An Application of Vision-Based Learning in RoboCup for a Real Robot with an Omnidirectional Vision System and the Team Description of Osaka University "Trackies"

Sho'ji Suzuki[1], Tatsunori Kato[1], Hiroshi Ishizuka[1], Yasutake Takahashi[1], Eiji Uchibe[1], and Minoru Asada[1]

Dept. of Adaptive Machine Systems, Graduate School of Engineering, Osaka University, Suita, Osaka 565-0871, Japan

Abstract. This paper gives a team description of Osaka University "Trackies" for RoboCup-98, and related research issues. We focus on behavior learning of our goalie robot which has an omnidirectional vision system. A Q-learning method is applied by defining substates from visual information of the ball and the goal. To reduce the learning time, we propose an attention control method for an omnidirectional vision by means of an active zoom mechanism. We perform computer simulation and real robot experiments to show the validity of the proposed method.

1 Introduction and the Team Description of Osaka University "Trackies-98"

One of major issues in robotics is to make a robot adapt itself to changes in dynamic environments. We are interesting in how a robot acquires a behavior in dynamic environments and how robots cooperate without explicit communication in the context of cooperative distributed vision [1]. For the first step of an application of cooperative distributed vision, we have build a goalie robot with an omnidirectional vision system and applied a Q-learning method. In order to reduce search space for learning, we propose an attention control method into the omnidirectional vision by means of an active zoom mechanism. In this paper, we summarize our method and experimental results.

Followed the team description of Osaka University for RoboCup-98, the rest of the paper is organized 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.

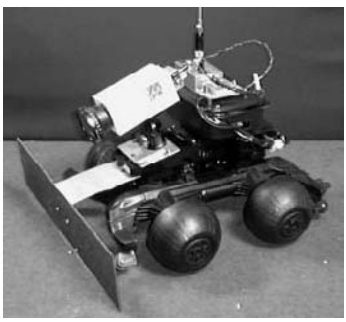
1.1 The Team Description of Osaka University "Trackies-98"

The team of Osaka University "Trackies-98" consists of four heterogeneous attackers and a goalie (see Figure 1). Three attackers have been replaced from the team "Trackies-97" which has following features;

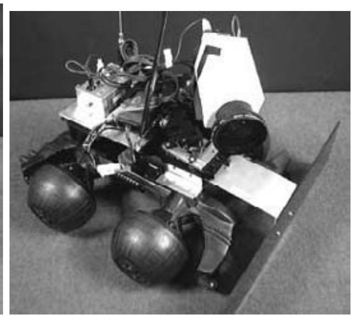
M. Asada and H. Kitano (Eds.): RoboCup-98, LNAI 1604, pp. 316-325, 1999.

1. The team consists of four homogeneous attackers and a goalie.
2. Every robot is controlled by its remote host computer via radio link.
3. An attacker has a CCD camera fixed on its body without any active mechanism and its shooting behavior is acquired by a Q-learning method.
4. The goalie has an omnidirectional vision and its behavior is hand-coded.

Details are given in [8].



(a) attacker with no active camera



(b) attacker with a panning camera

(c) self-contained attacker

(d) goalie

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

Attackers of "Trackies-97" have three major problems;

1. the cooperative behavior has not been realized.

2. the robot is easy to lose the ball and difficult to find it since the camera has a narrow view angle and no pan or tilt mechanism.
3. the control of the robot is not reliable because of noises on radio links.

Therefore, we have build three types of attackers shown in Figure 1 (a), (b), and (c) to cope with these problems. Since we are interest in cooperation without explicit communication, we do not use a global vision system and an inter-robot communication system to share/exchange information between robots.

The robot in Figure 1 (a) is the one used as an attacker of "Trackies-97". We apply a genetic programming method so that robots acquire a cooperative behavior. Since robots have no inter-robot communication system, they need recognize other robot's behavior through its vision system. We perform a computer simulation for a pass behavior by two robots. Details are discussed in [9] and [10]. The robot in Figure 1 (b) has a pan mechanism to extend a view angle. A Q-learning method is applied to acquire a shooting behavior with panning motion of the camera. The robot in Figure 1 (c) is a completely self-contained type which includes a CPU board, an image capture board, and motor drivers. The behavior of the robot is hand-coded. The robot shown in Figure 1 (d) is the goalie whose behavior is acquired by a Q-learning method which is described in the rest of this paper.

