Modelling the effects of emotional intensity in the lexical decision task

Abstract

This chapter provides the development and testing of an adapted version of the MROM (Grainger and Jacobs, 1996). A neurobiologically inspired affective evaluation mechanism will be introduced, which serves to enhance early affective activation associated with activated word units in the mental lexicon. Following the nested modelling approach, the new model includes its precursor model and is tested against it as a null model. As a result, the extended MROMe allows predictions concerning the processing of emotionally valenced words in the lexical decision task. Only the MROMe makes accurate predictions concerning the enhancement effect of emotional intensity, a collapsed category of positively and negatively valenced words.

Introduction

The experiments in chapters 2 – 4 clearly demonstrated a processing advantage of emotionally valenced words in implicit word recognition: positive and negative words affected subjects' responses in a comparable manner. Emotionally valenced words were responded faster and with fewer errors compared to neutral words. Most importantly, in chapter 4, I have shown that emotional arousal modulates this effect, at least with respect to negative words. Only high-arousal negative words have been shown to modulate subjects' reactions. Since this effect has not been investigated for high-arousal positive words[6], the term *emotional intensity* will be defined as collapsing both categories, positive valence and negative valence, into a conjoint category of emotional valence, where higher positive and negative values contribute to higher emotional intensity independent of their actual valence (see Bradley et al., 1992).

One goal of this chapter is to introduce a computational model of the effects of emotional intensity on lexical decisions. Current models of visual word recognition do not take into account such effects. Moreover, most computational models in the visual word recognition literature only simulate orthographic and/or phonological processes (e.g., Coltheart, Curtis, Atkins, and Haller, 1993; Coltheart, Rastle, Perry, Langdon, and Ziegler, 2001; Grainger and Jacobs, 1996, Jacobs, Graf, and Kinder, 2003), which means that they do not include explicit discussions of semantic or emotional valence effects (for a discussion see Wurm, Vakoch, Aycock, and Childers, 2003). Recent theories on reading aloud posit a semantic pathway that entails the activation of meanings of familiar words (Coltheart et al., 2001; Harm and Seidenberg, 2004; Plaut et al., 1996), but semantic influences in visual word processing are only considered when the normal processing route is slowed by inefficient or noisy processing in the network. This point is especially intriguing, because an increasing number of studies observed effects of semantic properties in visual word recognition (see Balota, Cortese, Sergent-Marshall, Spieler, and Yap, 2004), for example, ambiguity effects (Hino, Lupker, and Pexman, 2002; Rodd, Gaskell, and Marslen-Wilson, 2002), effects of the semantic neighborhood size (Yates, Locker, and Simpson, 2003), imageability effects (Woollams, 2005), or the effects of emotional valence as discussed in this thesis (see Kuchinke et al., 2005).

In sum, the above mentioned computational models of visual word recognition can not account for the facilitation effects of positive and negative words in the lexical decision

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[6] As a result of the preliminary word rating study in chapter 4, it appeared that it is not possible to match a sample of high and low arousal positive words on valence and arousal and further orthographic dimensions (see also Thomas and LaBar, 2005). This issue will be object of further discussion in Chapter 7.

paradigm. The reason for neglecting this discussion might be due to the idea that effects of emotional valence occur very early in the processing stream (Murphy and Zajonc, 1993), which challenges models of visual word recognition that propose only feature-based orthographic and phonological processing during the initial processing stages. However, I think that a model of visual word recognition that is able to account for the effects of emotionally intense words requires the implementation of an early affective evaluative mechanism as proposed, for instance, in the 'affective primacy hypothesis' (Murphy and Zajonc, 1993). In this regard, measuring brain potentials shed a new light on the time course of emotional encoding. Effects of emotional valence have been shown to modulate brain potentials as early as 80-116 ms past stimulus onset when processing liked and disliked faces (Pizzagalli, Regard and Lehmann, 1999) and 100-140 ms after the presentation of emotionally valenced words (Ortigue et al., 2004). In contrast, effects of semantic encoding are typically identified on subsequent components like the N400, i.e. a few hundred milliseconds later. As these results suggest, the network that is responsible for the early encoding of emotional valence might be dissociated from the networks that are responsible for higher order categorization effects of semantic information. As mentioned in chapter 3, the observed interaction effect between word frequency and emotional valence in the lexical decision task fits well with the assumptions of an early evaluation of emotionally valenced stimuli.

