Behavior Learning for a Mobile Robot with Omnidirectional Vision Enhanced by an Active Zoom Mechanism

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Abstract

The authors propose an attention control method for an omnidirectional vision by an active zoom mechanism. It is implemented by controlling focal length of the camera without pan or tilt mechanism. We install an omnidirectional vision with a hyperbolic mirror to a mobile robot and apply Q-learning for its behavior acquisition. In a goal defending behavior of a soccer game, the robot can learning the behavior and the attention control works to reduce learning time. In this paper, we explain our method and experiment.

1 Introduction

Omnidirectional vision has been receiving increased attentions as a method to capture the whole view all around the imaging system at any instant in time. This causes a wide variety of applications which include autonomous navigation [1], visual surveillance and guidance [2], video conference, virtual reality, and site modeling [3].

Since the omnidirectional vision can capture the visual information from the all directions, no pan or tilt control is necessary. Therefore, almost of the existing methods with omnidirectional vision system have focused on its optogeometric features to reconstruct 3-D scene structure. In this paper, we introduce an omnidirectional vision system on a mobile robot enhanced by an active zoom mechanism.

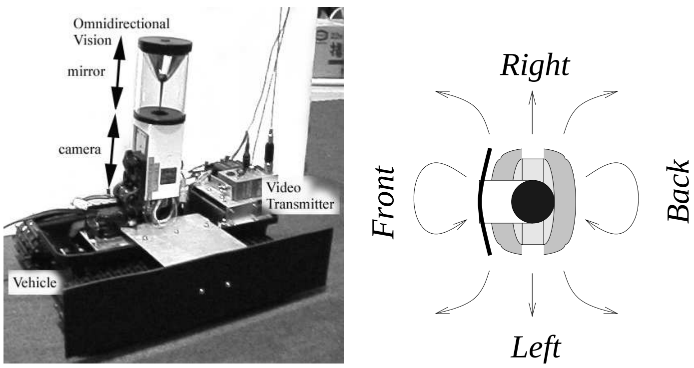
We implement a zoom servoing [4] by which the target image can be captured at the constant position if it moves on the ground plane. It is realized by controlling focal length of the camera. Due to the active zoom mechanism, the target motion in the radius direction can be canceled, and only circular 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. 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 obtain the desired behavior based on the reinforcement learning scheme.

2 The Task and the Robot System

Figure 1(a) shows our robot with an omnidirectional vision system that is installed on 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. Eight actions shown in Figure 1(b), moving toward left and right direction, turning to left and right, and combination of moving and turning, are installed on the robot and controlled from the remote computer.

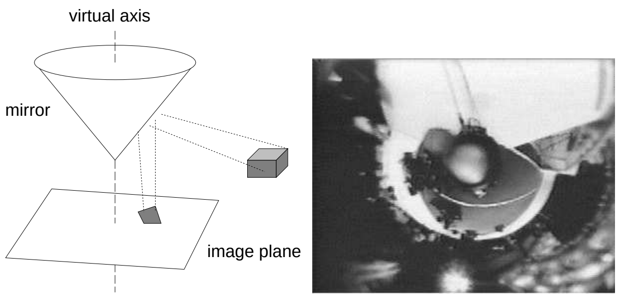
One of omnidirectional vision systems consists of a conic mirror and a TV camera [1]. The vertical axis of the mirror is aligned with the optical axis of the camera as Figure 2(a). The projection of the scene in the image plane is determined by the the shape of the mirror and camera configuration parameter(height of the camera, distance between the mirror and the lens, and focal length). These are designed according to the requirement of projection. Our omnidirectional vision system has a hyperbolic mirror and a sample of its image is shown in Figure 2(b). The omnidirectional image is transmitted to the remote computer via video transmitter and processed there.



(a) overview (b) action

Figure 1: The robot

We set up a simple soccer like 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 3). In order to keep the goal, the robot has to track the moving ball and move to appropriate position.



