

# Object Detection and Localization Using Omnidirectional Vision in the RoboCup Environment

M. Jamzad\*, A.R. Hadjkhodabakhshi<sup>1</sup> and V.S. Mirrokni<sup>2</sup>

In this paper, a design and construction method for an omnidirectional vision system is described, including how to use it on autonomous soccer robots for object detection, localization and, also, collision avoidance in the middle size league of RoboCup. This vision system uses two mirrors, flat and hyperbolic. The flat mirror is used for detecting very close objects around the robot body and the hyperbolic one is used as a global viewing device to construct a world model for the soccer field. This world model contains information about the position and orientation of the robot itself and the position of other objects in a fixed coordinate system. In addition, a fast object detection method is introduced. It reduces the entire search space of an image into a small number of pixels, using a new idea that is called jump points. The objects are detected by examining the color of pixels overlapping these jump points and a few pixels in their neighborhood. Two fast and robust localization methods are introduced, using the angle of several fixed landmarks on the field and the perpendicular borderlines of the field. Borderline detection uses the clustering of candidate points and the Hough transform. In addition, the omnidirectional viewing system is combined with a front view that uses a plain CCD camera. This combination provided a total vision system solution that was tested in the RoboCup 2001 competitions in Seattle USA. Highly satisfactory results were obtained, both in object detection and localization in desired real-time speed.

## INTRODUCTION

In RoboCup, a team of mobile agents plays soccer against another such team in a predefined environment. In the middle size league, each team has three players and one goalkeeper. A game is played in two, ten-minute half times. The dimensions of the robots are about  $50 \times 50 \times 60$  cm and they are fully autonomous agents. Their movements are not manually controlled but are carried out by their own actuators, sensors and decision-making devices.

The field dimensions of the middle size league are  $5 \times 10$  meters. There is a white color wall of height 50 cm all around the field (i.e., the rule until 2001). The field is covered with green carpet. Robots

play soccer with a size 4 FIFA red ball. Robots are mostly black, except for an identifying color marker of light blue or purple, on top of them. The goals are 2 meters wide and 90 cm high. One goal is yellow and the other one is blue. Figure 1 shows the picture of a middle size league field taken in Seattle during RoboCup 2001. A general report, which introduces the different teams that participated in RoboCup 2001, is given in [1].

The vision system of a robot detects objects according to their colors. These robots are usually equipped with one or more CCD cameras for their vision system and may also have other sensing devices, such as laser range finders and infrared. In addition, they are equipped with a computer system, hardware control boards and wireless communication devices that allow them to communicate with each other and with a server outside the field for coordination of the robots behavior. For details, information about RoboCup is available in [2].

Omnidirectional mirrors have been used in university labs and industry in recent decades. A general description of panoramic camera design and geometry

---

\*. *Corresponding Author, Department of Computer Engineering, Sharif University of Technology, Tehran, I.R. Iran.*

1. *School of Computer Science, Simon Fraser University in Vancouver, BC, Canada.*
2. *Laboratory of Computer Science, MIT, Cambridge, MA, USA.*



**Figure 1.** A picture of the middle size RoboCup field in 2001.

is given in [3]. Detailed theories on catadioptric image formation are given in [4,5]. The ability to view over 360 degrees has many useful applications in machine vision and robotics, for example, surveillance [6], collision avoidance [7], immediate detection of objects [8], robot localization [9], navigation and obstacle detection [10,11], outdoor navigation that uses dimension reduction with PCA and histogram matching [12], use of optical flow for motion detection by robots [13], localization and object detection using omnidirectional stereo vision [14], etc.

In RoboCup 1998, the first application of an omnidirectional vision system was introduced by Asada [15] who constructed a goal-keeper fitted with an omnidirectional vision with a learning capacity. In 2000, Lima [16] used an omnidirectional sensor for the self-localization of a robot in the field. In 2001, a goal keeper robot that used an omnivision system was introduced by the university of Padua team [17]. In this work, the authors provide a guideline for the design of an omnidirectional vision system for the Robocup domain and its software for object detection.

In the RoboCup 2001 competition, several teams, such as Artisti Veneti (University of Padua, Italy), Sharif CE (Sharif University of Technology, Iran), Fun2Mas (University of Milan, Italy), Fusion (Fukuoka University, Japan), IsocRob 2001 (Institute of Robotic systems, Lisbon), Minhø (University of Minhø, Portugal), Trackies (University of Osaka, Japan) and Eigen (Keio University, Japan), etc. used omnidirectional vision systems on their soccer robots. Descriptions of these teams are available in [18].

In the 2002 RoboCup competition, Isfahan University of Technology, Iran, presented omnidirectional mobile robots [19]. The main focus of this paper is on the mechanical design aspects of robots. The authors also provide a short description on omni-mirror and localization.

In 2003, the GMD team from Germany, in-

troduced a localization method, based on landmark detection and the triangulation method [20].

In recent years, almost all teams used an omnidirectional vision system because of its ability to provide the images usable for high speed object detection and, also, reliable robot localization. This high speed is obtained, due to the fact that only one single image, representing a 360 degree view around the robot, is needed to be processed and, also, the fact that the duration of the object appearance in the omnidirectional view field is longer. Several teams (e.g., such as Sharif CE and Artisti Veneti) designed and manufactured their own customized mirror, but many other teams purchased a pre-fabricated omnivision set that included the mirror and camera.

The vision system described in this paper has been installed on the robots of Sharif CE middle size robotic team since 2001. Sharif CE has participated in all RoboCup competitions from 1999 to 2002 and has achieved remarkable results (1st place in RoboCup 1999 in Stockholm, 1st place in European RoboCup 2000 in Amsterdam, 3rd place in RoboCup 2000 in Melbourne, best engineering challenging award for its paper on robot vision in RoboCup symposium 2001 in Seattle) [21,22].

Although one can take advantage of having different sensory devices on a robot, in order to design simple and efficient mobile robots with easier hardware handling, it is worth concentrating only on vision sensors.

To solve the problem of localization, collision avoidance and object detection in the RoboCup field, the authors have designed and constructed a customized omnidirectional viewing system that is combined with a front view vision system.