Typically, the amygdala is suggested to support this early and automatic encoding of emotionally valenced stimuli. Emotionally valenced stimuli are discussed to activate the amygdala even when the stimuli are unaware to the subjects (e.g., in backward masking procedures, Morris, Öhmann, and Dolan, 1998). The position of the amygdala and its connectivity are suggested to play a crucial role in the processing stream to evaluate the emotional value of incoming stimuli as it receives low-level sensory input from sensory cortices and from the subcortical superior colliculus and thalamic regions. Accordingly, Adolphs (2002) proposed that the amygdala encodes the emotional value of a stimulus without the need for full and conscious object recognition in higher association cortices (but see Pessoa, Kastner, and Ungerleider, 2002). Regarding performance in the lexical decision task, Kuchinke et al. (2005) failed to find an amygdala involvement in their neuroimaging study on the processing of emotionally valenced words, although a more recent study by Nakic et al. (2006) reports amygdala activations when the processing of highly negative words (words that comprise very low ratings on the valence dimension) is contrasted with the processing of neutral words.

Only a few computational models have been developed to simulate the interaction between emotion and cognition, e.g. by modelling the interaction of attention and emotion (Taylor and Fragopanagos, 2005), the appraisal mechanisms in emotion (Sander,

Grandjean, and Scherer, 2005), or the recognition of emotional faces (Fragopanos and Taylor, 2005; Ioannou, Raouzaiou, Tzouvaras, Mailis, Karpouzis, and Kollias, 2005). For example, the Taylor and Fragopanagos (2005) model is based on a psychological depression model (Mayberg, 1997) and can account for a variety of experimental and neuroimaging data concerning the attention circuits in the brain. According to this model, the amygdala acts as a separate controller of attentional focus that enhances those representations that have an emotional value. The central role of the amygdala and the implementation of an interactive top down control from the orbitofrontal cortex and the dorsolateral prefrontal cortex lead to a model producing a high qualitative agreement with the experimental data obtained by Anderson and Phelps (2001).

A model which accounts for the effects of emotional valence in the lexical decision paradigm has been introduced by Siegle (1999, see Figure 5.1). This computational model was developed to make predictions about the nature and the time course of the performance of depressed and non-depressed subjects in a valence identification task and a lexical decision task with emotionally valenced words. Similar to the Taylor and Fragopanagos (2005) model and to the predictions of LeDoux's (1995) neurobiological model of affective information processing the amygdala is modelled as the central evaluative instance where the emotional value of incoming stimuli is processed. Most importantly, the Siegle (1999)
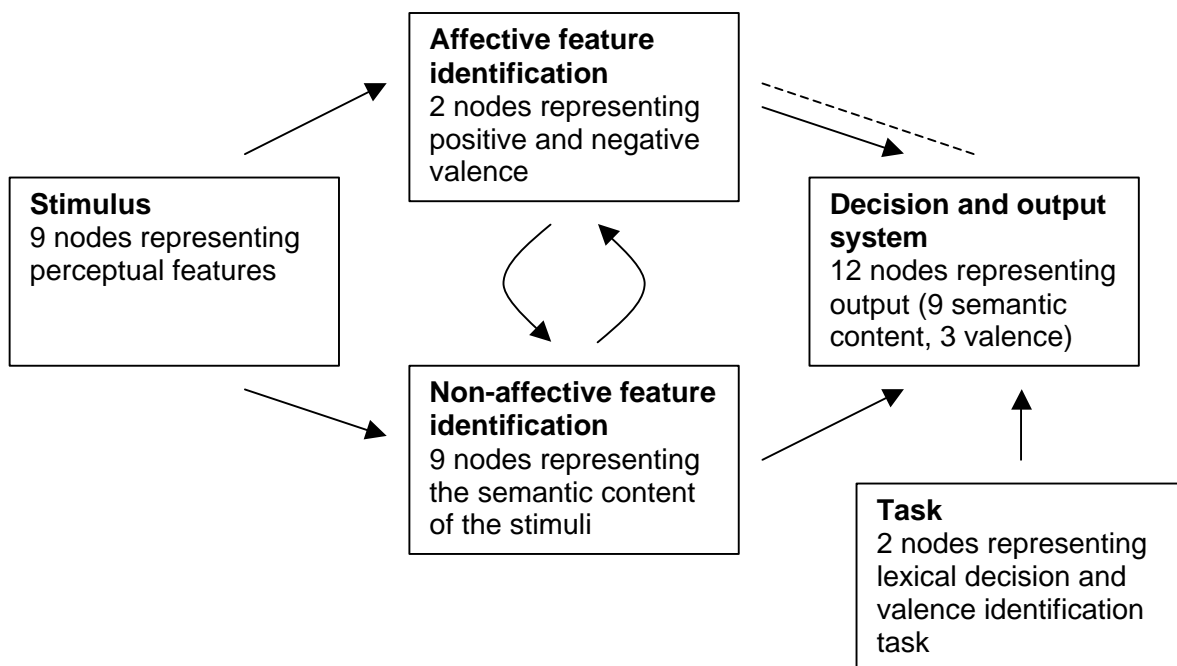

