

# Chapter 1

## Introduction

This thesis is about a computer vision system for autonomous mobile robots. Building robust vision systems is important in order to allow a mobile robot to perceive its environment and to navigate and operate in the real world using visual information. Since the real world is very complex, we chose the RoboCup Middle Size league as a test scenario, where fully autonomous robots play soccer.

This thesis describes a new image segmentation algorithm that is useful for a large domain of applications. When dealing with a sequence of images, existing methods compute the segmentation for each image from scratch. In contrast, the new algorithm adjusts the old segmentation to the new, only accessing a small portion of the image data and is thus more efficient.

Furthermore, a new method for robot self-localization by perceiving the field lines in the RoboCup environment is presented. The method for extracting the field lines builds upon the new image segmentation method. The field lines are represented in a form that allows the efficient recognition of features like the center circle or corners at the penalty area.

Robust, precise and efficient localization is then achieved in a three-layered process that combines dead-reckoning, relative registration and feature recognition. Here, *relative registration* is a method that allows the correction of small localization errors without the need for recognizing features.

## 1.1 Motivation

One of the dreams of Artificial Intelligence researchers is the construction of cognitive robots that can flexibly operate in the real world. However, for a long time research in Artificial Intelligence has been very theoretical, having brought forth IBM's super computer Deep Blue, which checkmated David Kasparov in 1997, but not having achieved a cognitive system that would be able to perceive, reason and act in our world. Therefore, a new paradigm emerged: the situated agent approach. According to this approach, in order to make real advances in Artificial Intelligence, one has to build real embodied systems that perceive, think and act in the real world. "Here and now" is the key phrase that emphasizes an abandonment of the unrealistic assumptions made before. Our world is dynamic. A lot of unknown and unpredictable situations occur and one has to react immediately without the luxury of infinite time to plan or think about a situation.

However, when dealing with real systems, the danger is that science gets lost in engineering details and this danger is increased if all researchers work on specialized, incompatible applications. The need for a benchmark problem to bundle research efforts was obvious and in 1992 Alan Mackworth proposed the idea of soccer-playing robots to the Artificial Intelligence community [56]. Such robots must be able to perceive and control the ball, avoid obstacles, communicate and cooperate with other robots and all this in real-time. The idea was widely accepted, and after five years of discussion and feasibility studies, it finally led to the foundation of the *RoboCup* research initiative in 1997. Since then, world wide robotic soccer competitions have been held annually, with over 150 teams participating in the meantime. The competitions are organized in different leagues in order to promote individual system aspects as much as possible. The Small Size league, with small robots playing on a field having approximately the size of a ping-pong table, the Middle Size League with bigger robots playing on a  $12 \times 8$ m field, the Sony Legged League based on Sony's quadruped dog-like robots, the Simulation League where soccer agents are simulated and finally, the Humanoid League with the focus on walking, human-like robots.

Our research group participates in the Small Size League in form of the "FU-Fighters" which succeeded in placing second at the world championships several times since 1999 and which achieved 1st placing in 2004. In 2002 we started our engagement in the Middle Size League. The main difference between the two leagues is that in the Small Size

League, the robots have no integrated perception. Instead, an external camera observes the game from above and an image processing system retrieves the necessary information to calculate the behavior of the robots. Thus, all the calculations are carried out by a central system external to the robots and the robots simply execute motor control commands sent through a radio link.

In contrast, the robots in the Middle Size League are fully autonomous. They have a built-in color camera and an embedded computer for visual perception and behavior computation. The visual perception is the most critical part of the system because all the other sub-systems depend on it. If an obstacle is not recognized, collision avoidance fails and if the position and the velocity of the ball are miscalculated, ball control becomes impossible.

## 1.2 The Middle Size League

In the Middle Size League, the soccer robots are fully autonomous. They integrate perception, behavior and motor control. Figure 1.1 shows a kick off at the championships in Padova 2003.