The vision system uses two fire-wire (IEEE 1394) digital CCD cameras. They are connected via a switching hub to a laptop computer on the robot body, that is, the main processor of the robot. In order for a mobile robot to react quickly and accurately to all changes in its environment, it should be able to detect objects (obstacles) very rapidly and with acceptable accuracy.

The rest of the paper is organized as follows. First, an omnidirectional mirror design for mobile robots is described. Then, the object detection algorithms are presented. After that, the localization problem in general, and methods for localization are presented. Finally, experimental results are given and this paper is concluded.

## OMNIDIRECTIONAL MIRROR DESIGN

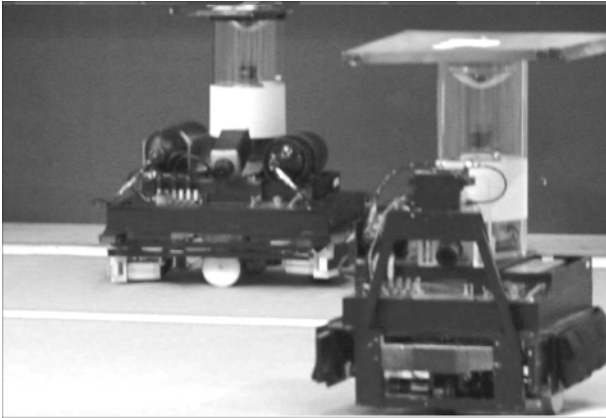
The most common omnidirectional mirrors have a spherical, parabolic, conical or hyperbolic shape. An extensive survey on these mirrors is given in [3,5].







**Figure 5.** A picture of a hyperbolic mirror fabricated by CNC machine.



**Figure 6.** Two robots with their omni-vision systems installed inside transparent vertical tubes. The front robot is a player and the one at the back is a goal keeper.

### Camera Calibration

As described above, the map between the points on the image plane and their corresponding points on the field, with respect to the coordinate system on the robot, is a function of the camera and mirror parameters. These parameters are  $f$ , as the camera focal distance, and  $a_1$ ,  $a_2$  and  $a_3$ , as given in Equation 6 for mirror parameters.

These parameters cannot be accurately obtained from the camera and mirror specifications, therefore, in practical experiments these parameters are determined by using a few sample points from the map function (Equation 10). This process is called: Vision system calibration. The method for such calibration is as follows.

Four points  $P_1(R_1, \theta_1)$ ,  $P_2(R_2, \theta_2)$ ,  $P_3(R_3, \theta_3)$  and  $P_4(R_4, \theta_4)$  are set on the field and, then, their corresponding reflected points;  $p_1(r_1, \theta_1)$ ,  $p_2(r_2, \theta_2)$ ,  $p_3(r_3, \theta_3)$  and  $p_4(r_4, \theta_4)$  are measured in the image plane. By putting these values in Equation 10, one will have four unknowns and four equations, by the solution of which will obtain the parameters,  $f$ ,  $a_1$ ,  $a_2$  and  $a_3$ .

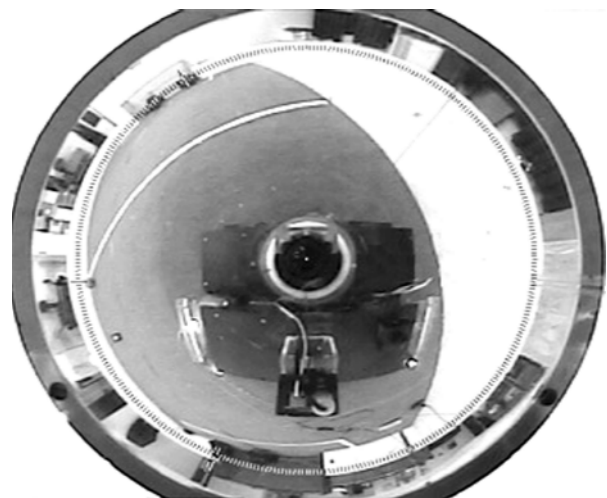
To improve the accuracy of this map, the actual values obtained for the above four parameters are used as an initial kernel in a local search to find a set of optimum values for them.

To perform this correction, a set of points,  $P_i$ , on the field are defined, such that these points are located on the circumference of a few concentric circles centered at the origin of the robot's coordinate system. For each point,  $P_i$ , its corresponding pixel,  $p_i$ , is located on the image plane and the coordinate of  $p_i$  is passed to the mapping function. The difference between the output of the mapping function and that of its real value is the error of the mapping function for sample point pair  $(P_i, p_i)$ . Then, in the neighborhood of the kernel, one tries to find new values for the mapping function parameters, such that these parameters minimize the sum of the squared errors for all sample points.

### Calculating the Parameters of a Hyperbolic Mirror

If one installs the hyperbolic mirror at such a height on the robot that the distance from the field to the focus of the mirror is the same as the height of the wall (50 cm), and one cuts the mirror hyperbola with a plane parallel to the field and at a height equal to 50.50 cm (Figure 3 shows this configuration), then, the picture projected on the resulting mirror will have the following properties:

1. No matter where the robot is located on the field, the upper edges of the walls are always projected on a circle with constant center and radius. The reason for this method of projection is explained in the following sections. Obviously, this circle always passes through both goals. Thus, to find the goals one can search only on the circumference of this circle. Figure 7 illustrates this property, where one can see the upper edges of the walls are projected on the circumference of a large circle;
2. The upper part of the two goals will always be



**Figure 7.** The edge of walls and goals are always projected on the circumference of the surrounding circle.

projected on the image plane. This is because of the 0.5 cm offset, as shown in Figure 3. This is very helpful for detecting the goals, especially in situations when a few robots and a goalkeeper are inside the goal area.

In these situations, the position of the goals, that is used as landmarks for localization, are detected by processing only the upper part of the goals. This part will never be blocked by any robot, because the maximum allowed height for the robots is smaller than the height of the goals (e.g., 90 cm). Using this setting, according to Figure 3, one can now compute the parameters of the mirror, as follows.

