An Application of Vision-Based Learning for a Real Robot in RoboCup - A Goal Keeping Behavior for a Robot with an Omnidirectional Vision and an Embedded Servoing -

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Abstract. We have applied Q-learning method so that a mobile robot acquire a shooting behavior of a soccer game. Thought the acquired behavior is tested in RoboCup-97, the performance is limited because of the narrow visual angle of the robot. Therefore, we install an omnidirectional vision into a mobile robot to enlarge a visual angle and apply Q-learning to behavior acquisition of the robot. An attention control method is also proposed for an omnidirectional vision system by means of an active zoom mechanism to reduce the learning time. We select a a goal defending behavior as a task and perform computer simulation and real robot experiments to show the validity of the proposed system.

1 Introduction

One of major issues in RoboCup is to make a robot adapt itself to changes in dynamic environments. We have approached to this problem with a reinforcement learning method, Q-learning. We have selected a shooting behavior as an example task by a mobile robot with a single camera [6] and tested four robots in RoboCup-97 [7]. The performance of the behavior shown there is limited by several reasons; noises in image, noises in motor control, limitation of image processing, perceptual aliasing, hidden states, and so on. Especially, the robots easily lose the rolling ball and is difficult to find out, since they have only fixed cameras and their view angles are narrow.

To enlarge a visual angle we have developed two types of robots. One has an omnidirectional vision system which can capture the whole view all around the imaging system at any instant in time. Another one has an active camera which can control the pan angle of the camera. Figure 1 shows our robots for RoboCup-98 which are categorized into three types; a fixed camera type used in RoboCup-97 (upper left), an omnidirectional vision type (upper right), and an active camera type (lower). The one with an omnidirectional vision will be used as a keeper since it can look at the ball and the goal simultaneously. Other two types of robots will be used as an attacker. In this paper, we particularly describe about learning of a goal defending behavior by a keeper robot with an ominidirectional vision system.

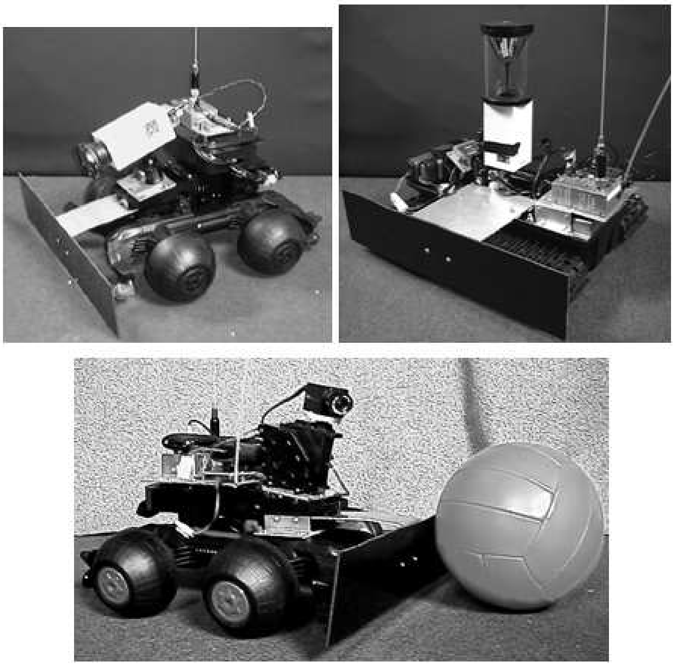


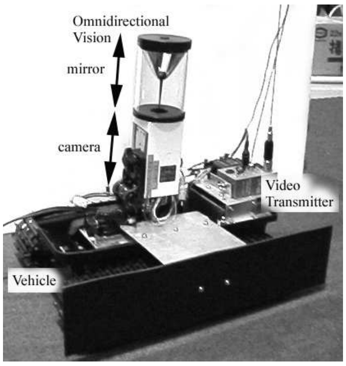
Fig. 1. Robots of University Osaka "Trackies" team

Several applications of the ominidirectional vision have been proposed, such as autonomous navigation [1], visual surveillance and guidance [2], video conference, virtual reality, and site modeling [3]. These methods have focused on its opto-geometric features to reconstruct 3-D scene structure. Our approach differs from their applications in two fold: we don to reconstruct any geometric structure from the omnidirectional views. Rather, we use it as a sensory system for a goal defending mobile robot. As a method of behavior acquisition, Q-learning is used with a state space consisting of ball and goal images.