Figure 1.1: The Middle Size League in Padova 2003.

The regulations of the Middle Size League change continuously. The size of the playing field, for instance, has changed from  $10 \times 5\text{m}$  in 2003 to  $12 \times 8\text{m}$  in 2004. Also, the structure of the field lines has changed as illustrated in figure 1.2 and figure 1.3. The field lines

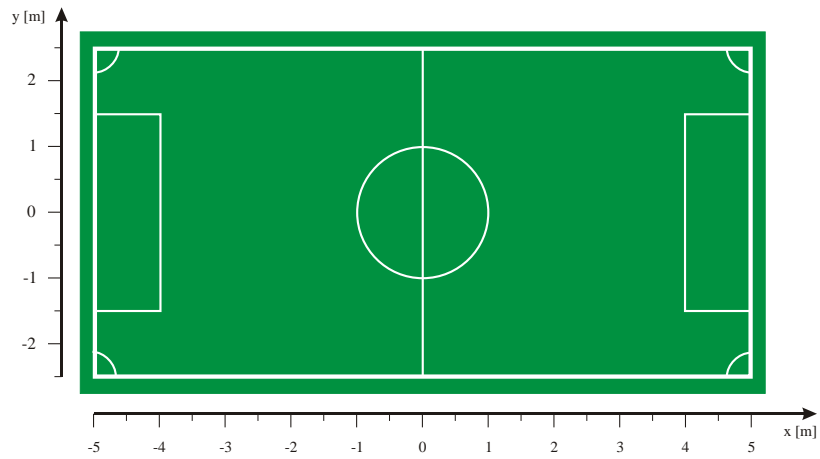


Figure 1.2: Model of the field lines in Padova 2003.

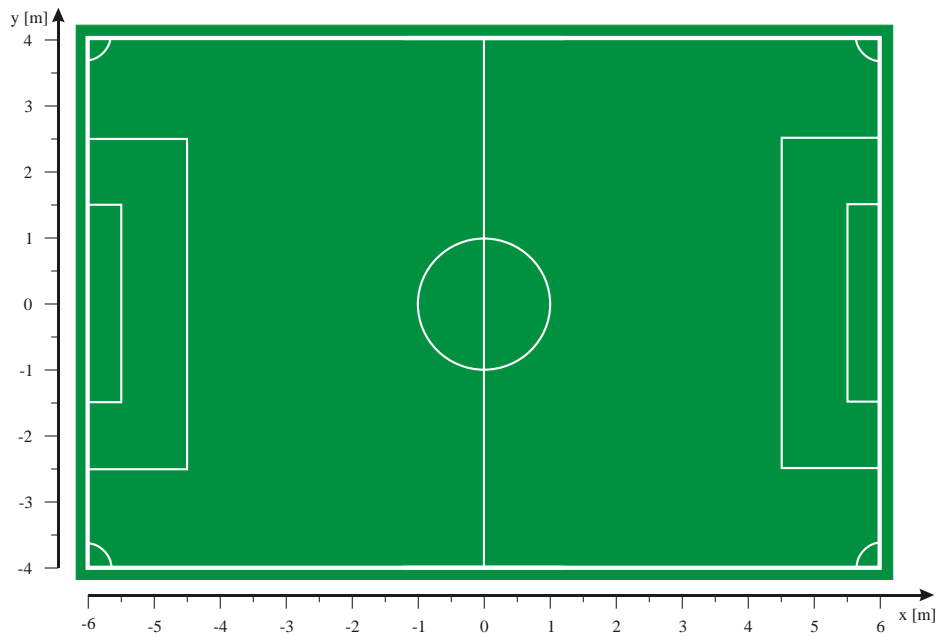


Figure 1.3: Model of the field lines in Lisbon 2004.

consist of the border lines having a width of 12.5 cm and internal lines having a width of

5 cm. The internal lines consist of the center line, the center circle (radius 1m), the lines marking the goal and penalty areas and the quarter circles (radius 40 cm) at the corners. In 2003 a 10 cm barrier around the playing field was introduced in order to prevent the robots from leaving the field. In the following chapters some figures have been made in 2003 and therefore will refer to the field model of 2003 while others, in particular when describing the feature recognition process, will be based on the field lines of 2004.