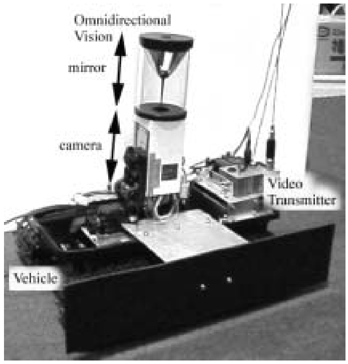
2 The Task and the Robot System for a Goal Keeping Behavior

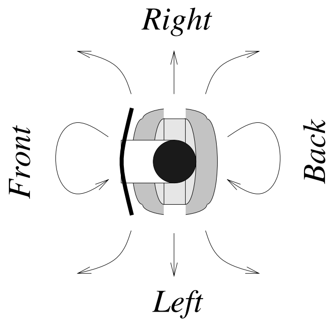
Several applications of the omnidirectional vision have been proposed, such as autonomous navigation [2], visual surveillance and guidance [3], video conference, virtual reality, and site modeling [4]. These methods have focused on its opto-geometric features to reconstruct 3-D scene structure. Our approach differs from their applications in two fold: we do not reconstruct any geometric structure from the omnidirectional views. Rather, we use it as a sensory system for a goal defending mobile robot. We apply Q-learning method [7] with a state space consisting of ball and goal images.

We introduce an active zoom mechanism into the omnidirectional vision in order to accelerate the learning. We implement a zoom servoing [5] so that the target image can be captured at the constant position when the target moves on the ground plane. This servoing 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.

Our robot is shown in Figure 2(a) where an omnidirectional vision system is installed onto the 2-DOFs non-holonomic vehicle such 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. The remote computer sends motor commands to control the robot motion.

An omnidirectional vision system consists of a conic mirror and a TV camera [2] of which optical axis is aligned with the vertical axis of the mirror as

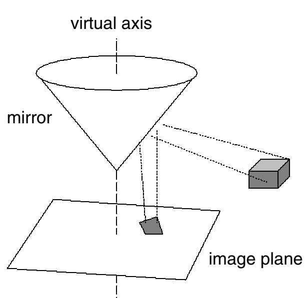


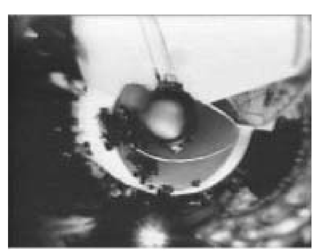


(a) an overview (b) actions

Fig. 2. The robot

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 are designed according to individual purposes. 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 on it.





(a) projection (b) a sample image

Fig. 3. Projection and a sample image by an omnidirectional vision

We set up a simplified soccer game according to the RoboCup context [6]. 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.

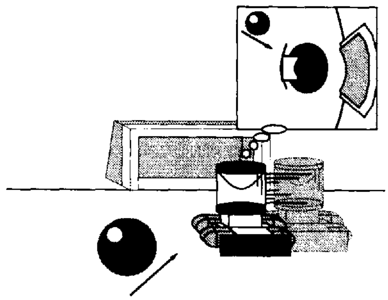


Fig. 4. The task of the robot

3 Learning by a Robot with an Omnidirectional Vision System and an Embedded Zoom Control

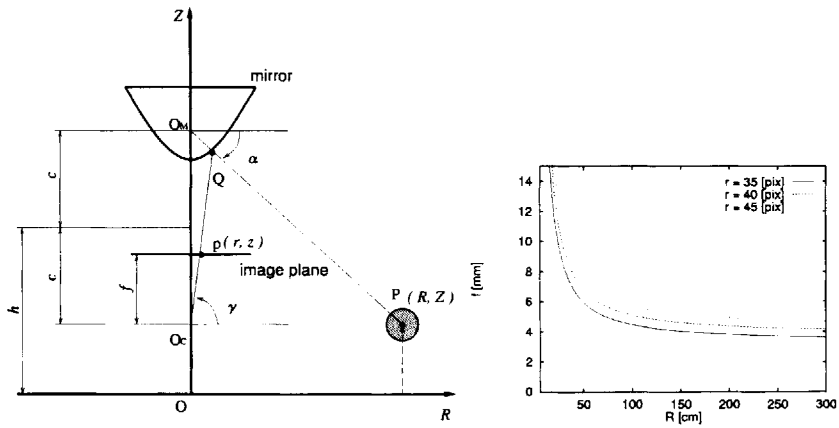
3.1 Active Zoom Control on the Omnidirectional Vision

