A Ground Truth Vision System for Robotic Soccer

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Abstract: Robotic soccer represents an innovative and appealing test bed for the most recent advances in multi-agent systems, artificial intelligence, perception and navigation and biped walking. The main sensorial element of a soccer robot must be its perception system, most of the times based on a digital camera, through which the robot analyses the surrounding world and performs accordingly. Up to this date, the validation of the vision system of a soccer robots can only be related to the way the robot and its team mates interpret the surroundings, relative to their owns. In this paper we propose an external monitoring vision system that can act as a ground truth system for the validations of the objects of interest of a robotic soccer game, mainly robots and ball. The system we present is made of two to four digital cameras, strategically positioned above the soccer field. We present preliminary results regarding the accuracy of the detection of a soccer ball, which proves that such a system can indeed be used as a provider for ground truth ball positions on the field during a robotic soccer game.

1 INTRODUCTION

This paper presents preliminary results on the use of a vision system designed for the monitoring and tracking of a robotic soccer game. The external vision system was designed with the purpose of being used as a ground truth validation system for the positions of the soccer ball and robots in real-world coordinates. The system we propose consists of two to four digital cameras strategically positioned above the soccer field. In this way 3D information about the soccer ball can be reconstructed from the images of the same scene acquired by all cameras. This paper intends to be a contribution for the area of computer vision, with application in robotic soccer, since up to date robotic vision systems used in soccer games do not use any kind of ground truth validations.

3D information recovery is of high importance in robotics applications, such as bin picking, object tracking or product profiling, just to name a few. 3D information can be obtained using passive or active methods. Passive methods, such as stereo vision, require that the environment is sufficiently illuminated. On the other hand, active methods such as structure laser light and pattern-based lighting systems use external light sources in order to obtain the 3D reconstruction of the environment (Design, 2014).

The system we are proposing is essential for the validation of object detection methods developed in this field. Until today, most of the information related to the detection of the objects of interest in a robotic soccer game was only obtained directly from the vision systems of the robots. The system that we propose is a passive one and integrates multiple digital cameras, installed in fixed positions on the soccer field.

The paper is structured in 6 sections, first of them being this Introduction. We present an overview of the work done in 3D information recovery and 3D tracking in Section 2. Section 3 presents the details of the camera calibration approach. The algorithm used for ball detection is presented in Section 4. Preliminary results are presented in Section 5. Finally, Section 6 concludes the paper, followed by the acknowledgement of the institutions that supported this work.

2 RELATED WORK

Industrial systems such as Simi Motion [1] or Kinovea [2] are designed for tracking a person based on their silhouette. Unlike other systems, these ones do not use infra-red technology. The silhouette is detected based on the articulations of the human body.

[1]http://www.simi.com/en/
[2]http://www.kinovea.org/

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In order to facilitate this process, additional markers can be placed on the human body for a higher precision. This kind of approaches are not suitable for robotic soccer since the rules do not allow the use of external markers.

Stereo vision was inspired by the human vision. The human eyes are located at 60mm from one another and each eye perceives the surrounding world in a different manner. The difference in the projections of the same point viewed by both eyes in the two retinas is defined as binocular disparity. The notion of disparity contributes to the understanding of the notion of depth (Qian, 1997). Our brain uses the horizontal disparity in order to estimate the depth information. Stereo vision is based on this principle and allows the reconstruction of a 3D scene based on the use of two digital cameras (Ramesh Jain Rangachar Kasturi, 1995) (Fig. 1).

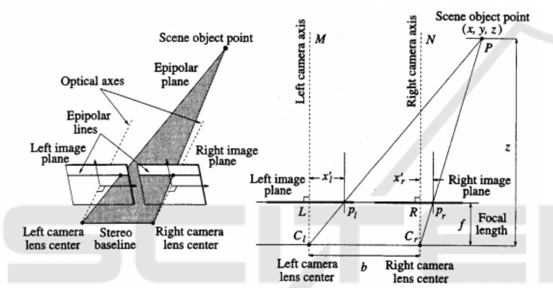


Figure 1: Illustration of the stereo vision principle of functioning.

A system for tracking sports players based on multiple cameras is presented in (Puwein et al., 2011). This method consists not only in the calibration of each frame from the cameras, but also in taking advantage of the multiple correspondences among frames. New cameras can be added to this system at any time, in order to improve its robustness. One of the challenges of this method is to establish correspondences among multiple cameras. This is done by finding invariant descriptors for each feature of the objects in the images. The locations of these features use a common coordinate system among all cameras. A comparison between the descriptors of a given frame and the ones of the previous frame is established and a bag of features is updated.

In (Yamada A, 2002) another approach for tracking soccer players and ball is presented. This method is used in TV broadcasting and is based on the rotation and zoom of a camera. Camera calibration is performed based on the extraction of interest points on the field, such as lines and circles. This calibration results in a straightforward relation between pixels and world coordinates.