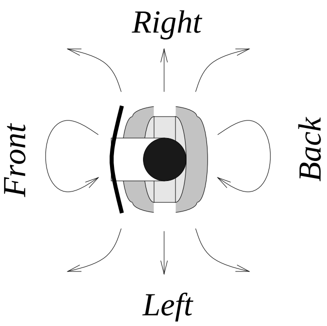
We introduce an omnidirectional vision system with an active zoom mechanism to accelerate the learning. We implement a zoom servoing [4] by which the target image can be captured at the constant position if the target moves on the ground plane. It is realized by controlling focal length of the camera. Due to the active zoom mechanism, the target motion in the radius direction can be canceled, and only circular motions around the image center can be observed. This simplifies the image processing and target tracking.

We apply the learning method [6] to a mobile robot with the enhanced omnidirectional vision system and the state space is designed for it. The rest of paper consists as follows. First, we examine the relationship between the target position in the omnidirectional view in terms of the focal length and the distance between the robot and the target. Then, we set up a control low to realize a zoom servoing, Finally, we design the state space for the robot to acquire the desired behavior based on the reinforcement learning scheme.

2 The Task and the Robot System for a Goal Keeping Behavior



(a) overview

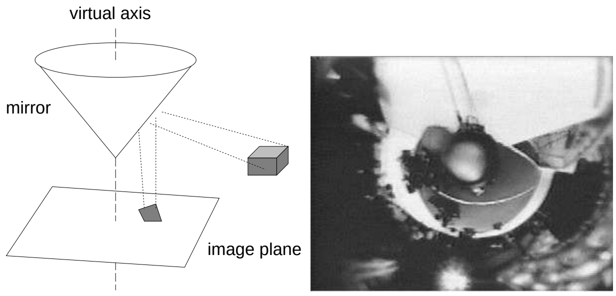


(b) action

Fig. 2. The robot

Our robot is shown in Figure 2(a) where an omnidirectional vision system is installed onto the 2-DOFs non-holonomic vehicle so that its optical axis can be coincident with the axis of vehicle rotation. The robot is controlled by a remote host computer via radio link. Figure 2(b) shows actions of the robot; moving toward left and right directions, turning to left and right, and combination of moving and turning. The remote computer sends motor commands to control the robot motion.

An omnidirectional vision systems consists of a conic mirror and a TV camera [1] of which optical axis is aligned with the vertical axis of the mirror as shown Figure 3(a). The projection onto the image plane is determined by the the shape of the mirror and the camera configuration parameters (height of the camera, distance between the mirror and the lens, and focal length) which can be designed according to the purpose. Our omnidirectional vision system has a hyperbolic mirror and a sample of its image is shown in Figure 3(b). The omnidirectional image is transmitted to the remote computer via video transmitter and processed there.



(a) projection (b) image

Fig. 3. A sample of an omnidirectional vision

We set up a simplified soccer game according to the RoboCup context [5]. The task of the robot is to block a ball in front of the goal, that is, a goalie task (see Figure 4). In order to keep the goal, the robot has to track the moving ball and move to appropriate position.

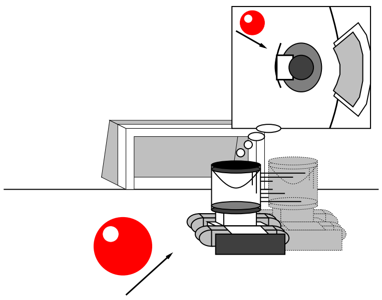


Fig. 4. The task of the robot

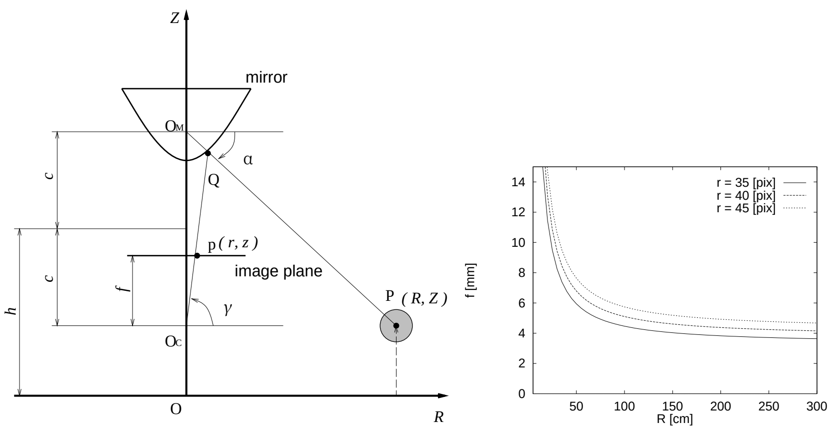
3 Learning of a Robot with an Omnidirectional Vision and an Embeded Zoom Control