(a) projection (b) image

Figure 2: A sample of an omnidirectiona vision

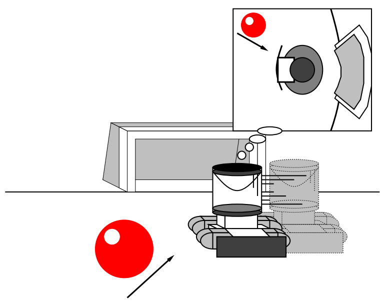


Figure 3: The task of the robot

3 Active Zoom Control on the Omnidirectional Vision

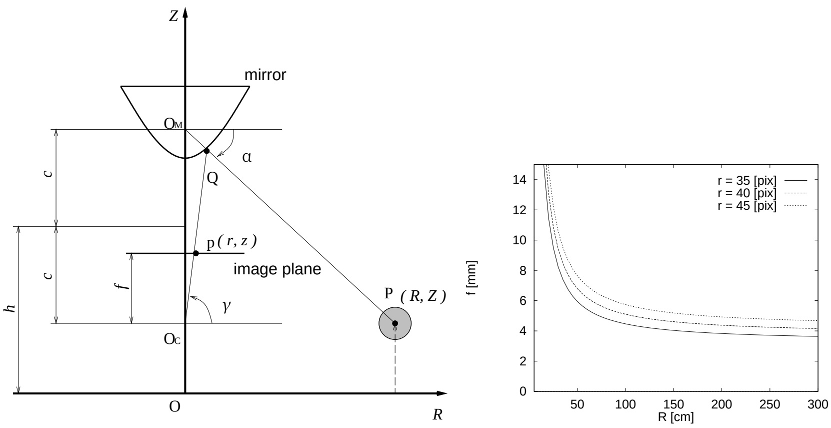
We assume that the object is on a flat surface and we define coordinates and parameters as Figure 4(a). Let $P(R, \theta, Z)$ and $p(r, \theta)$ donate a point in the environment donated and a projected point of P in the image plane. The relation of P and p is,

$$Z = R \tan \alpha + c + h$$

$$\tan \gamma = \frac{b^2 + c^2}{b^2 - c^2} \tan \alpha + \frac{2bc}{c^2 - b^2} \frac{1}{\cos \alpha} \tag{1}$$

$$r = \frac{f}{\tan \gamma}$$

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



(a) The projection of the hyperbolic mirror

(b) The relation between distances and the focal length

Figure 4: The basics of the hyperbolic mirror

We propose an attention control on an omnidirectional vision by controlling focal length of the camera. In general, an attention control is archived by seeing an object in a certain position in the image plane which is implemented by controlling pan and tilt angle of the camera. However, in an omnidirectional vision, matching of the object and the target in the image become complex since the projection is not simple. Therefore we propose an attention control by seeing the object in a certain distance in the image plane from center. It is simply implemented by controlling focal length of the camera as shown in Figure 5

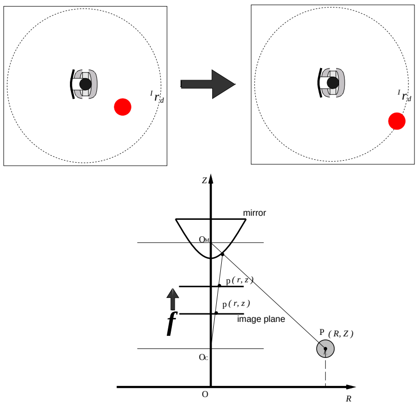


Figure 5: Attention control on the omnidirectional vision

Figure 4(b) shows the relation between the distance of the object in the image from the center donated by r, the distance of the object in the environment donated by 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 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 5.

4 Behavior Acquisition by Learning

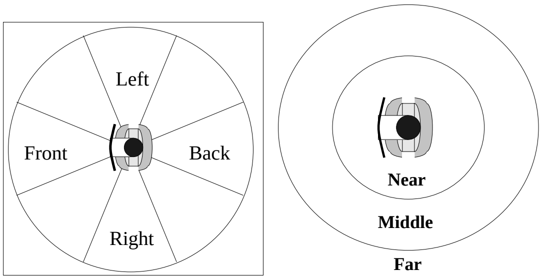
We apply Q-learning, one of major reinforcement learning method, to acquire a behavior. The state space need to be defined from observed image by the robot [**?**]. We define states as Table 1. For comparision, we define states for the robot with and without attention control.

For the case without attention control, states are defined by the direction and distance of the ball and the goal in the image. We define 8 substates for the direction of the ball as Figure 6(a) and 3 substates, far, medium and near, for the distance. In addition we define 3 substates, change in clock wise, counter clock wise, and no change for the difference of the direction, 3 substates, farer closer, and no change for the difference of the distance. Substaes of the direction of the goal is 8 same to the ball and the distance is two for and close. Total number of states is $\times 8 \times 3 \times 3 \times 3 \times 8 \times 2 = 3456$.