A first attempt to building a ground truth validation system for robotic soccer has been presented in (Silva et al., 2012) and was later reused in (Ahmad et al., 2014). The ground truth system consists of two cameras with a baseline of 12m. These works lack an explanation regarding the chosen positioning of the cameras on the soccer field. In the work that we propose, we extend this idea by using up to four cameras and we justify their positions on the field, such as to obtain a high coverage percentage at any point in time.

3 CAMERA CALIBRATION

The firs requirement of the ground truth system that we propose is to provide a correspondence between the referential of a camera and the real world, in this case, the soccer field. With this in mind, we have implemented a graphical tool which allows the calibration of the intrinsic and extrinsic parameters of a camera, in a supervised manner. The intrinsic parameters of a camera describe the geometrical properties of that camera, while the extrinsic ones relate the position of a camera to a given referential (the soccer field in this case).

3.1 Intrinsic Parameters

Intrinsic parameters define the coordinates of a given pixel in camera coordinates. They are: focal distance, optical center and distortion coefficient. The geometry of a camera is usually described based on the pinhole model (Fig. 2), which is used for determining the intrinsic parameters:

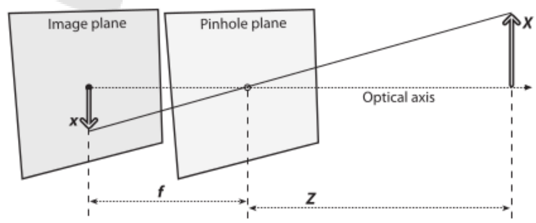


Figure 2: Pinhole Camera Model.

The following equations show the relation between pixels and camera coordinates, based on intrinsic parameters:

$$\begin{bmatrix} x_{pix} \\ y_{pix} \end{bmatrix} = \begin{bmatrix} \alpha_x & \gamma & c_x \\ 0 & \alpha_y & c_y \end{bmatrix} \cdot \begin{bmatrix} x_s \\ y_s \\ z_s \end{bmatrix} \quad (1)$$

where

$$\begin{aligned} \alpha_x &= f_x \cdot m_x \\ \alpha_y &= f_y \cdot m_y \end{aligned} \quad (2)$$

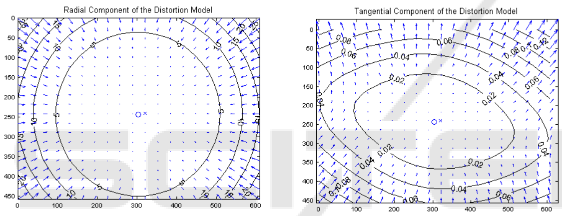
- f is the focal distance;
- m_x, m_y are scale factors that relate pixels to metric distances.

The equations system presented in 1 cannot be directly solved. Obtaining 2D information from 3D data is a trivial procedure, but the opposite one is not. To solve this system, one of the following parameters must be known: x_s, y_s or z_s. Having more than one image of the same scene makes it possible to find the missing parameter and thus recover the 3D information.

3.2 Lens Distortion

Two main types of lens distortion can be observed: radial and tangential. Radial distortion is given by the shape of the lens, while the tangential distortion is attributed to the mounting of the camera as a whole.

Figure 3 shows the impact of the radial and tangential distortion in an image.



(a) Radial distortion. (b) Tangential distortion.

Figure 3: Distortion effect for a given camera. Each arrow represents the displacement of a pixel due to radial and tangential distorsion. The cross indicates the center of the image and the circle indicates the principal point (Bouguet, 2014).

3.3 Extrinsic Parameters

The extrinsic parameters define the localization and orientation of the camera in relation to the world coordinates system. The relation between a world point, P_W and the same point P_C, in camera coordinates, is given by:

$$P_C = R \cdot (P_W - T) \tag{3}$$

where R e T are the rotation and translation matrices in the global referential.

We have developed an user supervised graphical tool for the calibration of the camera parameters. This tool has been built using the OpenCV Library .[3] One of the most used camera calibration algorithm has been proposed in (Zhang, 2000). This algorithm is based on the use of a well-known object with a regular pattern, most of the time a chessboard. Using an edge detection algorithm, the edges of the chessboard can be detected and the camera parameters are extracted based on the location of the edges. The intrinsic parameters are estimated in an iterative manner, by using multiple visualizations of the chessboard. Figure 4 exemplifies this process:

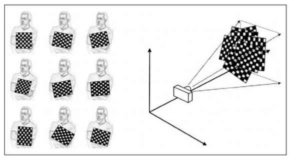


Figure 4: Chessboard images of different orientations (Kaehler and Gary, 2013) used for the calibration process.