Since 2004, each team consists of up to six robots, one being the goal keeper. The robots have a maximum size of  $50 \times 50 \times 80$ cm and are fully autonomous, i.e. sensors, vision and motion control are on-board. The robots use wireless communication to synchronize their team play. The match lasts two equal periods of 10 minutes and no external intervention by humans is allowed, except to insert or remove robots from the field.

At present, relevant landmarks on the field are color-marked: the ball is orange, the goals are yellow and blue, the corner posts have yellow and blue stripes. The robots are almost black and carry color markers in magenta or light blue.

### 1.3 The FU-Fighter's Middle Size Robot

Soccer playing robots must have flexible moving capabilities in order to be able to rapidly move behind the ball or dribble the ball around obstacles. Therefore, our robots have an omni-directional drive which consists of three geared 90 Watt DC motors. They drive three independent special wheels, allowing the robot to instantaneously move and rotate in any direction from any configuration.

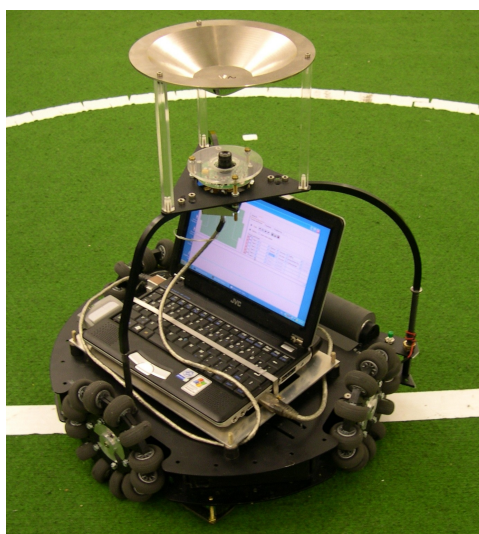


Figure 1.4: The Middle Size robot of the FU-Fighters team in 2003.

The wheel design is illustrated in figure 1.5. The original idea, the Mecanum wheel, was invented in 1973 by Bengt Ilon, an engineer with the Swedish company Mecanum AB.

Our design consists of a central wheel with 12 air cushioned rollers placed perpendicularly around the periphery of the wheel. The small rollers allow the wheel to move freely orthogonal to the wheel direction (the *passive* direction), while a force can be translated to the ground along the rotational direction of the large central wheel (the *active* direction). The three wheels are configured as two side wheels and one back wheel as can be seen in figure 1.6. By arranging them at different angles and driving them with individual motors, the forces can be combined to produce a total translational force vector and a rotational force in any desired direction. Figure 1.6 illustrates the relationship between the individual wheel movements and the resulting movement of the robot by some examples.

