Milan Robocup Team 2009

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Abstract. In our multi–university team, we have faced almost all the aspects of the design and implementation of Robocup MSL robots. In this paper, we focus on the upgrade of the robots in the last two years, including new sensor systems, ball-handling and kicking devices, and on the modifications in behaviors and world modeling systems needed to manage and exploit the new devices.

1 Introduction

The Milan Robocup Team has faced in the last years many research issues, including: catadioptric sensor design [16, 18, 19, 17], image analysis for omnidirectional vision [2, 15, 1], optical mice-based odometry [8], [6], sensor fusion [9], data reliability [7], conceptualization [10], anchoring [12], whistle recognition [5], self-localization [20, 21], behavior definition and management [3], [11], team coordination [13], learning and adaptation [4].

The team is currently composed of one goalie (Rabbiati, Figure 1), two Janus-III bidirectional bases (Figure 3), and three Triskar omnidirectional bases (Figure 2). All the bases have been already described in past Team Description Papers. Some technical improvements have been done in the last two years: the onboard PC for our robots is no longer a portable PC, but a MAC mini, providing enough computational power; moreover, we completely re-designed the control and power boards, which are now more reliable and less power hungry than in the past.

In this paper, we focus on the major achievements, namely the enhancement of the sensor equipment, including a second camera and a compass (Section 2), new actuators for kicking and for controlling the ball (Section 3), as well as the upgrades in behaviors and world modeling, needed to manage and exploit the new devices (Section 4).

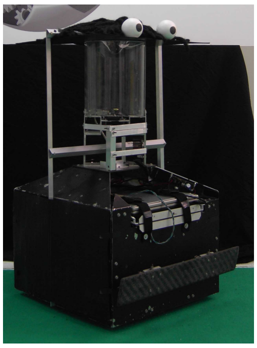

Fig. 1. Rabbiati, the goalie.

Fig. 2. Recam, one of our Triskars.

Fig. 3. Robaldo, one of our Janus III.

2 Sensors

In this section, we present the new sensors added to the omnidirectional camera already present, which is now used mainly for self-localization, global vision around the robot, and strategic considerations. The new sensors are a compass and a frontal camera.

Compass

Due to the increased dimension of field and the fact that goals are no longer colored, the self-localization system is expected not being always able to disambiguate between a finite set of potential solutions, i.e., robot positions in the field. To overcome such potential issue, we included a compass on board. It is a compass module which uses the Philips KMZ51 magnetic field sensor. It provides the absolute orientation w.r.t. the magnetic north with a resolution of 0.1 degrees. This device has been interfaced with a Microchip PIC board that sends data to the PC. Data are considered as all the data that come into our world model management system MAP [9], and are directly integrated as a source of information for the self-localization module, described in [20]. Surprisingly enough, despite the supposedly strong magnetic fields produced by the kicker and the engines, the deviation of the compass data from the correct ones is not significant and the overall information provided by it can be considered as quite reliable. We considered the introduction of a compass more robust with respect to relying on the continuous tracking of the relative robot-to-goals pose.

Frontal camera

A frontal camera is added to the robot, beside the catadioptric camera that we have developed the since the beginning of our participation to Robocup.

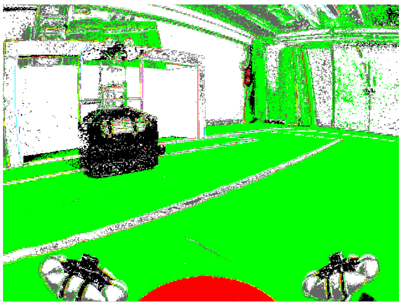

Fig. 4. Classified image from the frontal camera.

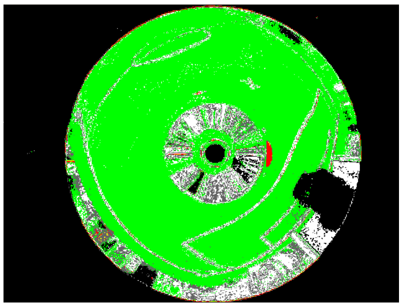

Fig. 5. Classified image from the omnidirectional camera.

This sensor has multiple purposes; the main task is to provide precise information about the ball when this is controlled by the robot, enabling more refined control and ball-handling. It could provides also more precise information about field lines, so enabling a more accurate local localization, and allows the implementation of a stereo system, jointly with the catadioptric camera, so to locate the ball accurately even when this is not on the floor, e.g., when it is coming from loop kicks.

