Creating a Robot Soccer Team from Scratch: the Brainstormers Tribots

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Abstract. This paper describes the team strategy of the robot soccer team of the Dortmund University. Key features are a simple but robust mechanical design, the use of omnidirectional view and motion and the implementation of Monte Carlo techniques in image understanding, sequential sensor integration and motion planning.

1 Robot hardware

The mechanical construction is inspired by the idea of omnidirectional motion. The robots consist of triangular basic platforms with three individually driven omnidirectional wheels. A robust metallic cage protects the wheels and motors from being damaged by collisions with other robots (fig. 1). This basic platform integrates a pneumatic driven kicking device.

The electronic equipment like motor controller and a standard notebook are placed in a second layer upon the chassis. We use a novel motor controller built by the Fraunhofer-Gesellschaft AIS to avoid the development of user-specific electronic components. The electronic equipment is completed by a wireless LAN transmitter to communicate with teammates.

On top of the robots we placed an omnidirectional camera consisting of a color camera and a hyperboloid mirror. Again, we used standard components to reduce the effort of individual development.

2 Software design

The main idea behind the software design was to obtain a quickly acting robot. We therefore refused to use time consuming operations like convolution of the camera image and searching in a large tree of possible actions. Hence, a certain observation of the surrounding remains noisy and the individual activities of the robots are non-optimal. But, on the other hand, the fast computation allows to react immediately to changes in the situation and thus to compensate flaws due to the simplified evaluation of sensory information.

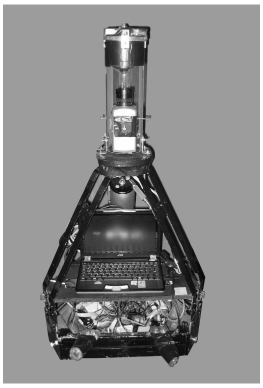

Fig. 1. One of the robots. The covering is removed to show the configuration with the basic motion platform, the electronic equipment, and the camera on top.

2.1 Image understanding and sequential sensor integration

The omnidirectional camera is the only sensor system we use. We need to extract all information like the position of the robot itself, the ball position and the position of the goals and the other robots from the camera image.

The image interpretation is so far based on color information. Interesting colors indicating the ball, the goals, etc. are represented in compact subsets of the space of RGB values and thus allow to classify a certain pixel to potentially be part of such an object. To avoid time consuming search over all pixels we use a Monte Carlo technique to search for interesting areas of the image.

Starting from the image position of a certain object in the last frame we search randomly in the surrounding of this position. Flavored by evolutionary algorithms, every appropriate pixel generates random search points in its local surrounding which generate themselves descendants whenever their color belongs to the respective color class. Thereby, the cloud of search points concentrates on large image areas of the respective color. Beside its small computational effort, this approach overcomes the problem of disrupted and unconnected areas due to misclassified pixels, highlights, shadows, and texture.

The shortcomings of the camera sensor are compensated by a sequential sensor integration based on a particle filtering approach [1]. Significant points of the soccer field like the edges of the goal and the landmarks at the corners are used as input sensor signals. The sensor inputs are combined with the information on the hitherto estimate of position and robot motion using probabilistic inference.

The second main function of the sensory system is the detection of obstacles. Since we do not use distance measuring or tactile sensors like laser range scanner or ultrasonic sensors and even resign measuring motor currents, the obstacle detection is only based on the segmentation of dark areas in the camera image. Due to the omnidirectional view we scan the camera image in radial lines from the center of the image to estimate the space left for robot motion in a certain direction of interest. Hence, we get a partial description of the configuration on the soccer field that serves as the basis for trajectory planning.

2.2 Strategy and trajectory planning

The strategy of our team is based on role allocation. Every role is assigned to a certain area of the soccer field, e.g. the defender is dedicated to stay in the backward half of the soccer field. Thus, the robots do not hamper their teammates. Only in the case of a robot holding the ball, the robot may leave its area to score a goal. We plan to use communication to dynamically change the role allocation when a robot is damaged and has to be taken off the game.

The roles are associated with a typical behavior like staying in front of the goal (goal keeper) or attacking an opponent (defender). The expected behavior serves as target for the trajectory planning which combines the target with obstacle avoidance, dynamic of robot motion and ball holding. The trajectory planning is based on a combination of abstract forces: e. g. the target position generates a strong attracting force while obstacles generate a repellent force. The resulting vector gives the intended direction of motion while the velocity is evaluated independently.

3 Future extensions and research goals

So far we developed soccer robots that are able to robustly locate themselves on the soccer field, find the ball, and score a goal. Beneath the general goal to make the hardware more reliable and to speed up the software, our major objective for the next months is to optimize object tracking in the camera image, the role allocation, and the velocity of robot motion.

For our long-term research goals the soccer robots serve as a testbed to develop, implement, and test techniques of artificial intelligence. We plan to integrate learning approaches like reinforcement learning [4] to optimize the robot behavior [2]. In our simulation league team [3] these techniques have been successfully used in past and we expect to transfer some of the results to the domain of middle-size robots.

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