FU-Fighters Omni 2001 (Local Vision)

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1 Introduction

Currently, the Small Size League is the only RoboCup competition that permits the use of external sensing systems. Most teams use a color camera that is mounted above the field to determine the positions of the robots and the ball. Since this simplified setup is not compatible with the idea of autonomous robots, we decided to build a second F180 team for the World Championships 2001 in Seattle, consisting of (only) three robots using local omnidirectional vision, the "FU-Fighters Omni".
Despite of the small number of robots the team was quite successful, since we scored several goals playing in the regular SmallSize league (having played together with the ViperRoos team). We even had a tie with a global vision team (4:4). We won the local vision contest, an extra competition between four local vision teams.
This paper describes the overall system and the principles that yielded the success.
The remainder of this paper is organized as the following: Section 2 gives an overview of the system. Section 3 describes how visual perception is performed in our implementation. This covers color segmentation, robot self-localization, ball, goal and obstacle detection and tracking. Finally, Section 4 summarizes the results, and describes our future goals.

2 System Overview

We used the same omnidirectional robots as in the global vision FU-Fighters team [4], but with a vision system mounted on top the robots. It consists of a small camera directed upwards, looking into a concave mirror that produces an omnidirectional view of the environment. Unlike most teams that use convex mirrors we took a concave mirror from a cheap flashlight.
Each robot is connected to an external computer via a wireless analog video link. The computer grabs the images and analyzes the video stream to extract information about the status of the game. The extracted local views are transmitted through a LAN to a fusion module that merges them to a global view. The reactive behavior control system now can either use a global view or a local

view, as appropriate. For example, if a robot cannot detect the ball, but other robots can, the first can use the calculated global ball position. We adapted the global vision behavior to the special needs of local vision. For instance, if a robot cannot find the ball, then it searches the playing field looking for the ball. Here localization is an important issue. The scanning is coordinated among the robots, ensuring that the search is well distributed over the playing field. If a robot can detect the ball and the opponent goal, then the robot does not care about localization but focuses on relative movements. It tries to move behind the ball, and to direct the kicking mechanism towards the opponent goal.

3 Visual Perception Techniques

3.1 Core Techniques

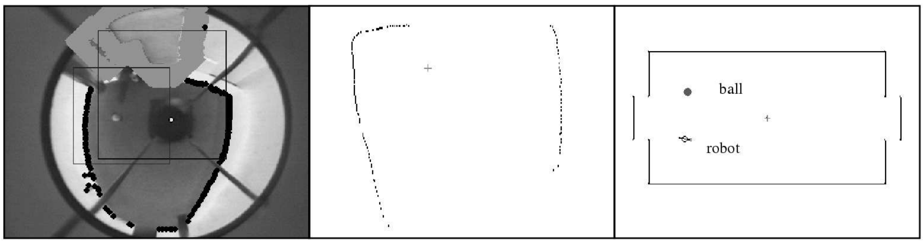
Color Segmentation Colors are a helpful simplification in RoboCup that ease the detection of objects. To use colors for classification it is necessary to specify a method to obtain the degree of membership of a particular instance of color to a color class. Since the classification must be performed very often, we decided to use the fastest classification possible with a software solution, a lookup table (LUT). Each color (we use 15 bit RGB values) can belong to different color classes. Each entry of the LUT consists of an 32-bit value, where each bit indicates class membership.
The LUT is defined by software tools that allow the user to comfortably select regions in images, whose colors then can be added to a specific color class.

Finding Color Regions When searching the ball, obstacles or goals, we search for all pixel-connected regions whose pixels satisfy a predefined color check-mask. Once we have found an object, we only search within a small rectangular region centered at the object in consecutive camera images. To segement regions, we use a fast region growing algorithm. It starts with a seed pixel and consecutively adds pixels (in the directions up, left, down, right) to the region until the color specification is not satisfied any more. To avoid the algorithm to stop growing because of the presence of noise, that may separate regions which belong together, the algorithm only stops growing when more than $k = 3$ consecutive pixels have been found that violate the color specification.

Finding Color Transitions along a Line For robot self-localization we use the transition of the green playing field to the white walls as features. To detect the borders we have developed a very fast (300000 lines of length 100 pixel) algorithm that finds a predefined color transition along a line. We also use the algorithm when searching for objects (i.e ball, opponents, goals) to discard candidate regions found by the above region growing algorithm. We check for each region whether it has a transition to the green floor (all objects with contact to the floor have this transition, with few exceptions, when an object is located next to a marking line for example). For a more detailed description of the algorithm see [1][3].

3.2 Robot Self-Localization

We have experimented with three different localization methods. The fist two are described in [1] and were not used in Seattle. The third, which was applied in Seattle, is based on generating range scans by using omnidirectional vision. We radially stretch out lines from the center of the omnidirectional image and search for transitions from the green floor to the white walls, as shown in Fig.1a). Then, we use the rotation search/least-squares method described in [2] to match the range scan to a model of the environment. However, our case is easier than in [2] since we have a known environment and the model of the environment is precise and polygonal (Fig.1c)).
Figure 1 shows the obtained range scan that was produced by transforming the transition pixels to a local coordinate system. This transformation uses a calibrated monotonic function that maps distances between an image point and the image center to the distance between the corresponding world point and the robot.
A special adaption of the localization has been made for the goal keeper. Here we create a range scan by searching for transitions from yellow to white (if our goal is the yellow one).



a) b) c)

Fig. 1. Detection of ball, goal and localization of the robot: a) Transition search, ball and goal detection; Black dots correspond to found transitions between the wall and the field. Rectangles (their centers) mark the ball and the goal. b)Obtained range scan after transforming the points; c)Localization of the robot in global coordinates;

3.3 Active Vision and Visual Attention

Consider the following two situations:
Situation S1: The robot has lost orientation and does not detect the ball.
Situation S2: The robot can see the ball and the opponent goal.
In situation S1 it is important that the robot finds the ball. This can be accomplished by two means. The first is that it searches the ball. The second is that another robot sees the ball and informs it. When deciding on the first possibility

(searching) the robot has to know, where it is located on the playing field, since otherwise it would crash with the border when searching. Therefore, in situation S1 localization is an important issue.
In contrast, in situation S2 the robot has not to care about localization but can concentrate all the computing power to exactly determine and track the position of the ball and the goal (in particular a free gap in the opponent goal) *relative* to its own position. Therefore visual attention and active vision are very important topics.

4 Results and Future Work

We were able to localize the robots and track the ball and goals with a rate of 25 fps. The localization was correct in about 95 % of all cases. However, the precision of localization must be improved further. Here, the primary problem is the distance mapping of a point in the real world to a pixel in the image. This mapping is imprecise due to misalignments of the optical system that are enforced by robot movements. To cope with the above problem, we plan to develop an automatic calibration method, which autonomously adapts to changing mapping situations.
Another problem is color classification. Although our color classification was very robust and successful compared with other teams, the fact that the user has to interact with the program to specify color classes infringes the idea of an autonomous system. Thus, we will focus our research on finding auto-configurative methods. Furthermore, we want to develop a vision system that is able to fuse many different techniques for localization, detection and tracking of objects. On a higher level such a vision system will allow to define different visual behaviors, enabling the user to specify how active vision and visual attention is used in different situations. We want the system to be flexible, such that RoboCup is just one application the system can cope with.

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