3.1 Active Zoom Control on the Omnidirectional Vision

The coordinate system and parameters are shown in Figure 5(a). Let $P(R, \theta, Z)$ and $p(r, \theta)$ denote a point in the environment and a projected point of P in the image plane, respectively. We assume that the object is on the ground plane, therefore Z becomes a constant and P is uniquely projected onto p. The relation between P and p is given by,

$$
\begin{aligned}
Z &= R\tan\alpha + c + h, \\
\tan\gamma &= \frac{b^2+c^2}{b^2-c^2}\tan\alpha + \frac{2bc}{c^2-b^2}\frac{1}{\cos\alpha}, and \\
r &= \frac{f}{\tan\gamma},
\end{aligned}
\tag{1}
$$

where a and b are the parameters of the hyperbolic mirror, $\frac{R^2}{a^2} - \frac{Z^2}{b^2} = -1$, and $c = \sqrt{a^2+b^2}$. In our system these parameters are $\alpha^2 = 233.3[mm], \beta^2 = 1135.7[mm]$, and $h = 250[mm]$.



(a) The projection of the hyperbolic mirror

(b) The relation between distances and the focal length

Fig. 5. The basics of the hyperbolic mirror

We add an attention control on an omnidirectional vision by controlling focal length of the camera in order to reduce the learning time for behavior acquisition. In general, an attention control is realized by tracking an object in the image plane, which is implemented by controlling pan and tilt angles of the camera. However, in an omnidirectional vision, matching of the object with the target image is complicated since the projection is not simple. Therefore we propose an attention control by seeing the object in a certain distance from the center in the image plane. The change of the distance of the target in the image is tracked by changing focal length of the camera as shown in Figure 6.

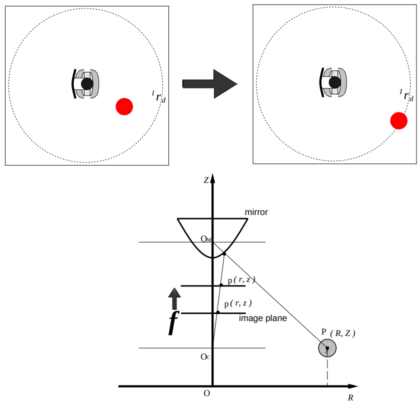


Fig. 6. Attention control on the omnidirectional vision

Figure 5(b) shows the relation between r the distance of the object in the image from the center, R the distance of the object in the environment, and f the focal length of the camera. We control the focal length of the camera with a following equation;

$$u_f = K({}^I r_d -{}^I r), \tag{2}$$

where u_f is the focal length of the camera, ${}^I r_d$ is the desired distance in the image, ${}^I r$ is the current distance in the image. For example, if ${}^I r$ is smaller than ${}^I r_d$ it comes closer by increasing f as shown in Figure 6.

3.2 Learning of a Goal Keepint Behavior

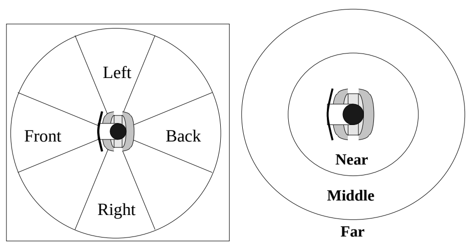
We use Q-learning, one of major reinforcement learning methods, to acquire a goal defending behavior. The state space needs to be defined from the image observed from the robot [6]. We define the substates as shown in the first column in Table 1. The second column shows the numbers of quantisation for each substates. In addition, the numbers of the quantisation of the substates without the attention control are shown.

For the case without attention control, the states are defined in terms of the direction and the distance of the ball and the goal in the image. We define 8 substates for the direction of the ball as shown in Figure 7(a) and 3 substates (far, medium and near) for the distance as shown in Figure 7(b). In addition we define temporal changes of the direction and the distance, respectively. They are clock wise/counter clock wise/no change and farther/nearer/no change, respectively. The numbers of the substaes for the direction of the goal is 8, the same quantisation for the ball, and the that of the distance is two (far and near). The total number of states is $3456 (= 8 \times 3 \times 3 \times 3 \times 8 \times 2)$.