The following equation presents the mathematical expression of the positioning of the camera relative to a global referential.

$$C = -R^{\intercal} \cdot T \tag{4}$$

The application works as follows: the user provides several views of the chessboard, at different orientations. The corners of each square is calculated and the intrinsic parameters of the camera are estimated based on this relation.

For the calculation of the extrinsic parameters, the user has to click on a point in an image and manually introduce its coordinates in real-world referential. The positioning of the camera relative to a global referential can be estimated by the correspondence of a pixel in a 2D image and the 3D coordinates of the same point. In order to facilitate the calibration procedure, every time the user clicks on a pixel in the image, he has the possibility of zooming-in, thus defining the pixel position with a higher precision. The correspondence between pixels and world coordinates is done manually, by clicking on a chosen pixel and inserting the 3D real coordinates, within the soccer field, of the same pixel.

4 3D BALL DETECTION

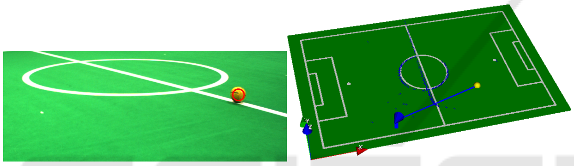
We have developed a graphical tool for visualizing the position of the cameras on the soccer field. Moreover, this tool supports the visualization of the projection of the ball direction vectors, for different cameras, as well as the ball position on the field (Fig. 6). We have conducted initial experiments using two digital cameras.

The ball detection algorithm follows the approach presented in (Neves et al., 2014), in which blobs of the color of the ball are detected. The ball is validated

[3] www.opencv.org

based on a series of measurements such as as: roundness, size and width/height relation. In order to find the 3D position of the ball, we detect the ball in an image acquired by the first camera and we calculate its center. This procedure is repeated for the frame acquired by the second camera. For each ball center, a vector is projected from the optical center towards the center of the ball. In a triangulation of two vectors, due to errors in the ball position, these vectors might not intersect. To overcome this, instead of calculating the intersection between two vectors, we calculate the closest point between them.

Figure 5 a) shows the detection of the ball in an image and Figure 5 b) shows the projection of a 3D vector towards the pixel corresponding to the center of the ball. The intersection of the vector with the plan of the field does not correspond to the real coordinates of the ball and this is due to the height of the ball, which is higher than the plan of the floor. To compensate this, more cameras should be used.



(a) (b)

Figure 5: a) Ball detection using the library UAVision. e b) Projection of a vector, from the optical center towards the center of the ball.

Figure 6 shows the projection of two vectors for the two different cameras used in this first test. The closest point between them defines the 3D coordinates of the ball.

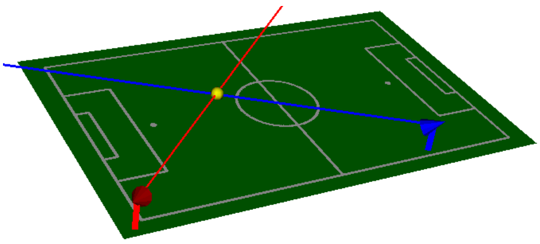


Figure 6: Projection of the two vectors towards the center of the ball; the intersection of these vectors defines the 3D center of the ball.

5 EXPERIMENTAL RESULTS

In these preliminary tests, the accuracy of the system is tested by placing the ball in known positions on the soccer field and comparing these positions to the ones returned by our software.

The two cameras were placed in two corners of the soccer field. Several images were capture with the ball placed in known positions on the field (Fig. 7). The ball is gradually moved away from the cameras.

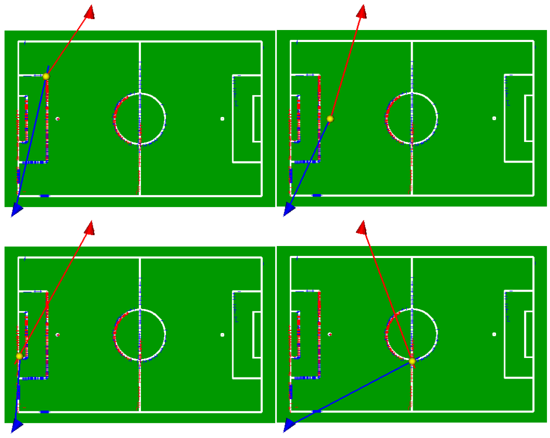


Figure 7: Triangulation method for obtaining the 3D coordinates of the soccer ball.

Figure 8 shows the setup that was used for these results.

Figure 8: Illustration of the soccer field and the placement of the two cameras.

Figure 9 shows the ball coordinates on the field (in blue points) and the coordinates calculated by the system we propose (in red). Table 1 shows the error, in mm, between the two sets of coordinates.

We can verify that, as the ball is moved away from the cameras, the error is not linear. The ball is placed at distances starting in 2.880m in a) up to 17.875m in p) and the errors obtained are quite low.