First, one needs to fix the radius of the mirror (i.e.,  $d$  in the equations), such that there is a good quality image for processing. This parameter depends on the quality of the mirror itself. One can use a very small mirror, if it is accurate enough, with very low image distortion, otherwise, one needs to use a bigger one. The mirror that is used in this system has the radius of about 5 cm.

Now, one can compute the value of the parameter,  $c$ , of the mirror from the following equation:

$$\tan \Phi = \frac{d}{2c + 0.5}, \quad (11)$$

where  $\Phi$  is half of the viewing angle of the camera.

On the other hand, since point  $m$  is on the mirror surface, it satisfies the mirror Equation 1, therefore:

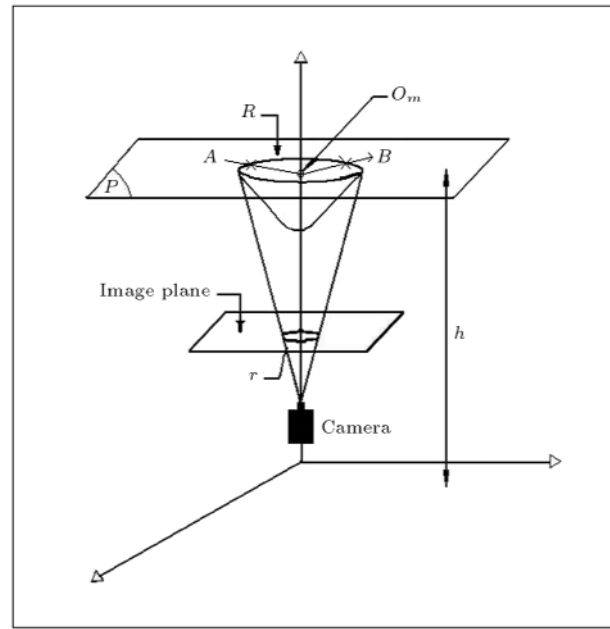
$$\frac{d^2}{a^2} - \frac{(c + 0.5)^2}{b^2} = 1. \quad (12)$$

Thus, by solving the system of equations, including Equations 12 and 1, one can easily compute the values of  $a$  and  $b$ .

### Projection of Wall Edges on Image Plane

There were white walls of height 50 cm all around the soccer field in the middle size league of RoboCup until 2001. In the following, it is shown why the projection of the upper edge of the walls will be located on the circumference of a fixed circle on the image plane, no matter where the robot is on the field.

As seen in Figure 8, plane  $p$  is parallel to the field plane and passes through  $O_m$ , which is the focal point of the hyperbolic mirror. All points on plane  $p$  will be projected on the circumference of a circle with radius  $R$  on the hyperbolic mirror. This circle is the intersection of plane  $p$  with the hyperbolic mirror. To explain the reason for this fact, let one assume that two points,  $A$  and  $B$ , are located on plane  $p$ . To find the projection of these points on the mirror surface, the light beams initiated from them will be extended to point  $O_m$ . The intersection of these light beams with



**Figure 8.** An explanatory three-dimensional view for projection of objects in height  $h$  on a circle in image plane.

the mirror surface are the projections of points  $A$  and  $B$  on the mirror surface. Because both  $O_m$  and points  $A$  and  $B$  are located on plane  $p$ , such light beams intersect the mirror surface on the circumference of the circle that is the intersection of plane  $p$  and the hyperbolic mirror.

It is clear that in an omnidirectional viewing system, as described before, the projection of a circle with radius  $R$  on a hyperbolic mirror will be a circle with radius  $r$  in the image plane, where  $R$  and  $r$  are determined according to the system setting.

Considering the fact that the height of the walls is taken to be equal to the distance between point  $O_m$  and the field (e.g.,  $h$  in Figure 8), the upper edge points of the walls always will be located on plane  $p$ . Thus, the projection of the upper edges of the walls is located on the circumference of a circle with radius  $r$  on the image plane.

One can take advantage of this property of omnidirectional viewing to install the whole omni-view system, including its mirror and camera, on a vertical sliding mechanism. This mechanism that will be driven by a motor can slide up and down using, for example, a rack and a pinion. The sliding mechanism can be stopped at the desired height,  $l$ , from the field.

In this way, if one wants to search for objects located at height  $l$ , one only needs to examine the image data on the circumference of a circle with radius  $r$  on the image plane. This device can have some industrial applications, when one needs to look for objects that one can guess are located at a certain height from the ground (e.g., assume the robot moves on the ground). Moreover, the ability to precisely

control the displacement of this sliding mechanism in an omnidirectional vision system enables one to verify an initial guess and continue the search for finding the desired object.

### Flat Mirror as a Collision Sensor

One of the rules in RoboCup indicates that a robot should not collide with another. Some teams use infrared sensors to detect close objects. But, since only vision sensors were used in the robots, this problem was solved by adding a flat circle shape mirror on top of the omnidirectional mirror, as seen in Figure 4. Depending on the height of the robots main body, the height at which the mirror is installed and the position of the camera, there is always a blind area around the body of the robot that cannot be seen by the hyperbolic mirror.

To reduce this blind area, a flat mirror of radius 11 cm was installed at the top of the hyperbolic mirror. Such a flat mirror reduces the width of the hyperbolic mirror blind area by the amount of Zone “A”, as shown in Figure 4.

Because the omni-vision CCD camera can see both images projected onto the hyperbolic and flat mirrors, therefore, to determine if an object (i.e., robot) has reached Zone “A”, the object detection algorithm can only be performed on a ring shaped area of the image that corresponds to the flat mirror. The method of object detection is similar to the one used for that part of the image corresponding to the hyperbolic mirror, which is described in the following section.

In practice, this mechanism of object detection by a flat mirror worked well as a vision sensor for collision detection.

This design of using a combination of hyperbolic and flat mirrors compared to that of [17], as described previously, has the advantages of requiring less time for image processing and having less distance measurement errors.

### OBJECT DETECTION ALGORITHM

In a highly dynamic environment, like RoboCup, very fast and relatively accurate vision analysis routines are used that can respond in near real-time speed (e.g.,  $\frac{1}{25}$  seconds).