For the case with attention control, substates of the distance and the temporal change of the distance of the ball are not necessary since the distance in the image is constant. The direction of the ball and the goal are defined in the same manner as above. The distance of the goal is far and near, however, the observed image of the goal changes when the attention control is used. The distance of the goal can be represented by a monotonic function in terms of the actual distance between the robot and the ball. The total number of states is $320 (= 8 \times 3 \times 2 \times 8)$.

	with attention control	without attention control
direction of the ball in the image	8	8
change of the direction of the ball	3	3
distance of the ball in the image	–	3
change of the distance of the ball	–	3
direction of the goal in the image	8	8
distance of the goal in the image	2	2
total number of the state	3456	320

Table 1. Substates



(a) directions (b) distances

Fig. 7. Substates

4 Experiments

We performed a computer simulation to acquire a goal defending behavior. Figure 8 shows the environment and the initial positions of the robot and the ball. The environment is built according to the RoboCup middle league regulations. The size of the field is 4575[mm] in width and 4110[mm] in length which is equivalent to the half size of the field. The goal size is 1500[mm] in width and 600[mm] in height and the diameter of the ball is 200[mm]. The goal and the ball are painted in blue and red respectively for easy detection.

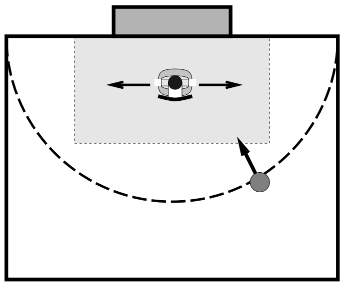


Fig. 8. Initial position

The ball is located on a half circle defined by the center of the goal and two corners, and the robot is located inside the circle randomly. The ball rolls toward the goal at a constant velocity. One trial terminates when the ball comes into the goal or goes out from the field. Figure 9 shows the task success rate with the learned behavior. When the attention control is used the robot learn quicker than the case without the attention control.

After learning in the simulation, the acquired behavior is implemented on the real robot. Figures 10(a)-(f) show a sequence of the real behavior, when the robot succeeded in blocking the ball in front of the goal.

5 Conclusions

We have proposed an attention control for an omnidirectional vision by controlling focal length of the camera and implemented it on a mobile robot. We have applied Q-learning method for acquisition of a goal defending behavior and

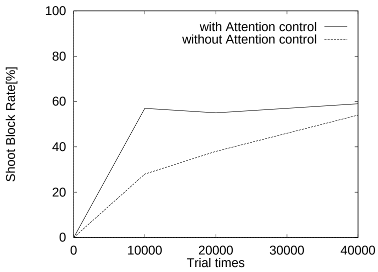
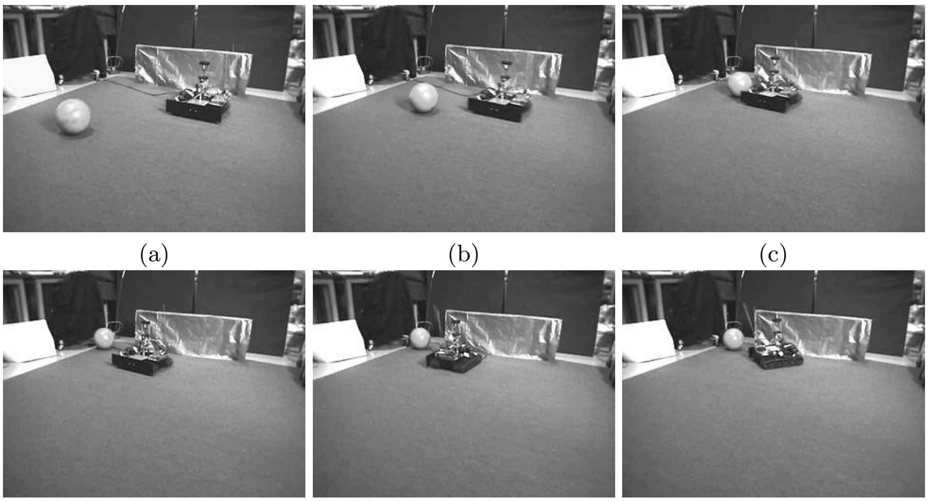


Fig. 9. Result



(a) (b) (c)

(d) (e) (f)

Fig. 10. A sequence of behavior

shown that the attention control effectively worked to reduce the learning time. We will test our method in RoboCup-98.

In this paper, we have shown a case that an embedded servo worked effectively for learning of the robot. However, we have not considered on a trade-off between installing a servoing mechanism and reduction of the learning time. This is the future work.

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