Figure 5.1 A sketch of the Siegle model for affective and semantic information processing (adapted from Siegle, 1999)

model assumes the parallel processing of affective and non-affective features (as proposed by Kitayama, 1990). Activation of affective and non-affective nodes is fed forward to an output system (proposed to be situated in the frontal lobes). After training this model with 10 positive, neutral, and negative words, Siegle (1999) was able to predict the pattern of normal and depressed subjects (depression modelled here as an overlearning of negative information) for behavioral as well as pupil data.

The starting point for the present model was different. Based on a model of visual word recognition that accounts for many empirical findings in the word recognition literature, the MROM (Grainger and Jacobs, 1996, in the following referred to as MROM96), a localist connectionist model was developed further by adding an affective evaluation mechanism. This extended model (MROMe) will then be used to simulate lexical decision data for emotionally intense and neutral words. By doing this, the MROMe follows the *nested modelling* approach requiring that a new developed model includes its successful precursor (Jacobs and Grainger, 1994; Perry, Ziegler and Zorzi, in press). A nested modelling strategy is intended to lead to more powerful models which overcome the weaknesses of their predecessors while keeping their strengths. Accordingly, the simulation outlined here has to show its appropriateness for effects of emotional intensity (collapsed positive and high arousing negative stimuli) in the lexical decision task as compared to the predictions of the old MROM96 serving as a 'null-model'.

Model description

The MROM96 is a localist connectionist model based on the Interactive Activation Model (IAM; McCelland and Rumelhart, 1981) and its extension, the SIAM (Jacobs and Grainger, 1992). It simulates the basal processes underlying reading and does account for many empirical findings in a variety of tasks, in particular the lexical decision task. Like the IAM, the MROM96 consists of three interconnected levels of representational units, a feature level that includes visual, a letter level containing letter representations, and a word level representing the mental lexicon (see Figure 5.2). During the word recognition process activation spreads to connected units in neighboring levels, and intra- and inter-level connections can either be excitatory or inhibitory. Excitatory connections increase the activation of certain units and inhibitory connections decrease it. The major output of the model are activation functions for single words which reflect activity of word units in the mental lexicon and the global lexical activity function, i.e. summed activity in the mental lexicon. Both kinds of activity (or intra-lexical information) are used to define the variable criteria that determine lexical decisions and perceptual identifications.