We have performed another test for evaluating the global performance of the system. We have placed two cameras on the field, with a wide baseline between them and we have repeated the previous tests. Figure 10 shows the positions of the cameras.

Figure 11 shows the ball coordinates on the field (in blue points) and the coordinates calculated by the system we propose (in red) for this setup.

Table 1: Euclidian distance between the coordinates on the field and the ones calculated by our system, in mm.

a)	b)	c)	d)	e)	f)	g)	h)
50.30	40.03	37.90	41.65	40.16	47.12	5.15	31.52
i)	j)	k)	l)	m)	n)	o)	p)
48.15	69.09	56.01	21.11	14.21	22.73	9.30	7.53
Average: 33.88							

Table 2: Euclidian distance, in mm, between the ball coordinates on the field and the coordinates calculated by the system.

a)	b)	c)	d)	e)	f)	g)	h)	Mdia
10.53	70.74	67.59	55.83	72.01	35.24	33.04	44.25	48.65

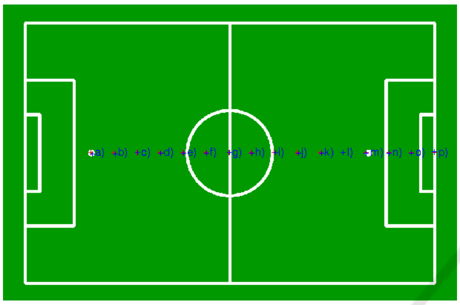


Figure 9: Ball coordinates on the field (in blue points) and the coordinates calculated by the system we propose (in red).

Figure 10: Two cameras with a wide baseline setup.

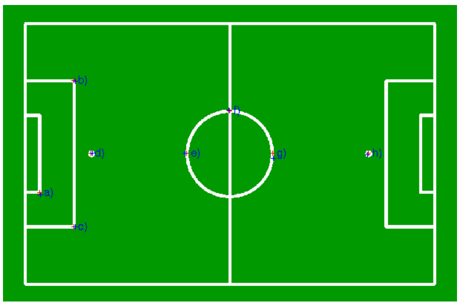
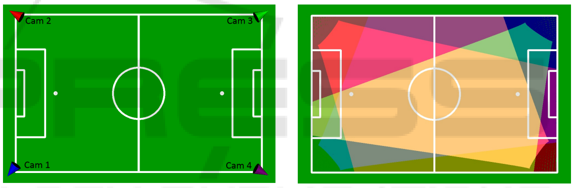


Figure 11: Ball coordinates on the field (in blue points) and the coordinates calculated by the system we propose (in red).

Table 2 shows the error, in mm, between the two sets of coordinates.

In both of the previous setups, the errors were small for all ball positions, of the orders of millimetres. This proves that the system could be used only with two cameras, if needed. We complement these results with the study of the system when using four cameras, in an attempt to improve the errors that have been presented so far.

Figure 12 a) shows a configuration with four cameras and Fig. 12 b) shows their field of view. Figure 13 shows the color map corresponding to the field of view of each of the cameras.



(a) (b)

Figure 12: a) Setup integrating four cameras b) Field of view of the different cameras. For this configuration, 10% of the field is seen by one camera, 27 % is seen by two cameras, 21 % is seen by three cameras e 42% is seen by the four cameras.

For this configuration of cameras, the triangulation should be performed for information coming from the four cameras, given that most of the field is seen by three or more cameras. A very small percentage of the field is seen by only one or two cameras.

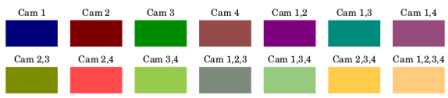


Figure 13: Color map corresponding to the field of view of each of the cameras.

This configuration of the cameras is considered to be optimal for improving the detection results obtained only with two cameras. The following algorithm has been used for choosing this configuration:

- A set of 3D points along the soccer field has been chosen.

- We verify which of all these 3D points is seen by the four cameras.
- For each point that is seen by two or more cameras, we project the vectors from the optical center of each camera until the respective 3D point. We calculate the angle between all cameras and this is saved in a data structure.
- In the end, for each 3D point we choose the angle that is closest to 90deg.

6 CONCLUSIONS

We have presented in this paper an autonomous system for the detection of the objects of interest in a robotic soccer game, based on the use of multiple digital cameras. We presented preliminary results on the triangulation of the information acquired from two cameras, applied to the detection of the soccer ball. These results show errors of the orders of millimeters for the detection of the center of the ball. Moreover, we proposed the use of this system with three or four digital cameras, whose strategic positions on the field have been thoroughly researched in order to guarantee an optimal joint field of view. We are confident that these configurations can lead to even better results on the object detection and this will be the future step in the development of this system. The final and complete system is intended as a ground truth vision system that can be used for the validation of robotic vision systems in soccer games.

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