy. For a Kantian, associations as an implementation of statistical regularities would belong to the so-called world itself ("Welt an sich"; Kant, 1993). In contrast, assuming taxonomic hierarchies of semantics are an issue of the logic of the human mind ("Verstand"). Time, space, and causality – as the principle perspectives the mind can take – are necessary to logically subdivide the world, and thereby provide logically

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definable hierarchies. Thus, I propose that "semantics" is a term belonging to the world of the mind, and "associations" as statistical regularities belong to the world itself.

From the statement that "semantics belongs to the subjective perspective of the human mind" follows that it is impossible to provide a semantic hierarchy that would be universally applicable (cf. Kiang, Prugh, & Kutas, 2008). Logical classification always depends on the perspective of the observer: "Is the ayers rock a mountain?" – "Surely no" would answer a geologist, because for him "mountain" is defined by its genealogy, i.e. tectonic processes lift limescales. On the other hand, big, stone-like risings may define "mountains" for a naive observer: Thus for another one, ayers rock is surely a mountain (cf. Eco, 2003, pp. 258-263). In Southern Germany, where huge mountains reside, the definition of [mountain] ("Berg") starts at a height of about a mile – smaller risings may be termed [hill] ("Hügel"). In the North, where the land is more flat, a part of Berlin is termed [mountain] from a rising of about a few hundred feet ("Kreuzberg"). Again, this demonstrates that any approach to meaning must consider the context in which a word occurs.

Therefore, it is impossible to generate semantic hierarchies universally valid for every observer. The AROM's computational approach predicts performance completely without relying on any subjective performance measures (cf. e.g. Talmi & Moscovitch, 2004; Roediger & McDermott, 1995). The observed responses of the AROM nevertheless seem to reflect constructs that are necessary to define semantic hierarchies (cf. Schrott & Jacobs, 2011). I suppose that co-occurrence-based models provide the only way to define something objective with respect to 'semantics'. Associations simply reflect semantic relations likely for many people. Thus only the definition of associations is very broadly applicable to many subjects, because each of them to some degree has her or his own semantic taxonomies. Egoism is a vice for most people, but might be considered a virtue for the most unselfish martyr (cf. Figure 19). Defining different semantic taxonomies as deviation from the 'average' associative

structure, is a challenge, and a potential practical application for the general psychology framework presented here. In sum, the present associative-probabilistic model may account for semantic effects, because semantics is the logical rationalization of the statistical properties of the world itself.

Conclusions

From the tiniest sub-lexical representation to lexical processing IAMs so far provided a theoretical framework. By virtue of this dissertation, they can address associative relations between words.

Localist connectionist models are a powerful tool that can bring structure into the vast research field of word recognition. They explain why frequencies of sub-lexical units affect word recognition (Study 1). When no direct simulations of the word recognition process are available, they can help to attribute function to behavioral and neuroimaging findings (Study 2; cf. Jacobs & Hofmann, subm.). When word recognition is directly simulated, an IAM can predict performance and electrophysiological responses at the level of single items (Study 3). They allow for specifying potential functional loci at which affective word features may influence lexical processing. Either they may boost lexical activation (Kuchinke, 2007), or affective effects may result from semantic cohesion between words (Study 4). Study 5 has set the stage for investigating this issue in the future. Moreover, the AROM extends the range of tasks at which IAMs can be applied. Explicit memory processing is not any longer an unanswered challenge. IAMs can now be tested in any situation at which contextual-associative relations between words can be assumed to take effect, e.g. during sentence processing.

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Erklärung

Die Studien dieser Dissertationsschrift wurden in marginal modifizierten Versionen in internationalen Fachzeitschriften veröffentlicht oder eingereicht:

Studie 1:

Hofmann, M. J., Stenneken, P., Conrad, M., & Jacobs, A. M. (2007). Sublexical frequency measures for orthographic and phonological units in German. *Behavior Research Methods, 39*, 620-629.

Studie 2:

Hofmann, M.J., Herrmann, M.J., Dan, I., Obrig, H., Conrad, M., Kuchinke, L., Jacobs, A.M., & Fallgatter, A.J. (2008). Differential activation of frontal and parietal regions during visual word recognition: An optical topography study. *NeuroImage*, 40(3), 1339-1348.

Studie 3:

Hofmann, M. J., Tamm, S., Braun, M. M., Dambacher, M., Hahne, A., & Jacobs, A. M. (2008). Conflict monitoring engages the mediofrontal cortex during nonword processing. *NeuroReport, 19*, 25-29.

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Hofmann, M. J., Kuchinke, L., Tamm, S., Võ , M. L.-H, & Jacobs, A. M. (2009). Affective
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Studie 5 wurde bei „Frontiers in Language Science" eingereicht:

Hofmann, M. J., Kuchinke, L., Tamm, S., Biemann, C., & Jacobs (subm.). Remembering
  words in context as predicted by an Associative Read-Out Model.

Die angeführten Ko-Autoren können bestätigen, dass ich für das Entstehen
dieser Studien hauptverantwortlich war. Hiermit versichere ich, dass ich die vorliegende
Arbeit selbständig verfasst habe. Andere als die angegebenen Hilfsmittel habe ich nicht
verwendet. Die vorliegende Arbeit war nicht Gegenstand eines anderen
Promotionsverfahrens.