In RoboCup, objects have predefined colors. Therefore, the problem of object detection is reduced to the problem of color classification. For object detection in an omni-view image, the idea of “Radial Method” to find color transition has been introduced [26,27]. In this method, straight lines are stretched radially from the robots perception origin and a search for transition from the floor color to the specified color class of the object of interest is performed. Although such methods work correctly, they are slow, because, for example,

in searching for the red ball, in the worst case, one might end up searching along almost all radial lines, where, for each radial line, one has to check for the color of all pixels on that line. This fact is also true, when searching for a blue or yellow goal. To ensure accurate object detection, most methods (after finding a color transition for the object of interest) use region growing or create blobs corresponding to the object of interest [17,27].

A fast vision system has been proposed, based on checking a set of jump points in a perspective view of the robot front CCD camera [28,29]. In short, an advantage of using jump points is that it dramatically reduces the search time, that is, in the worst case, for an unsuccessful search, one has to test all jump points. In this application, the number of jump points is 1500 points. Another advantage is that, if the object of interest exists in image, it will surely be found by testing only the jump points, because they are distributed in such a way that at least 7 jump points overlap with the smallest object of interest (the ball), regardless of its position on the field. For larger objects, such as robots or goals, more than 7 jump points will overlap them.

In addition, it should be mentioned that a reduction of search space, by using jump points, is not equivalent to reducing the image resolution, because, in a later case, one may lose information, where in many machine vision applications, this loss of data cannot be accepted. In the authors’ approach of using jump points, a reduction of search space is obtained with no loss of image data.

The idea of jump points has been extended to an omnidirectional view as well, where a set of jump points is defined on the image plane, as visualized by white dots in Figure 9. The distribution of these jump points is of high importance. These points are located on the circumference of concentric circles. The center of these circles is the same as the center of the image plane. As one moves toward the center of the image, the number of jump points on each circle reduces and, also, the distance between consecutive circles increases. However, the distance between each two jump points and each two consecutive circles is determined in such a way that at least nine jump points can be located on the smallest object, that is the ball, independent of the distance of the object from the robot.

To determine an object, the color of the image pixels is examined at the jump points. The color detection routine, described in [29], returns a color code for a pixel. This color code stands for one of the standard colors in RoboCup (e.g., red, green, white, black, blue, yellow, light blue and purple). In addition, all other colors are considered as unknown that are represented by only one color code.

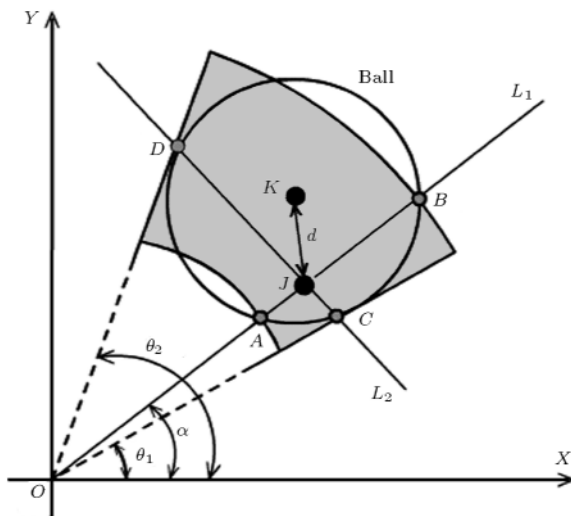
In the following, there is an explanation of how



**Figure 9.** Jump points shown by white dots are distributed on circumference of circles.

the ball is detected. If the color at a jump point is red, a search is made in a neighborhood of that jump point to find the ball. Although there are many algorithms, such as region growing and boundary detection for this purpose [30] and they give a very accurate solution to finding object boundaries in a fast changing environment, like RoboCup, there is a preference for using fast and almost correct algorithms rather than slow and accurate methods. The object detection algorithm works, as follows.

As seen in Figure 10, one starts from a jump point,  $J$ , and moves onto two perpendicular lines,  $L_1$  and  $L_2$ , that cross each other at point  $J$ . Line  $L_1$  passes through points  $O$  and  $J$ . From jump point  $J$ , one starts moving toward each end of lines  $L_1$  and  $L_2$ , until hitting the border points,  $A$ ,  $B$  and  $C$ ,  $D$ . A border point is a point on which there is



**Figure 10.** An initial rough estimate to surround the ball by a sector.

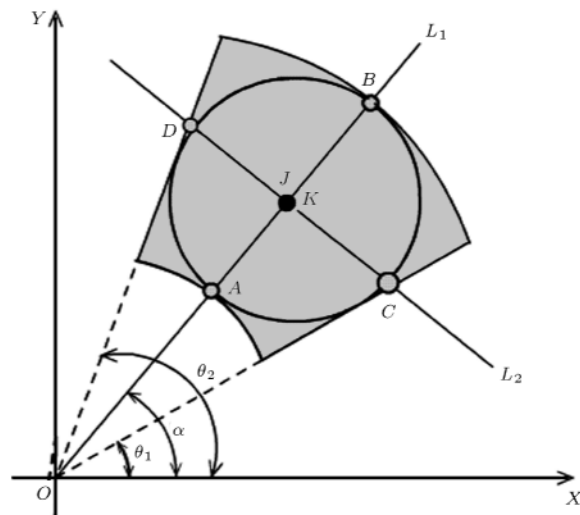
a change of color, from red to a non-red color (ball is red). These four points determine the minimum and maximum angle ( $\theta_1$  and  $\theta_2$ ) and the radius of sectors intersecting (or in a best case, surrounding) the ball, as shown in Figures 10 and 11. The area inside the sector passing through points  $A$ ,  $B$ ,  $C$  and  $D$  is taken as an estimate for the ball. However, if  $K$  is the center of this sector, the distance,  $d$  (i.e., the distance from jump point  $J$  to  $K$ ), is a measure to check the accuracy of this estimate. If  $d$  is larger than a certain threshold, the estimate is not a good one. In this case, point  $K$  is taken as a new jump point and the above procedure is repeated, until  $d$  becomes less than the desired threshold. Figure 11 shows an accepted estimate for the ball.