The M-criterion is reached when a given whole-word orthographic representation reaches a preset level of activation after presentation of a word. If any of the word units reaches this criterion, the stimulus is identified as a specific word. This also leads to a 'WORD' response in the lexical decision task. A second criterion, S, is implemented as a fast-guess mechanism based on the global lexical activity in the mental lexicon. If the summed activation of all word units exceeds this criterion, a 'WORD' response is being given that does not depend on the identification of a particular word. Thus, lexical decisions in the MROM96 do not necessarily require the identification of a word stimulus, but can also be based on stimulus familiarity. The last criterion, T, can best be described as a temporal deadline mechanism, which generates a 'NONWORD' response, when neither single unit activity nor global lexical activity has reached their criterions. The S and T criteria are flexibly set depending on the stimulus or task demands, e.g., higher values when accuracy is stressed and lower values when speed is stressed. Accordingly, omission errors in the lexical decision task (falsely responding 'NONWORD' to word stimuli) are generated by a low T criterion. False alarms are generated by a low S criterion.
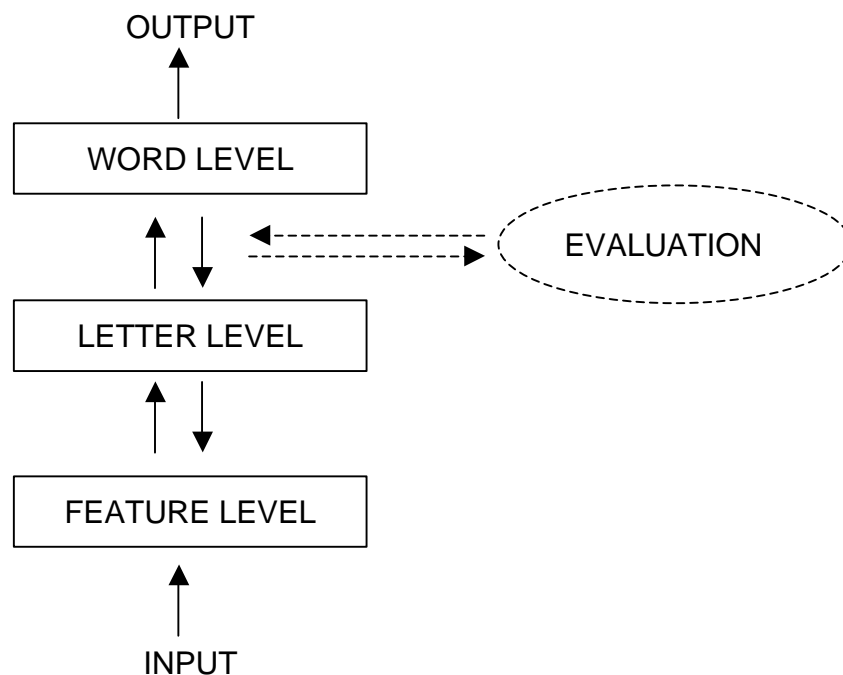

Figure 5.2 A sketch of the processing levels of the MROM96 with their interconnections (The new affective evaluation mechanism of MROMe is indexed by dotted lines)

Until now, the MROM96 has not been used to model the effects of emotional intensity. However, it appears to have sufficient structure to also tackle this issue. As a first step, in accordance with the neurobiological models, an affective evaluation mechanism will be introduced. This receives information from the early processing stages (the letter level and the initially activated word units) and processes the emotional intensity of the incoming stimulus independent of its actual valence (Figure 5.2). This affective evaluation mechanism is intended to simulate human amygdala functioning. Although the Siegle model also contains a neurobiologically inspired affective evaluation system (the affective feature identification nodes, see Figure 5.1) which interacts with the non-affective feature identification, the MROMe differs from the Siegle model in important ways. The affective feature identification system of the Siegle model does contain two nodes, one for positive valence and one for negative valence. In contrast, the affective evaluation mechanism in the MROMe represents emotional intensity on a single dimension. Two main proposals are made concerning the functioning of the affective evaluation mechanism in the MROMe:

(1) word units are associated with affective information: activation of a word unit automatically leads to activation of the associated affective information identified by the affective evaluation mechanism

(2) any basal activation of a word unit is enhanced by the affective evaluation mechanism through shifting word-level activity to activated affective (emotionally intense) word units

As a result, any activation of emotionally intense word units in the mental lexicon is enhanced, which means that they receive more activation than neutral word units. It is important to note that this affective evaluation mechanism does not operate in terms of predefined resting levels for emotional intensity as is the case with word frequency (Grainger and Jacobs, 1996; McClelland and Rumelhart, 1981). Different resting levels for emotional arousal have been discussed by Eysenck (1969; 1990) as physiological correlates of personality traits, but there is little evidence for the proposed differences (see Stelmack, 1999). Moreover, the examination of the pupil data in chapter 3 did not support a resting level hypothesis for emotional valence. In contrast to assumptions of higher resting levels for affective material, no differences in the pupillary responses were observed when comparing emotionally valenced words and neutral words (see chapter 3). I argue that if higher resting levels related to higher values of emotional intensity of a stimulus are associated with greater activations in the mental lexicon, such differences should affect the pupil data (as is the case with word frequency).