Berlin, den 20. Juni 2011

(Markus J. Hofmann)

Curriculum Vitae

Wissenschaftlicher Werdegang

2001 Zwischenprüfung Philosophie

2005 Diplom in Psychologie an der Katholischen Universität Eichstätt

2005/2006 Wissenschaftlicher Mitarbeiter im DFG-Projekt (JA 823/3-1): "Zur Rolle
    phonologischer Prozesse beim Lesen komplexer Wörter. Ein
    sprachvergleichender Ansatz".

seit 2006 in DFG-Forschergruppe FOR 778, "Zwischen Interferenz und Optimierung:
    Konflikte als Signale in kognitiven Systemen" (JA 823/4-1 und JA 823/4-2).

Lehre

Empirische Praktika: WS2006/2007, SS2007, WS2007/08.

Computer Simulation Methods: This was an 8 lesson lecture in the Statistics Course of
    the Master program "Social, Cognitive and Affective Neuroscience", WS
    2010/2011.

Neurocognitive Psychology (Seminar in the Psychology Bachelor program), SS 2011.

Vorträge

Extracting associative memory signals to predict which word is recognized with what probability in a study-test task (3.8.2010). Annual Summer Interdisciplinary Conference, Bend Oregon, USA.

Fronto-striatal circuits: Does contextual control act via decision criteria adaption and/or sensory gating? (24.3.2010). Teap, 2010, Saarbrücken.

Semantic cohesiveness, but not emotional valence increases error rates to new words in a recognition memory task: Introducing an Interactive-Associative Memory Model (25.7.2008). International Congress for Psychology 2008 (ICP).

Modeling electrophysiological responses of conflicting lexical representations (3.4.2008). Lecture Series "Behavioral Research Methods and Experimental Design" at the Berlin Mind and Brain School. Bernstein Center for Computational Neuroscience, Berlin.

Connecting a connectionist model of word recognition to empirical data (22.9.2007). Workshop "Conflicts as Signals II", 21.-23.9.2007, Binz.

Funktionale Nah-Infrarotspektroskopie in der Worterkennung - Von den ersten Befunden zur validen Verwendung von fNIRS bis hin zu Einsatz zur Diagnose von Dyslexie (27.2.2007 und 20.3.2007, zweiteilig). Bernstein Center for Computational Neuroscience, Berlin.

Der Lexikalitäts- und Wortfrequenzeffekt bei funktionaler Nah-Infrarotspektroskopie (6.3.2007). Universitätsklinik für Psychiatrie und Psychotherapie, Würzburg.

Poster

Brockhaus, W.-R., **Hofmann**, M. J., Jacobs, A.M., Kuchinke, L. (2010) Sequential dependencies in the lexical decision task. A role of the basal ganglia? Poster auf dem Decision Neuroscience Workshop, Berlin, 23.-25.9.2010.

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Tamm, S., Klonek, F., **Hofmann**, M., Jacobs, A. M. (2007). Does GLA predict response times in a stem completion task? Poster auf dem Workshop "Conflicts as Signals", 11. 12.05.2007, Berlin.

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Briesemeister, B. B., **Hofmann**, M. J., Kuchinke, L., & Jacobs, A. M. (2011). The BAWL databases in research on emotional word processing. In J. Heister, E. Pohl & K.-M. Würzner (Eds.), *Lexical Resources in Psycholinguistic Research: Proceedings of the Workshop Held at the Forth Conference on Quantitative Investigations in Theoretical Linguistics (qitl4) on the 28th of March 2011* (Vol. 3).

Jacobs, A. M., & **Hofmann**, M. J. (subm.). Neurokognitive Modellierung. In S. Kölsch (Ed.), *Affektive und kognitive Neurowissenschaft*.

Kuchinke, L., **Hofmann** M., Briesemeister, B., Krumm, N., Jacobs, A. M. (2009). Conflict signals in the explicit stem completion task. Psychophysiology, 48(1), S45.

Gutachtertätigkeiten

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Braun, M., Jacobs, A. M., Hahne, A., Ricker, B., **Hofmann**, M., & Hutzler, F. (2006). Model-generated lexical activity predicts graded ERP amplitudes in lexical decision. *Brain Research, 1073-1074*, 431-439.

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Brink, T. T., Urton, K., Held, D., Kirilina, E., **Hofmann**, M. J., Klann-Delius, G., Jacobs, A. M., & Kuchinke, L. (2011). The role of orbitofrontal cortex in processing empathy stories in 4- to 8-year-old children. *Frontiers in Psychology*, 2, 1-15.

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Hutzler, F., Braun, M., Võ , M. L.-H., Engl, V., **Hofmann**, M., Dambacher, M., Leder, H., & Jacobs, A. M. (2007). Welcome to the real world: Validating Fixation Related Potentials for Ecologically Valid Settings. *Brain Research, 1172*, 124-129.

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Kuchinke, L., **Hofmann**, M.J., Jacobs, A.M., Frühholz, S., Tamm, S., Herrmann, M. (2011). Human striatal activation during adjustment of the response criterion in visual word recognition. *NeuroImage*, 54, 2412-2417.

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