Although this iterative approach seems to be time consuming, it is more accurate compared with methods that can simply estimate the ball position by examining a few adjacent red pixels. The accuracy in determining the correct boundary around the ball (i.e., the most important object of interest during the game) is vital to the correct estimation of the ball distance and angle from the robot.

At this stage, some features of the ball, such as its distance and angle, with respect to the robot, are calculated. As seen in Figure 11,  $OA$  and  $\alpha$  are good estimates for the distance and angle of the ball, with respect to the robot.

## LOCALIZATION

Localization is one of the most important and difficult tasks in mobile robots. In RoboCup, where a team of robots should display cooperative behavior to achieve certain goals, the importance of localization is very clear. In short, robots will not be able to perform



**Figure 11.** A final good estimate to surround the ball by a sector.



teamwork in a multi agent system, unless they have relatively accurate information about their own position, the position of the robots on their team and, also, those of the opposing team on the field. For self localization in RoboCup environments, methods that use Laser Range Finders and, also, situations in other mobile environments are studied in [31-33].

In [14] the authors have introduced an omnidirectional stereo vision system for localization. Basic ideas for robot localization using three fixed landmarks (triangulation method), were introduced in [34]. In addition, a localization method, based on landmark detection and a triangulation method, was introduced in [19]. In this method, the authors divided the omnimage into sectors, then, by analyzing the color of the sectors, they determined the sectors containing the blue and red goal and the corner posts. If at least three known landmarks are detected, then, they draw three circles (a circle can be drawn passing through two landmarks and the robot itself). The position and orientation of the robot is estimated to be on the intersection of these three circles. However, during the times when the vision system cannot locate three distinct known landmarks, the proposed localization method cannot locate the robot.

In [16], Lima introduced a self-localization method using omni-vision that performs by finding some known fixed reference points in the field. This method assumes a priori knowledge of the actual distance between 6 horizontal and 5 vertical lines on the soccer field. A world model is determined, having its center at the field center. The image processing method determines a set of points on these lines, by detecting their corresponding color transitions. Then, by using the Hough transform [30], the line equations and the intersecting points of these lines are determined. If the system can determine at least three intersecting points, then, these intersecting points are determined as fixed known landmarks, or reference points, whose coordinates are known in the world reference frame from the field model. Then, using the known triangulation method, the robot position and orientation are determined.

The main difficulty of this approach is that the selected candidate points sent to the Hough transform might not be accurate. In addition, usually, there are many robots on the field and determining enough correct points on the field lines is not always possible. So, one may end up in many situations where the Hough transform is not able to find enough lines thus, not knowing which three reference points should be determined. Therefore, in these cases, the proposed method can not localize the robot.

In [23], the authors presented a localization system, based on a combination of odometry and vision. For odometry, a differential method was used that uses

shaft encoders. However, their vision based localization system assumes to have detected the blue and yellow goal upper corners and the robot location is assumed to be on the intersection of two circles passing through the robot center and the goal corners. The authors do not provide detailed vision procedures for this localization.

In the following, two localization methods are introduced that are based on the omnidirectional viewing system. The first method, as described in the following section uses the angle of three known fixed landmarks, with respect to the robot. These three landmarks are selected from the four intersection points between the field and the two posts of each goal.

The second method, that is described in the following sections uses the equation of fixed known lines. These lines are the border lines between the goals and the field and the borderlines between the walls and the field.

### Localization Using Angles from Three Fixed Points

In the following, a localization method is described that uses the angle of three fixed landmarks, with respect to the robot coordinate system.

These three landmarks are selected from four intersection points of the posts of goals with the green field. Let these three landmarks be called  $P_1$ ,  $P_2$ , and  $P_3$ . As seen in Figure 12, the locus of points  $P$ , that have a fixed angle  $\theta$  for  $P_1\hat{P}P_2$ , is located on a chord with center  $C$  and radius  $r$ . The center,  $C$ , is located on the perpendicular bisector of line segment  $P_1P_2$ , such that  $CH = \frac{P_1P_2}{2 \cdot \tan \theta}$  and  $r = \frac{P_1P_2}{2 \cdot \sin \theta}$ , where  $\theta = \theta_2 - \theta_1$ .

Similarly, the locus of points  $P'$  that have a fixed angle for  $P_2\hat{P}'P_3$  is located on a chord with center  $C'$  and radius  $r'$ . The center,  $C'$ , is located on the perpendicular bisector of line segment  $P_2P_3$ . The rest of the calculations is as described in the above paragraph for line segment  $P_1P_2$ . For simplicity, in

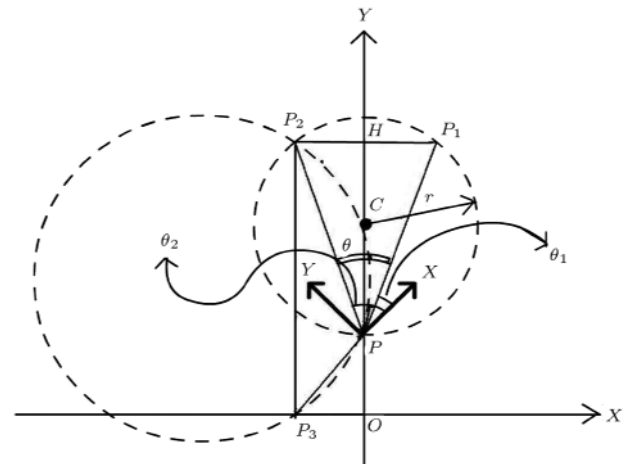


Figure 12. Localization using angle from fixed points.

Figure 12, points  $P'$ ,  $C'$  and radius  $r'$ , etc. are not shown, but the corresponding chord is shown with the larger circle.

Now, it is necessary to find points  $P_1$ ,  $P_2$  and  $P_3$  and their angle, with respect to the robot. Using these angles, one can calculate the above mentioned two chords. These two chords intersect each other at a maximum of 2 points, such that one of these two points is either  $P_1$ ,  $P_2$  or  $P_3$  and the other point is  $P$ , which indicates robot location.