In contrast to a resting level approach, the data in the previous chapters support the assumption of perceptual enhancement effects of emotionally intense words in the lexical decision task. Emotional intensity is therefore assumed to describe inherent characteristics of the word units, like an associated basal semantic feature. Enhancement effects of emotionally intense words in the lexical decision task are thought to affect lexical activity in the word level of the MROMe. Summed lexical activation across the first seven cycles of processing has been shown to be a stable measure of lexical activity in the MROM96 (Grainger and Jacobs, 1996; Jacobs et al., 2003).

The affective evaluation mechanism in the MROMe operates at the interaction stage between the letter and the word levels, where the actual word unit activation is checked for emotional intensity. In every processing cycle, the excitatory and inhibitory weights between all word units are updated by the affective evaluation mechanism. The weights are multiplied with a fixed emotional intensity weight (set at 0.06) and a standardized factor of the actual affective activation at this cycle. The standardized factor is greater than zero for words that have an emotional intensity greater than the actual mean affective activation at this processing cycle and smaller than (or equal) zero otherwise (see Appendix D). As a result, the overall activation in the word level is shifted toward activated words with higher emotional intensity values and shifted away from activated words with lower emotional intensity (neutral
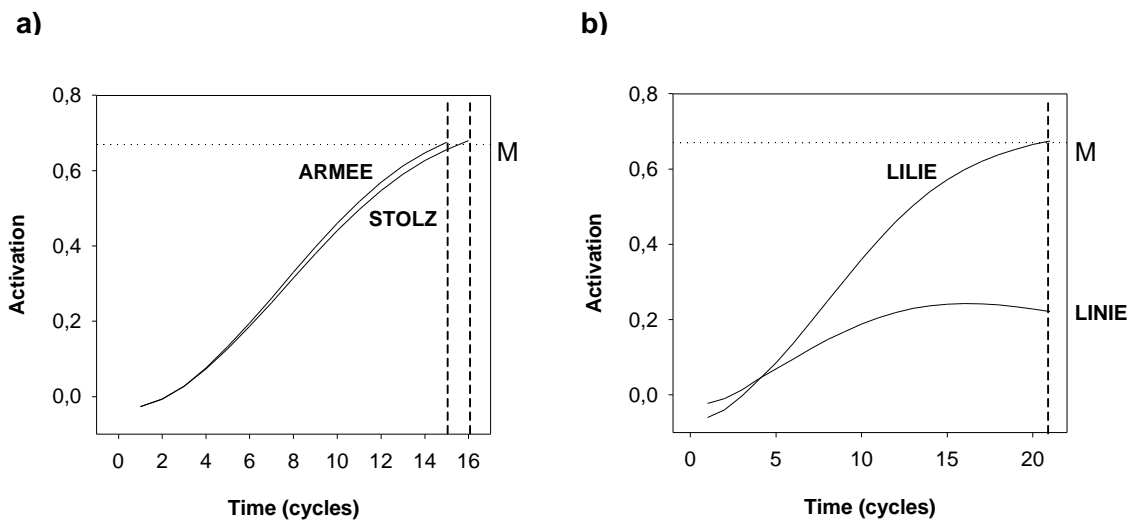

Figure 5.3 Example simulations showing word activation predicted by the MROMe
a) the emotionally intense stimulus 'ARMEE' reaches the M criterion one cycle earlier than the neutral stimulus 'STOLZ' although both stimuli showed similar curves in the MROM96; b) example of the neighborhood frequency effect as predicted by the MROMe: processing of the low frequency stimulus 'LILIE' is slowed during the first four processing cycles due to partial activation of its higher frequency orthographic neighbor 'LINIE'; dashed lines in both examples show the point in time where the M criterion is reached by either stimulus

words). Thus, the affective evaluation mechanism does not affect the amount of activation at a processing cycle, but it increases the probability of detecting an emotionally intense word.