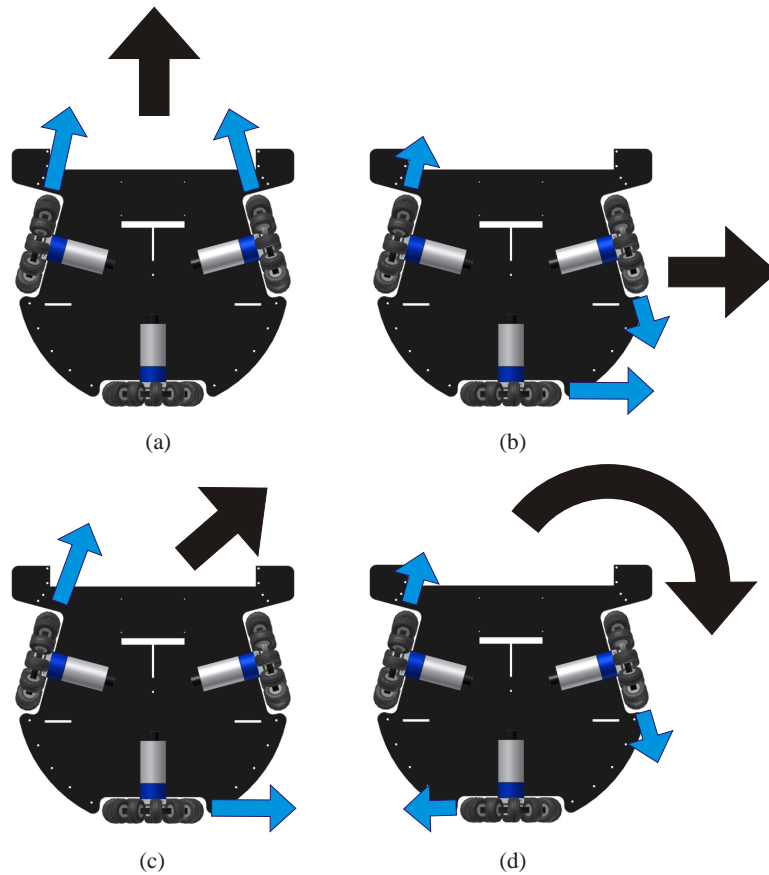


Figure 1.6: Some examples illustrating the wheel movements when the robot (a) moves forward (b) moves to the right (c) moves aslant forward or (d) rotates to the right.

The profile of our robots was designed to produce a low center of gravity. This allows our robots to move with high speed and prevents over-balancing. The base of the robot is 40 by 40 cm, but the height of the base is just 10 cm. On top of this base we placed a 1.3 kg laptop. The laptop is connected through the serial interface to the control electronics for the wheels. The control electronics are based on Motorola's HC012 16-Bit microcontroller. It runs a program that reads the control commands, which consist primarily of a desired speed vector and a rotational velocity. The microcontroller calculates the required speeds of the individual wheels and regulates the necessary power. Each motor has an impulse generator that generates 64 impulses per revolution. Since each motor has a 12:1 gear, 768 impulses arise per revolution. This information about the wheel rotations is used for feedback control, and it is also sent back to the laptop in order to supply the computer vision component with the available motion data. This odometric information is valuable

for the visual processing, because the location of objects and their features in the images can be predicted more rapidly and precisely.



Figure 1.5: The omnidirectional wheel.

A camera was placed on top of the robot, at 40 cm height, looking on an omni-directional mirror that is supported by three acrylic glass bars. The convex mirror above the camera reflects the light from all 360 degrees around the robot and thus the robot has an omni-directional view. A typical image as seen from the robot's perspective is depicted in figure 1.7.