The camera is a Unibrain Fire-I, a standard low-cost IEEE 1394 camera, as the one we are using for the catadioptric sensor. The image analysis module has been provided with new functionalities to interpret the data from this camera. The color classification system is the same as the one used for the other camera (Figure 5), as well as the blob growing algorithm, but the image subsampling and organization are different. While for the catadioptric sensor the image is subsampled in circular crowns by averaging color values of pixels around each receptor and then [2] classifying the color [16], for the front image (Figure 4) we base on classical down-sampling.

To speed up computation, specific color classification, devoted only to the detection of the color of the ball is applied on the subsampled image. A blob growing algorithm is then applied to the classified image to detect possible regions containing the ball. When the ball is the ball is nearby the robot, then it appears quite large and often it is also only partially visible; on the other hand, when the ball is quite far, the blob size is reduced, but typically fully visible (see Figure 6)

When the ball is not in the nearby area (i.e., ball not in control of the robot) the main issue is whether the ball is laying on the floor or flying; we fit an ellipse to the blob contour pixels and determine the ball location using the a priori known ball size and the geometry of the ellipse (see Figure 7); when the the ball is quite near, we found much more robust to fit a circle instead of the apparently more appropriate ellipse due to the partial view of the ball perimeter[1].

[1] In Figure 7 we present the fully undistorted image; however, undistortion is only applied to points on the edge to be fitted to reduce the computational load.

Fig. 6. Connected regions extracted from the frontal camera; some false positives are present.

Fig. 7. Ellipses and circles fitted on the selected blob. False positive have been detected and removed.

The circle and the ellipse fitting modules developed for the frontal camera constitute the basis of the processing that we will use for detecting a generic ball. We are already working in this direction and we are exploiting the use of circular Hough transform on the edges extracted from a color invariant transformation [14]. The circles extracted from the Hough transform are feed into a Kalman filter and the 3D position of the ball is recovered and tracked. Since the Kalman Filter gives a prediction on the position of the ball in the next image, we use this prediction to further reduce the computational load of the algorithm applying only in the predicted area the circular Hough transform.

The computational burden is increased by the processing of this second camera, but the overall activity of image interpretation still requires just the 60% of each control cycle, fixed at 20Hz by our real-time middleware [11].

3 Actuators

In this section, we present the new actuators: the magnetic kicking device and the active ball-handling mechanism.

Magnetic kicker

Following the common trend in MSL, we have developed a new magnetic kicker, providing a kick stronger than that provided by the old pneumatic device. It must be noticed that, despite several teams have developed this kind of device since many years, none has published enough details about it to enable other teams to replicate it. To fill this gap we are trying to do this here. Our new

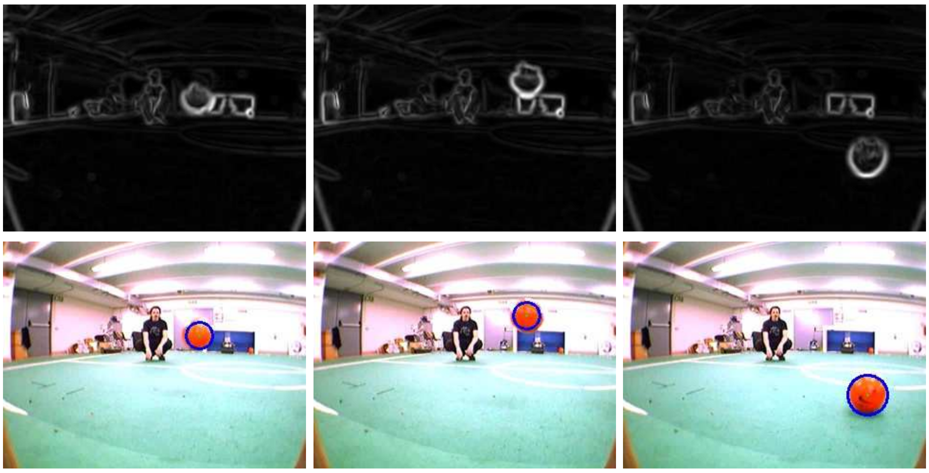

Fig. 8. Circular Hough (below) applied to the edges extracted in the color space after a color invariance transformation (above).

kicker consists of a pure iron core, connected to an aluminum cylinder, as shown in Figure 9. This system can slide inside a plastic cylinder (made of PVC) that holds 620 copper coils (wire diameter: 0.8mm). The external cylinder is blocked into a steel system, which plays also the role of stopping the action of the kicker and of supporting the retaining spring fixed on the back of the core (spring k value=30N/m). The coil is magnetically isolated from the rest of the robot by a sheet of FINEMET material.