In addition, the orientation of a robot in the field can be computed using the robot coordinate system and its relative angle to one of landmarks  $P_1$ ,  $P_2$  and  $P_3$ . However, the fourth landmark is used as a tester to verify the validity of the result. In the following section, the image processing method is described for finding the landmarks and their angles, with respect to the robot coordinate system.

### ***Finding the Angles of Landmarks with Respect to Robot Coordinate System***

There are two main interesting points that help in finding these angles efficiently and reliably in the image plane. The first point is that the reflection of a line (e.g., a vertical column of a goal) that is perpendicular to the field is a straight line in the image plane that passes through the center of the image plane. So, all points on this straight line have the same angle in the image plane.

Also, as mentioned before, independent of the robot position in the field, the upper edges of the wall will always be projected on a circle with a constant radius, such that the center of this circle is located on the image center. In the rest of the paper, this circle is called “surrounding circle”. Because the surrounding circle passes through both goals, to find the angle from four landmarks, there will be a search only on the circumference of this circle. In the following two steps, there is a description of how to find enough data to determine the angle of the landmarks, with respect to the robot coordinate system. The search algorithm is, as follows:

1. For each point,  $P_i$ , on the surrounding circle, determine if it is located on a blue goal, yellow goal or the wall. To do this, the algorithm checks some points in the neighborhood of  $P_i$ , that are located along a radius of the surrounding circle that passes through  $P_i$ . In situations where  $P_i$  is located on a moving object, such as the ball or a robot, the algorithm should determine if this moving object is located near the wall, or it is in a goal area. In such cases, the authors' algorithm checks the pixels on a neighborhood of  $P_i$  that is outside the surrounding circle. Therefore, even in cases when the goal area is blocked by robots, the algorithm will be able to

find the landmarks correctly. At the end of this step, the points on the surrounding circle can be classified into three categories: Points on the blue goal, points on the yellow goal and points on the wall.

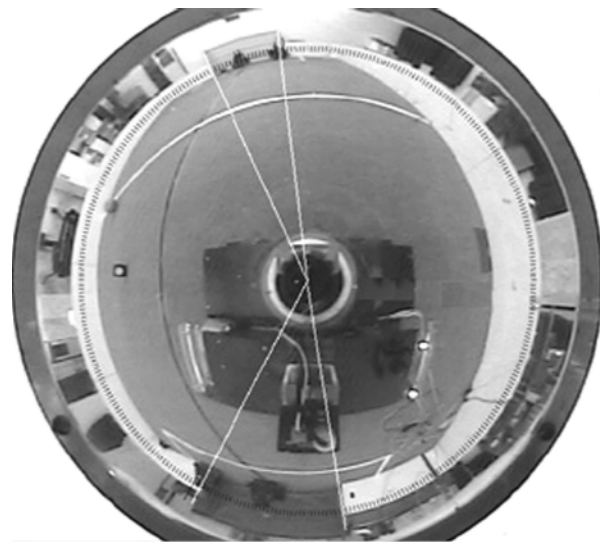
2. In this step, the algorithm finds the goal positions. For example, for the blue goal, it finds the largest consecutive number of points on the surrounding circle that are located on a blue goal.

Figure 13 shows how the angles from the image plane center to the four landmarks are calculated in a case when the goal area is blocked by more than one robot. One can see two small black objects inside each goal. These objects are robots.

### **Localization Using Fixed Lines**

Lines are some of the most convenient landmarks used for localization. Assume one knows the equation of two field borderlines that are perpendicular to each other (i.e., the borderline between goals and the field and the one between side walls and the field). Then, a robot can localize itself by determining its distance from these two lines.

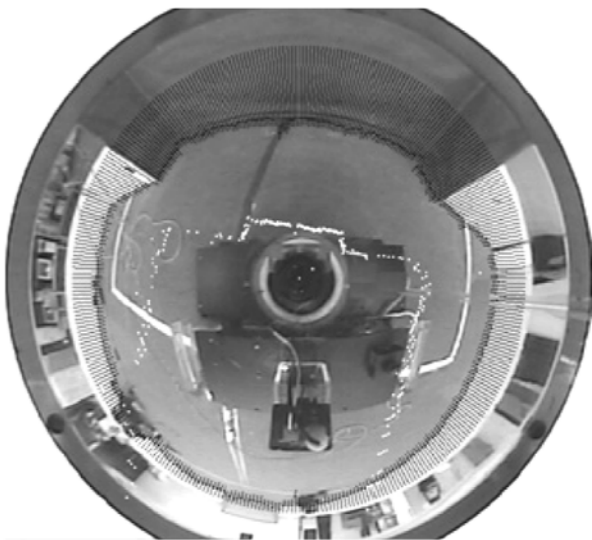
Now, the problem is how to determine the equation of such borderlines accurately. Some of the most common methods of line detection are Robust regression and the Hough transform. Both methods use a set of candidate points that are supposed to be located on the line. The Hough transform is more robust, with respect to noise, and as there is a noisy environment, regarding the accuracy of border point detection, the Hough transform is used to determine the borderline detection.



**Figure 13.** Angles of goal posts, with respect to robot, when goal area is blocked by some robots.

The steps needed for line detection are summarized, as follows.

1. **Finding Border Points:** To find border points, the search starts from the points on the circumference of the surrounding circle and moves on a radius line toward the center of the circle. A border point is the one detected on its corresponding color transition;
  2. **Mapping the Points:** At this step, the algorithm maps all border points on their corresponding points in the robot coordinate system. But, due to the inaccuracy existing in the mapping of points that are too far from the robot body, such far points are neglected after they are found. In addition, in order to increase the accuracy of the line detection, a few points might be added to the neighborhood of each detected mapped point. This technique is described in the following section.
- Figure 14, shows a visualization of mapping the field border points (border of walls and the goals with the field) on the robot coordinate system. The mapped points are shown as white dots that are scattered along straight lines near the left, right and front side of the robot body;
3. **Using Hough Transform:** Since the accuracy of the slopes of the detected lines are of great importance in the authors' localization algorithm, the idea of adding a number of new border points (i.e., depending on a weight that is defined to be a probability) to the neighborhood of each detected point has been introduced, then, the Hough transform has been applied to this new set of points. A more detailed description on this idea is given in [35].