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,

$$Z = R\tan\alpha + c + h,$$
$$\tan\gamma = \frac{b^2+c^2}{b^2-c^2}\tan\alpha + \frac{2bc}{c^2-b^2}\frac{1}{\cos\alpha}, and \qquad (1)$$
$$r = \frac{f}{\tan\gamma},$$

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

We add an attention control on an omnidirectional vision by controlling focal length of the camera in order to reduce the search space of the learning for



(a) The projection of the hyperbolic mirror

(b) The relation between distances and the focal length

Fig. 5. The basics of the hyperbolic mirror

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 system, matching of the object with the target image is not simple. Therefore, we propose an attention control by observing 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.

Figure 5(b) shows the relation between the distance of the object in the image from the center r, the distance of the object in the environment R, and the focal length of the camera f. 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 change of 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 Keeping Behavior

We apply 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 [7]. We define the substates as shown in the first column in Table 1. The second column shows the numbers of quantization for each

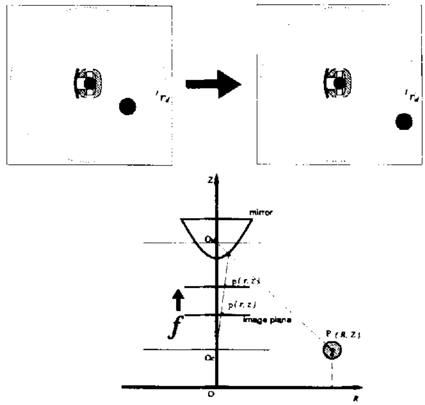


Fig. 6. Attention control on the omnidirectional vision

substates. In addition, the numbers of the quantization of the substates without the zoom servoing are shown.

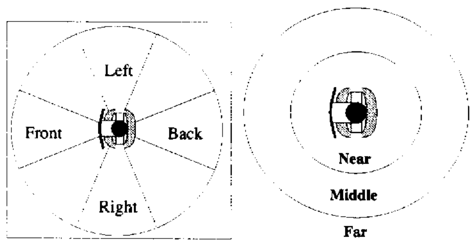
zoom servoing	with	without
direction of the ball in the image	8	8
change of the direction of the ball	3	3
distance of the ball in the image	–	3
change of the distance of the ball	–	3
direction of the goal in the image	8	8
distance of the goal in the image	2	2
total number of the state	3456	320

Table 1. Substates

In the case of no zoom servoing, 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, (clock wise, counter clock wise, no change) and (farther, nearer, no change), respectively. The numbers of the substates for the direction of the goal is 8, the same quantization for the ball, and substates of the distance is 2 (far and near). The total number of states is $3456(= 8 \times 3 \times 3 \times 3 \times 8 \times 2)$.

In the case of active zoom servoing, substates for the distance of the ball and its temporal change 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 $320 (= 8 \times 3 \times 2 \times 8)$.



(a) directions (b) distances

Fig. 7. Substates

4 Experiments

First, we performed a computer simulation to acquire a goal defending behavior. Figure 8(a) 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 regulations. 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.

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 8(b) 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 9(a)-(f) show a sequence of the real behavior, when the robot succeeded in blocking the ball in front of the goal.