Simulation

Extending the MROM96 by an affective evaluation mechanism does not affect the basic processes of the 1996 model which are known to allow precise quantitative predictions of reaction times and error data. The model parameters were held as constant and identical as possible to those used by Grainger and Jacobs (1996) although a different lexicon was used (e.g., Jacobs et al., 2003). To simulate the effects of emotional intensity in the lexical decision task, the mental lexicon consisted of the 525 five-letter German words for which normative ratings of emotional valence are reported in the BAWL (Võ et al., in press). For each word, emotional intensity values were computed as the absolute value of the rated emotional valence. In a first step, parameter tuning was employed to check whether the model can account for emotional intensity effects while not showing chaotic or catastrophic model behavior. To avoid higher word level activity as a result of the smaller lexicon used (that would affect the overall model behavior), the excitation parameter between the letter unit and the feature units was decreased from 0.07 to 0.055 in the simulations presented here. All other parameters were held constant. To check whether the parameter tuning and the affective evaluation mechanism showed the predicted results, the model was tested on example stimuli (see Figure 5.3). The neutral stimulus 'STOLZ' (pride) and the emotionally intense stimulus 'ARMEE' (army) which both have a comparably high word frequency were presented to the MROMe. While the MROM96 predicts that both stimuli are recognized after 15 cycles of processing, the MROMe predicts faster response times for the highly intense stimulus 'ARMEE' (15 cycles) than for the neutral stimulus 'STOLZ' (16 cycles).

A second example simulation was then carried out to examine whether the MROMe does account for the neighborhood frequency effect, i.e. the ability to predict a slowing of the activation function of a low-frequency word that has a higher frequency orthographic neighbor (see Grainger and Jacobs, 1996; Jacobs et al., 1998).[7] As a consequence of the nested modelling approach the MROMe makes comparable predictions on this effect (see Figure 5.3 for an example). Following these example simulations, the whole 525 stimuli were presented to the MROM96 and the MROMe and a multiple regression analysis on the predicted number of cycles for each word was computed using word frequency, number of

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[7] Note, that the neighborhood frequency effect is a standard effect that any model of orthographic processing in the lexical decision task should be able to account for (Grainger and Jacobs, 1996): activation of a low-frequency word is slowed, when the word has a higher frequency orthographic neighbor.

orthographic neighbors, number of higher frequency neighbors and emotional intensity as regressor variables. If the implementation of an affective evaluation mechanism is necessary to model lexical decision performance with affective word material, then only the simulated response times in the MROMe should show the expected effect. The results are in accordance with these predictions (see Table 5.1). While the predicted response times in the MROM96 did not depend on emotional intensity, the rated emotional intensity accounted for unique variance in the number of cycles to process a presented stimulus in the MROMe with higher values predicting fewer processing cycles.

Table 5.1
Results of the Multiple Regression Analysis for the predicted number of cyclces (dependent variable) as simulated by the MROM96 and the MROMe on 525 words

	MROM96		MROMe	
	Beta	**P**	**Beta**	**P**
Word Frequency	-0.171	<0.001	-0.199	<0.001
N	0.368	<0.001	0.326	<0.001
HFN	0.355	<0.001	0.363	<0.001
Emotional Intensity	0.001	0.978	-0.182	<0.001
R-square	0.446		0.470	
adjusted R-square	0.442		0.466	

Predictor variables: Word frequency per million, Number of Orthographic Neighbors (N), Number of Higher Frequency Orthographic Neighbors (HFN), Emotional Intensity; Beta = standardized regression coefficient; (all predictor variables are included in the analysis in the first step) P = associated probability that a predictor is greater than zero.

A third step of the model evaluation comprised the comparison of the model behaviour with the performance of human subjects. Figure 5.4 summarizes the simulation results for an subset of 81 five-letter words for which empirical data were available from an experimental lexical decision study with 87 subjects (run by Markus Conrad, unpublished data; see Appendix D). The subset consisted of 52 emotional intense and 29 neutral five letter words taken from the original study list of 243 words. These 81 stimuli were presented to the MROMe. The number of cycles until a 'WORD' response was given by the model was recorded as a dependent measure of the lexical decision performance (see Grainger and Jacobs, 1996). Figure 5.4 depicts the simulated performance of the model for emotionally intense and neutral words. As is evident, emotionally intense words are associated with fewer numbers of cycles than neutral words. Computed t-tests revealed that this effect is significant in the number of cycles as predicted by MROMe (P = 0.014) and the subject's

response times (P = 0.046). A follow-up simulation with MROM96 did not show this effect when emotionally intense and neutral words did not differ in their predicted number of cycles (P = 0.588).