The strongest kick is obtained by powering the coil for 25msec by a 3.300μF capacitor, charged at 400V, controlled by a PIC-based board that we have developed. Under these conditions, the ball reaches a maximum speed of 8.8 m/sec. In order to pass the ball to team-mates, it is possible to modulate the kick strength by varying the voltage over the capacitor. The capacitor is fully recharged in about 4 seconds.

The point attached to the core hits the ball either directly or through a device intended to produce a loop kick.

Ball-handling

The new kicker needs a more precise ball positioning to transfer the mechanical energy to the ball, and a better ball control was also needed for dribbling. We decided to implement an active ball-handling mechanism to substitute the passive one that required a lot of adjustments on the field for each specific ball. The present system is based on omniwheels held by sticks raised and lowered by an electromagnetic linear actuator (visible in Figure 4 and Figure 2). The omniwheels are lowered when the ball is in the proper place, as detected by the vision system. Since their length is greater that one third of the ball, they are lowered for the maximum amount of time allowed, then raised and lowered again,

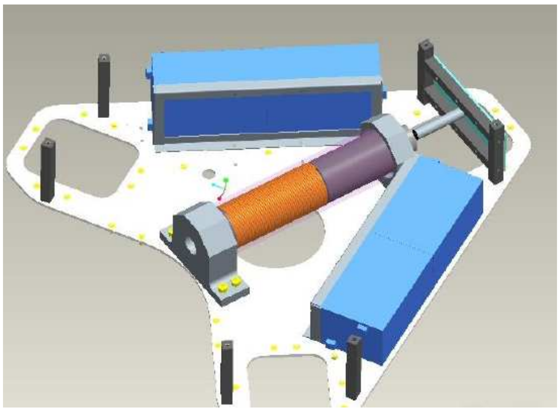

Fig. 9. A schematic view of the kicking device

thus providing a discontinuous ball control action. We decided to take this way to rely on good control for at least a given amount of time, accepting a lower quality control for the needed interval. New dribbling and kicking behaviors have been designed to exploit this new actuator. The kicking behavior guarantees that the ball is in contact with the kicker when this is activated, while the dribbling behavior obtains dribbling curves with a radius as small as 50 cm.

4 Software

In this section we describe SW improvements different from the ones already mentioned, more directly related to sensors and actuators, namely behaviors to receive passage kicks, the introduction in the world model of the concepts of “computed target“ and of ”best position“, used to implement behaviors to get positions appropriate to receive passages, and other strategic positions.

Ball passing

The Milan RoboCup Team is focusing on team playing, involving complex coordination schemes. Ball passing is an elementary soccer skill required to realize effective joint strategies. For this reason, using a mathematical model based on the robot kinematics and the estimated movement of the ball, we compute the best trajectory (i.e., the one that minimizes the passage time) to receive the ball. In order to perform such trajectory, we produce virtual points (see Section 4) that are processed by the behavior management module [11]. Furthermore, in order to receive high-speed passages we exploit the ball handling mechanism previously described (see Section 3). By lowering the two sticks, most of the energy of the impact is absorbed when the ball slots in below them.

Virtual points in world model

We consider all points that do not correspond to physical features as "virtual points". These may be, for instance, points where a robot, a teammate or the ball should be at a given moment in order to successfully perform a complex action, such as a passage. Each virtual point is described by means of fuzzy predicates. An algorithm (which runs inside the world modeler and is activated by the coordination module [13]) computes the position of the virtual point by maximizing the degree of truth of the related fuzzy predicate. Examples of virtual points computed by the world model are: the position to avoid markers, the position to kick at goal, or the position to block an opponent movement.

5 Conclusion

In this paper, we have presented main research achievements since our last participation to Robocup in Bremen 2006. In summary: we have re-designed robots to include new computers, new sensor systems, ball-handling and kicking devices, and we have added behaviors and world modeling capabilities needed to manage and exploit the new devices and to improve the game.

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