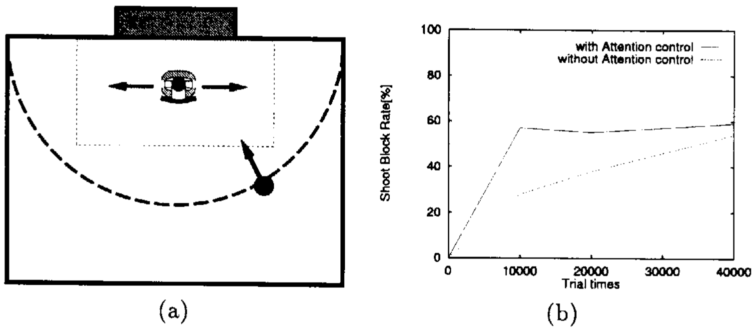


Fig. 8. (a)Initial position and (b)Result

5 Conclusions and the Result of RoboCup-98

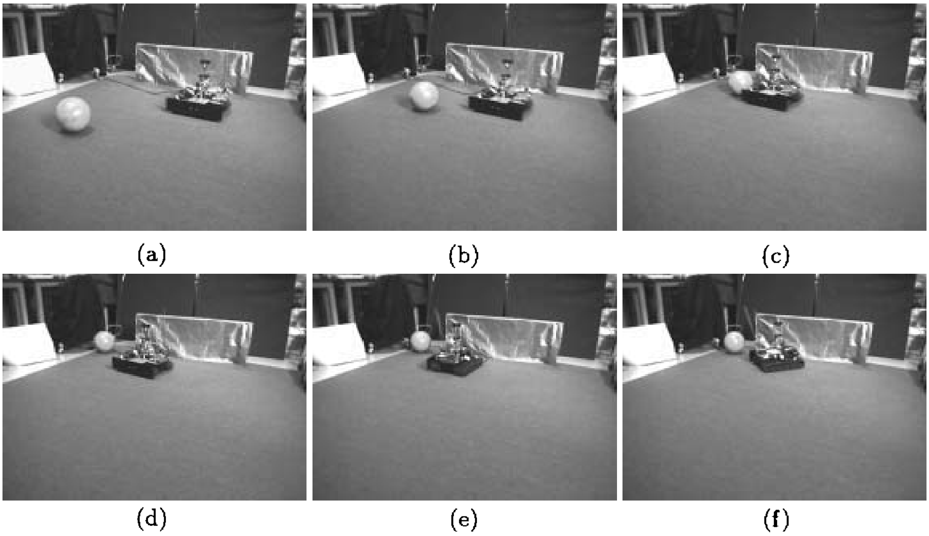
We have proposed an attention control for an omnidirectional vision by controlling focal length of the camera and implemented it on a mobile robot. We have applied Q-learning method for acquisition of a goal defending behavior and shown that the attention control effectively worked to reduce the learning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

Though the team "Trackies-98" is third place in the middle size robot league, we are not satisfied the performance of our robots. From the view point of learning, we have not treated a behavior in an environment with opponents. This is the next issue.

This work was supported by the Cooperative Distributed Vision project in the Research for the Future Program of the Japan Society for the Promotion of Science (JSPS-RFTF96P00501).

References

1. T. Matsuyama. Cooperative Distributed Vision – Dynamic Integration of Visual Perception, Action, and Communication –. In *Proc. of Image Understanding Workshop*, 1998.
2. Y. Yagi and S. Kawato. Panoramic scene analysis with conic projection. In *Proc. of IEEE/RSJ International Conference on Intelligent Robots and Systems 1990 (IROS'90)*, pages 181–187, 1990.



(a) (b) (c) (d) (e) (f)

Fig. 9. A sequence of behavior

3. H. Ishiguro. Distributed vision systems: A perceptual information infrastructure for robot navigation. In *Proc. of IJCAI-97*, pages 36–41, 1997.
4. V. N. Peri and S. Nayar. Generation of perspective and panoramic video from omnidirectional video. In *Proc. of 1997 Image Understanding Workshop*, pages 243–245, 1997.
5. K. Hosoda, H. Moriyama, and M. Asada. Visual servoing utilizing zoom mechanism. In *Proc. of IEEE Int. Conf. on Robotics and Automation*, pages 178–183, 1995.
6. H. Kitano, M. Asada, Y. Kuniyoshi, I. Noda, E. Osawa, and H. Matsubara. "RoboCup: A challenge problem of AI". *AI Magazine*, 18:73–85, 1997.
7. M. Asada, S. Noda, S. Tawaratsumida, and K. Hosoda. "Purposive Behavior Acquisition for a Real Robot by Vision-Based Reinforcement Learning". *Machine Learning*, 23:279–303, 1996.
8. S. Suzuki, Y. Takahashi, E. Uchibe, M. Nakamura, C. Mishima, and M. Asada. "Vision-Based Learning Towards RoboCup: Osaka University 'Trackies' ". *RoboCup-97: Robot Soccer World Cup I*, Springer, pp.305–319, 1997.
9. E. Uchibe, M. Nakamura, and M. Asada. "Cooperative Behavior Acquisition in A Multiple Mobile Robot Environment by Co-evolution". *Proc. of the second RoboCup Workshop*, pp.237-250, 1998.
10. E. Uchibe, M. Nakamura, and M. Asada. "Cooperative Behavior Acquisition in A Multiple Mobile Robot Environment by Co-evolution". *RoboCup-98: Robot Soccer World Cup II*, Springer.