**Figure 14.** A visualization of the mapping of field border points on the robot coordinate system.

The weight of a point is the probability that a point will be a boundary point, with respect to the noise of the environment. To compute the probability of a cell,  $C$ , the number of cells, whose colors are the same as the color of  $C$  in some small neighborhood, are counted and are divided by the total number of cells in that neighborhood. The definition of neighborhood can be any of 8, 15 and 24, depending on the desired accuracy and the speed of calculations.

At this stage, a point  $C$ , can be duplicated  $K$  times in the neighborhood of  $C$ , where  $K$  is proportional to the above-mentioned probability. In other words, more copies of those points are used which have more weight and, thus, such points will have more effect on determining the direction of the estimated line. The reader is referred to [36] for further details on the use of weight.

At this stage, the Hough transform is applied to the new set of border points. The equation of those lines that cross each other at an angle of 90 degrees are determined to be the equation of two borderlines perpendicular to each other.

Now, as described above, the robot can localize itself in the field by calculating its distance from these two borderlines. In addition, it shall be mentioned that, by using the color information of border points, one can distinguish the position of the detected lines.

A similar self-localization method, that uses omni-vision and Hough transform, is given in [16]. The advantage of the proposed method is based on introducing new candidate points, depending on the probability of the correctness of the detected border point. This approach increased the accuracy of the detected line equation and, as a result, the accuracy of self-localization as well.

## EXPERIMENTAL RESULTS

The omnidirectional viewing algorithms were tested on a processor with an AMD K6, 500MHz processor and 64MB of RAM. The speed of the localization algorithm itself was about 48 frames per second and that of object detection was about 41 frames per second. As a result, the construction of the world model was performed at about 22 frames per second.

During a game, a robot does not always need to localize itself, such times are, when the robot is moving toward the ball, dribbling another robot, kicking the ball, etc. This means that there is no need to have the localization routine run in parallel to other game routines, but it should be called upon request. That is, any time that the robot needs to know its location, the localization program must run.

The proposed vision system was tested at the RoboCup world competition in Seattle in 2001. Error free object detection was obtained whenever the color segmentation was done correctly. In addition, the robot could accurately localize itself in all cases when three fixed landmarks or two crossing border lines were correctly detected.

Therefore, the performance of the object detection and localization methods depends on the performance of color segmentation and fixed landmark detection. Having accurate color classification and segmentation routines will definitely improve the overall performance of the proposed algorithms.

## CONCLUSION

The experiments in RoboCup have shown that, if one uses only a front view vision system on a robot, there will be several cases when the robots line of sight is blocked by other robots. In such situations, localization methods that are based on only one front view CCD camera will fail, simply because their line of sight is blocked. Moreover, even if a front view CCD camera can see the necessary scene, depending on the position of the robot on the field and the content of the image acquired by the front view, the robot might fail to find its location.

In this paper, it has been shown how to use omnidirectional vision for localization, object detection and collision detection. Although it is possible to use infra-red and Laser Range Finders to do some of these jobs, it is believed that it is a good idea to reduce the number of sensors and the hardware complexity of the robot by using only vision sensors. However, one of the problems with vision sensors is that, very fast algorithms must be developed that can be run in real-time speed on the main processor used in the robot. Thinking of the complexity of the real-time environment on a robot soccer field, the accuracy and real-time speed of a robot vision system remains a challenge.

For self localization, the performance of the proposed algorithm, or any other vision based algorithm, highly depends on the accurate detection of predefined landmarks, or a set of correct points on the field border to be used for the Hough transform. In RoboCup, the role of color classification in landmark detection is very important. In this paper, the color classification method, based on the idea of Jump Points, proved to be very fast and reliable in practice, in RoboCup competitions.

However, more work needs to be done in this field when environment light change occurs during the game. This is a new challenge for researchers working in this field.

## ACKNOWLEDGMENT

The authors would like to especially thank all Sharif CE team members from previous years, specially A. Fourghnasiraie, R. Ghorbani, M. Kazemi, B. Sadjad, H. Chitsaz, F. Mobbaser and M.T. Hajiaghayy who made many contributions to the development of the team. The authors also would like to express their sincere gratitude to all high-ranking managers of Sharif University of Technology, especially Professor S. Sohrabpoor, the chancellor, for several years of support in developing this research. In addition, the financial sponsors are gratefully acknowledged for their valuable contributions.

## REFERENCES

1. Lima, P., Balch, T. and Fujita, M. et al. "RoboCup 2001, a report on research issues that surfaced during the competitions and conference", *IEEE Robotics and Automation Magazine*, pp 20-30 (June 2002).
2. www.robocup.org.
3. Svoboda, T. "Central panoramic cameras design, geometry, Ego-motion", Ph.D Thesis, Center for Machine Perception, Department of Cybernetics, Faculty of Electrical Engineering, Czech Technical University, Czech Republic (Sept. 1999)
4. Nayar, S. "Omnidirectional video camera", In *Proceedings of the 1997 DARPA Image Understanding Workshop*, pp 1431-1437, New Orleans, Louisiana (1997).
5. Baker, S. and Nayar, S.K. "A theory of single-viewpoint catadioptric image formation", *International Journal of Computer Vision*, **35**(2), pp 175-196 (1999).
6. Ollis, M., Herman, H. and Singh, S. "Analysis and design of panoramic stereo vision using equi-angular pixel cameras", *Technical Report CMU-RI-TR-99-04*, Carnegie Mellon University, Pittsburgh Pennsylvania (1999).
7. Bogner, S., Hanna, D. and Brosinsky, C. "Application of panoramic viewing systems to unmanned vehicles", In *Proceedings of the 1996 Conference of the International Association of Unmanned Vehicle Systems*, pp 853-862 (1996).
8. Yagi, Y., Kawato, S. and Tsuji, S. "Real-time omnidirectional image sensor for vision-guided navigation", *IEEE Transactions on Robotics and Automation*, **10**, pp 11-22 (1994).
9. Paletta, L., Frintrop, S. and Hertzberg, J. "Robust localization using context in omnidirectional imaging", In *2001 IEEE Intl. Conf. on Robotics and Automation (ICRA 2001)*, pp 2072-2077, Seoul, Korea, May 21-26 (2001).
10. Thorpe, C. et al. "Vision and navigation for the Carnegie-Mellon Navilab", *IEEE Trans. Pattern Anal. Mach. Intell.*, **PAMI-10**(3), pp 362-373 (1998).