To examine the appropriateness of the model, the Spearman correlation coefficient between the empirical response times and the model simulated number of cycles was computed. For the sample of 81 five-letter words the obtained correlation coefficient was higher for the MROMe (r = 0.222, P = 0.046) than for the MROM96 (r = 0.180, P = 0.108) suggesting that the new model shows a higher appropriateness in predicting empirical response times (although this issue has to be tested in further evaluation studies).
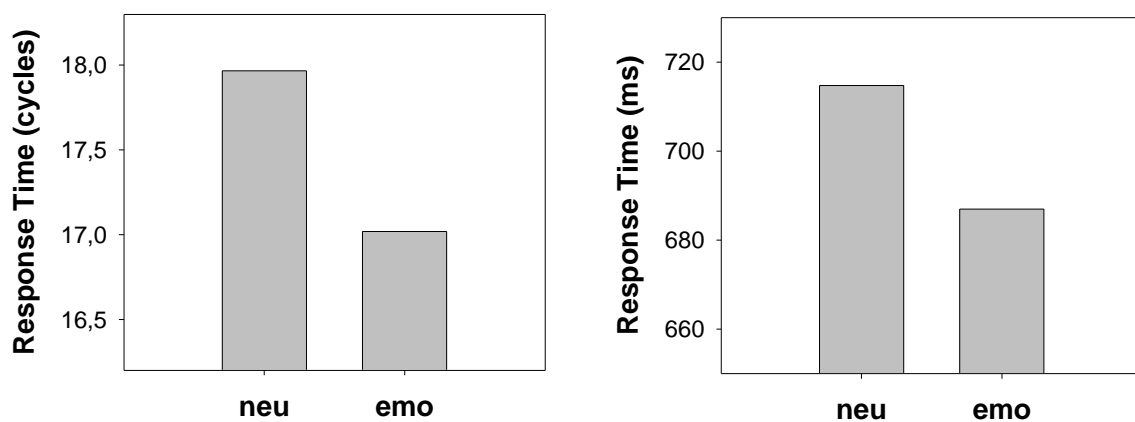

Figure 5.4 Predicted response times simulated with MROMe (left) and response times obtained in an experiment by Conrad (unpublished data; right) as a function of emotionally intense (emo) and neutral (neu) words (see text for further information, Appendix D).

Discussion

Emotionally intense words (collapsed across the emotional valence categories) enhance lexical decision times. The results of the present computational study show that with only minimal assumptions a standard model of visual word recognition, the MROM96, can be adapted to account for the empirically observed facilitation effects. Compared with the MROM96 as a null model, the MROMe predicts faster response times for emotionally intense words than for neutral words, as revealed by means of a multiple regression analysis. Moreover, when comparing the predictions of the models with empirical data, MROMe also shows a better fit to the performance of human subjects than does MROM96. An important

characteristic of any evaluation mechanism early in visual word recognition should be its independence of attention demanding processes. The affective evaluation mechanism implemented in the MROMe was designed to shift word level activity to initially activated word units that have a higher emotional intensity. Activation of emotionally intense words is facilitated in the MROMe by affecting processing time.

It might be asked whether assuming a central valence independent affective evaluation mechanism is an appropriate way to model the effects of emotional valence in the lexical decision task. Although neurobiological data, neuroimaging results and electrophysiological data commonly point to the amygdala as the subcortical region that processes the emotional significance of incoming stimuli, amygdala involvement has mainly been reported as a response to negative or fearful stimuli (Dolan, 2002; Hamann, 2001; LeDoux, 1995). Only a few studies associated the amygdala with the processing of positive stimuli (Pessoa et al., 2002; Sommerville et al., 2004). Moreover, orbitofrontal cortex has been identified to support the processing of positive affect and reward (Ashby et al., 1999; Rolls, 2000). But it is still discussed whether this region supports initial processing of positive information and how this is related to amygdala functioning (Vuilleumier; 2005). Thus, the present configuration of the affective evaluation mechanism might represent a simplification of the evaluation of positive and negative valence. One should note, however, that the affective evaluation mechanism presented in this chapter was not intended to simulate the functioning of the amygdala (or associates brain regions) on a neuronal basis, but was used to operate at the outcomes of these neuronal networks which provide the emotional valence information that can be taken to enhance perceptual processing. In this sense, the affective evaluation mechanism is related to amygdala functioning. It is also important to note, that recent neuroimaging results support the idea of a collapsed emotional intensity scale where neural activity increases with higher values of emotional intensity independent of their actual valence (see Lewis, Critchley, Rotshtein and Dolan, 2006). Moreover, the results of the chapters 2 – 4 support the notion of valence independent effects of emotional intensity on response times for low-frequency words as well as high-arousing high-frequency words – although the neuroimaging data suggested valence-specific neural networks. Interestingly, the Siegle model also predicts enhancement effects of positive and negative words for non-depressed subjects in the lexical decision task (Siegle, 1999). Models that comprise an affective evaluation mechanism inspired by neurobiological models of amygdala functioning predict enhancement effects of positive and negative words. The question of the appropriateness of such an evaluation mechanism, independent of whether it is based on a single affective dimension or on two valence nodes, has to be addressed in future research. It is obvious that the two valence nodes in the Siegle model are necessary to predict the performance of depressed subjects. This clinical issue is beyond the scope of the present MROMe, but it is likely that the