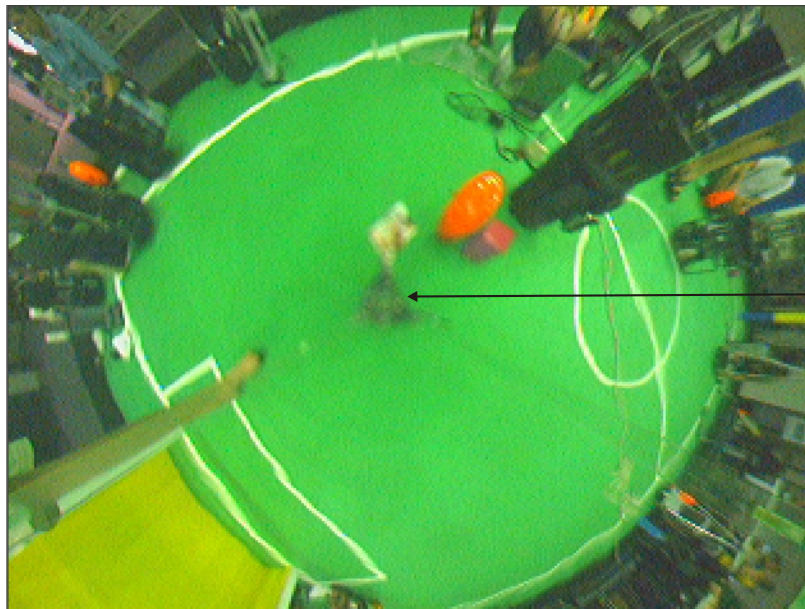


Figure 1.7: A typical image as seen from the robot's perspective. This is the reflection within the mirror above the camera. The centre of the mirror reflects parts of the robot itself, for example the plate where the camera is mounted.



## 1.4 Localizing the Robot by the Field Lines

In the first years of the Middle Size League, walls had been placed around the playing field and the most successful teams used laser range scanners as the primary sensor, yielding range scans in which the surrounding walls were clearly represented. Localization was achieved by matching the range scans to a model of the walls [38].

However, in 2002 the walls were removed and laser range scanners became difficult to use, because the rotating laser beam often hit unpredictable objects outside the playing field, for instance spectators. Therefore, many teams removed their laser range scanners and replaced them with omni-directional vision systems, the currently most-used system setup. Together with the laser range scanners, the localization based on matching range scans vanished. Instead, methods based on landmark detection and triangulation were mainly used. However, using visual information, it should be possible to detect the white field lines and to match them to a model for initial pose estimation, similarly to what was previously done with the laser range scans.

For robot self-localization in the Middle Size league, it would seem to be much easier and efficient to use the goals and corner posts for localization, and indeed, many teams use them as landmarks for triangulation or Monte Carlo localization methods. However, using the field lines has some advantages. The first are of practical nature: Localization will be more precise, since there are always some lines close to the robot. Although occlusion by other robots happens, it will almost never occur that all potentially visible lines are hidden. Furthermore, landmarks like the colored corner posts and goals will be removed in the future. However, the most important reason is the aim to research methods that can not only be used for RoboCup, but also for other applications. The field lines contain a lot of shape information, so developing methods that can extract this shape information in real-time and allow the recognition of objects by this shape information will be of great use for other applications.

The field lines also allow the investigation of an interesting question: For initial localization, the extracted lines have to be matched to a pre-defined model, and the question is whether the recognition of sub-structures is useful to accomplish this task. Leaping ahead to the conclusions of this thesis, the question can clearly be answered in the affirmative.

## 1.5 Organization of the Thesis

The remainder of this thesis is organized as follows: In chapter 2 we review the state of the art concerning mobile robot navigation and relevant computer vision methods. In chapter 3, a new method for tracking large homogeneous regions is proposed, which is the base of the entire computer vision system and the main contribution of this thesis. It is able to compute the segmentation of a new image from the old accessing only a small fraction of the image data (about 10 percent on average). Running the system at 30 frames per second, the method needs only 5-10 percent of the processing power of a Pentium III 800 MHz processor. Nevertheless, the method tracks large image regions and is able to compute their precise boundary contours. In our application, the method is used to track the green regions of the playing field and the white field lines are extracted by searching along the boundaries of the green regions.

In chapter 4, we describe a new localization technique. It consists of three layers: Dead reckoning, relative registration and feature recognition. Dead reckoning allows to estimate the movement of the robot by measuring the wheel rotations. Relative registration assumes the initial knowledge of the robot's pose and is able to correct small positional errors by matching the extracted field lines to a model. Relative registration works without recognizing structural information. Finally, we present an efficient method to recognize features like the center circle and corners at the penalty area. This feature recognition process constitutes the third level in our localization technique and is the reason for its robustness. Even when odometry information is incorrect or when the robot is suddenly manually placed in another location, the method is able to find the robot's true position after a short time period (typically below 1s).

We conclude and discuss this thesis in chapter 5. As a result of the discussion, directions of future work are indicated. Finally, chapter 6 summarizes the contributions of this thesis.