11. Yamazawa, K., Yagi, Y. and Yachida, M. "Obstacle detection with omnidirectional image sensor hyper-omni vision", *IEEE International Conf. on Robotics and Automation*, pp 1062-1067 (May 1995).
12. Gonzalez, J.J., Lacroix, B. and Lacroix, S. "Rover localization in natural environments by indexing panoramic images", *Proceedings of the 2002 IEEE International Conference on Robotic Proceedings Robotics and Automation* (2002).
13. Stratmann, I. "Omnidirectional imaging and optical flow", *Proceedings of the IEEE Workshop on Omnidirectional Vision (OMNIVIS 2002)*, held in conjunction with ECCV '02 (June 2, 2002, Copenhagen, Denmark), IEEE Computer Society, pp 104-114, Los Alamitos, CA, USA (2002).
14. Matsuoka, T., Araoka, M. and Hasegawa, T. et al. "Localization and obstacle detection using omnidirectional vertical stereo vision", *RoboCup-2001: Robot Soccer World Cup V*, pp 428-434, LNCS, Springer (2001)
15. Suzuki, S. and Asada, M. "An application of vision-based learning in RoboCup for a real robot with omnidirectional vision system and the team description of Osaka University "trackies"", In M. Asada and H. Kitano, Eds., *RoboCup 98: Robot Soccer World Cup II*, **1604**, pp 316-325, LNCS Springer (1999).
16. Marques, C.F. and Lima, P.U. "Vision based self-localization for soccer robots", *Processing of the 2000 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Takamatsu, Japan (2000).
17. Menegatti, E. and Pagello, E. et al. "Designing an omnidirectional vision system for a goal keeper robot", *RoboCup-2001, Robot Soccer World Cup V*, pp 81-91, LNCS, Springer (2001).
18. Birk, A., Coradeschi, S. and Tadojoro, S., Eds. *RoboCup 2001: Robot Soccer World Cup V*, LNCS, Springer (2002).
19. Samani, A.H., Abdollahi, A., Ostadi, H. and Rad, S.Z. "Design and development of a comprehensive omnidirectional soccer player robot", *International Journal of Advanced Robotic Systems*, **1**(3), pp 191-200 (2004).
20. Junhong, J.I., Ploeger, G. and Bredenfeld, P. "An omni-vision based self-localization method for soccer robot", *Proceedings of Intelligent Vehicles Symposium*, pp 276-281, IEEE 9-11 (June 2003).
21. *The RoboCup Federation*, RoboCup-99 Stockholm, Award Winners, <http://www.robocup.org/games/99stockholm/3132.html>.
22. *The RoboCup Federation*, RoboCup-2000, Melbourne, Award Winners, <http://www.robocup.org/games/2000Melbourne/3144.html>.
23. Ishiguro, H., *Compact Omnidirectional Sensors and Their Applications*, M & E, Kougyou-Chosakai, March 1998 (In Japanese), available at: <http://www.accowle.com/english/spec.html>.
24. Bonarini, A. et al. "An omnidirectional vision sensor for fast tracking for mobile robots", In *IEEE Trans. on Instrumentation and Measurement*, **49**(3), pp 509-512 (June 2002).
25. Suzuki, S., Asada, M. et al. "Behavior learning for a mobile robot with omnidirectional vision enhanced by an active zoom mechanism", In *Proc. of Intelligent Autonomous System 5 (IAS-5)*, pp 242-249 (1998).
26. Hundelshausen, F.V. "An omnidirectional vision system for soccer robots", Master Thesis, Institut for Informatik, Freie University Berlin, Berlin (April 2001).
27. Hundelshausen, F.V., Behnke, S. and Rojas, R. "An omnidirectional vision system that finds and tracks color edges and blobs", *RoboCup 2001: Robot Soccer World Cup V*, pp 374-379, LNCS, Springer (2002)
28. Jamzad, M., Chiniforushan, E. and Sadjad, S.B. "Object detection in changing environment of middle size RoboCup and some applications", *IEEE Int. Symp. on Intelligent Control*, Vancouver, Canada, pp 807-810, October 27-30 (2002).
29. Jamzad, M. et al. "A fast vision system for middle size robots in RoboCup", In *RoboCup-2001: Robot Soccer World Cup V*, Birk, A. et al., Eds., pp 71-80, LNCS, Springer (2002).
30. Gonzalez, R.C. and Woods, R.E., *Digital Image Processing*, 2nd Ed., Prentice-Hall (2002)
31. Gotmann, J.S., Weigel, T. and Nebel, B. "Fast, accurate, and robust self-localization in the RoboCup environment", *RoboCup 99: Robot Soccer World Cup III*, **1856**, pp 304-317, LNCS, Springer (2000).
32. Iocchi, L. and Nardi, D. "Self-localization in the RoboCup environment", In *RoboCup 99: Robot Soccer World Cup III*, **1856**, pp 318-330, LNCS, Springer (2000).
33. Olson, C.F. "Probabilistic self-localization for mobile robots", In *IEEE Transactions on Robotics and Automation*, **16**(1), pp 55-66 (February 2000).
34. Krotkov, E. "Mobile robot localization using a single image", *Proc. IEEE Int. Con. J. Robotics and Automation*, pp 978-983 (1989).
35. Hajiaghayi, M.T. and Jamzad, M. "Simple, fast and robust self-localization in environments similar to the RoboCup environment", In *CARs and FOF'2002, 17th International Conference of CAD/CAM, Robotics and Factories*, Porto, Portugal (July 2002).
36. Parhami, B. "Voting algorithms", *IEEE Transactions on Reliability*, **43**(3), pp 617-629 (1994).