For the case with attention control, substates of the distance of the ball can be canceled since the distance in the image is constant. Direction of the ball, direction and distance of the goal is define in the same way as above. However, the view of the goal is different. It corresponds to the distance of ball and the goal, hence it is the distance of the robot and the goal in the case without attention control. Total number of states is $8 \times 3 \times 2 \times 8 = 320$.

	without attention control	with 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

Figure 6: Substates

5 Experiments

We performed a simulation to acquire a goal defending behavior. Figure 7 shows the environment and initial position of the robot and the ball. The environment is defined according to the RoboCup middle league regulation. The size of the field is 4575[mm] width and 4110[mm] equivalent to the half size of field. The goal size is 1500[mm] width and 600[mm] height and the diameter of the ball is 200[mm]. The goal and the ball is painted in one color blue and red respectively for easy recognition.

The ball is located on a circle defined by corners and the center of the goal. The robot is located in the circle randomly. The ball rolls toward the goal with a constant velocity A trial is finished when the ball comes into the goal or goes out from the field. Figure 8 shows the result when the robot finished 10000, 20000, 30000, 40000 trials. It shows a task success rate with the learned behavior. When the attention control is used the robot can learn quicker than without the attention control.

After learning on simulation, the acquired behavior is implemented on the real robot. Figure 9(a)-(f) shows an example of the real behavior.

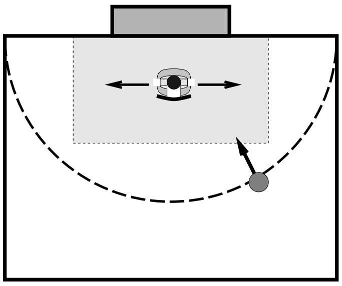


Figure 7: Initial position

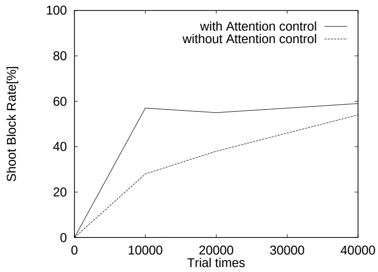
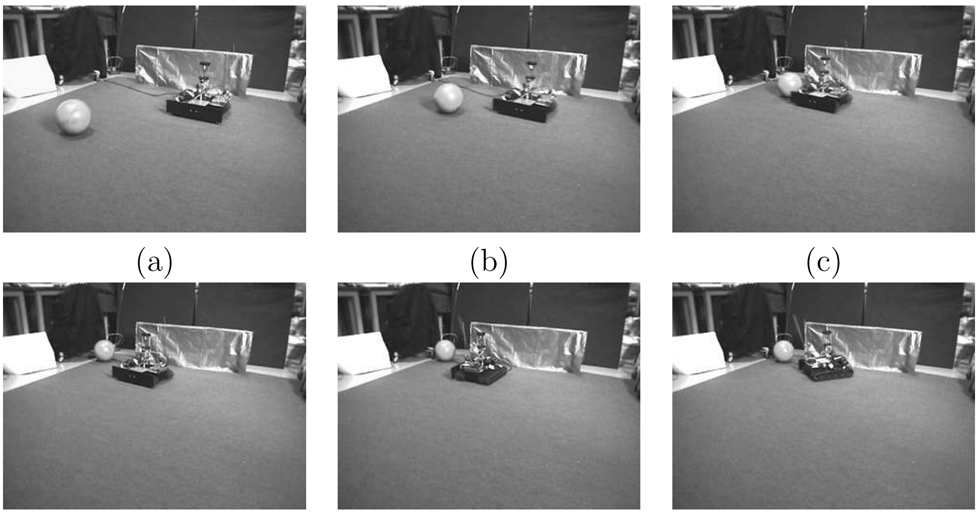


Figure 8: Result



(a) (b) (c)

(d) (e) (f)

Figure 9: A sequence of behavior

6 Conclusions

We propose an attention control for an omnidirectional vision by controlling focal length of the camera. We used the system to robot learning and it helped reduce learning time. Formulation of the relation between the implemented serve and learning is future discussion.

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