consideration of orbitofrontal cortex functions in the evaluation of the emotional valence of words might question these assumptions of a conjoint emotional intensity category. Thus, future simulations should demonstrate whether a single affective evaluation mechanism for emotionally intense words is sufficient to account for the emotional valence effects in visual word recognition.

In the preceding chapters, the facilitation effect of positive and negative words has been related to the lowering of the response criterion. As is evident in the present simulation, the response criteria to answer 'WORD' are not affected for two reasons: A fixed M criterion to identify individual single word units is emphasized by the authors of the MROM96 for reasons of model falsifiability (Grainger and Jacobs, 1996). Second, the present simulation did not affect the S criterion directly. Because the S criterion depends on the summed activation after 7 cycles of updating, a higher activation in the mental lexicon due to a presented emotionally valenced word increases the probability of lowering the S criterion. Hence, although not manipulated directly, the familiarity-based S criterion is affected by the emotional intensity of a word, which might be interpreted as lowering the response criterion (response bias).

However, the present results also support further interpretations. The time course of affective activation in the MROMe depends on the number of activated words in the mental lexicon. Only word unit activation of emotionally intense words that are activated contributes to the summed affective activation (as detected by the affective evaluation mechanism). Thus, initial affective activation is zero until different word units receive activation from lower processing levels. In the following, a number of word units gets activated (including the target word and a number of orthographic neighbors), and the affective activation reaches its maximum at this early stage. Because most of these word unit activations decrease during the further processing, the overall affective activation exhibits a similar decrease.

As mentioned, the MROMe differs from the Siegle model (Siegle, 1999) in important ways: in contrast to Siegle (1999) the affective evaluation mechanism operates on a single affective dimension, and the basis of the current simulation is a mental lexicon of 525 words. Moreover, emotional intensity is modelled in the MROMe as a feature that is associated with the orthographic word form in the mental lexicon, while Siegle (1999) proposed the activation of learned semantic patterns in the lexical decision task (which has not been shown in the literature yet). Thus, the MROMe exhibits a simplicity that is intended to provide a greater basis for a generality of the predictions. At the same time this simplicity increases the falsifiability of the model (the models ability to generate predictions that can be falsified). One should still keep in mind that the present simulations were only conducted on a small sample of five-letter words in the lexical decision task. Nonetheless, the simple assumptions that are the basis of the present mechanism and the nested precursor model allow quantitative

predictions that can be tested in a straightforward way (see Jacobs et al., 1998, for discussion on simplicity and falsifiability).

In conclusion, given that the MROM96 has been shown to account for virtually all dependent variables in the lexical decision paradigm (Grainger and Jacobs, 1996; Jacobs et al., 2003), the present simulation study shows that an adapted version of MROM96 that includes it in a nested modelling approach does account for the facilitation effects of emotionally valenced words. A neurobiologically inspired affective evaluation mechanism together with simple assumptions about the nature of affective activations in the mental lexicon have shown their appropriateness in accounting for enhancement effects in the lexical decision data related to emotional valence. Since only a small lexicon of 525 words was implemented in the MROMe, future research will test whether this mechanism can explain the data of a larger basis of words or whether the integration of positive and negative information in the early processing stages holds true.