Orientation Extraction and Identification of the Opponent Robots in RoboCup Small-Size League

Saori Umemura, Kazuhito Murakami, and Tadashi Naruse

Graduate School of Information Science and Technology, Aichi Prefectural University
Kumabari, Nagakute-cho, Aichi, 480-1198 Japan
im051005@cis.aichi-pu.ac.jp,
{murakami,naruse}@ist.aichi-pu.ac.jp

Abstract. In RoboCup small-size league, it is necessary to analyze the opponent robots' behavior in order to make a strategy of the own team. However, it is difficult to prepare image processing methods in advance in order to detect opponent robots' sub-markers used for the orientation detection and identification of the robots, because there is no limitation in the rule in shape, color, arrangement, and the number. This paper proposes a new method to select the most specific sub-marker attached on the top of the robot based on the features such as the size, area, and color values by using the discriminant analysis, and also explains how to extract opponent robots' orientations with some experimental results.

1 Introduction

It is necessary to analyze the opponent robots' behavior in order to make a strategy of the own team in RoboCup. Almost all of the teams utilize one or a set of sub-markers attached on the top of the robot for the orientation extraction and identification[1]. Even though it is not so easy to extract own robots in real time, it becomes more difficult for a team to recognize opponent team's robots, because we have no knowledge about opponent team's sub-markers and also we can't prepare the image processing algorithms for the recognition of them in advance. Figure 1 shows some examples of sub-markers. There is no limitation in the rule in shape, color, arrangement, and the number of the sub-marker in the Small-Size League (SSL)[2]. The freedom of designing sub-markers of own team rises, at the same time the recognition rate of sub-markers of the opponent team falls.

This paper proposes a new method to select the most specific sub-marker attached on the top of the robot based on the features such as the size, area, and color values by using the discriminant analysis, and also presents how to extract opponent robots' orientations. This method realizes a strategic planning of the robots based on the locus and the direction of the opponent robots. First, this paper describes how to utilize the orientation of the robots in the section 2, and then explains the recognition method of the opponent robots and experimental results in the sections 3 and 4, respectively.

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(a) team A (b) team B (c) team C

Fig. 1. Examples of sub-markers

2 How to Utilize the Orientations of the Opponent Robots for Planning

SSL's robot has a kicking device and a dribbling device. In this paper, let the orientation of them be the 'front' of the robot. To recognize the opponent robots' orientations realizes a strategic planning as follows.

2.1 Judgment of Kicking or Holding a Ball

If the orientation of the opponent robot nearby a ball is known, the system can judge whether the opponent robot is kicking or holding the ball. More strategic planning as shown Figure 2 could be realized by this information.

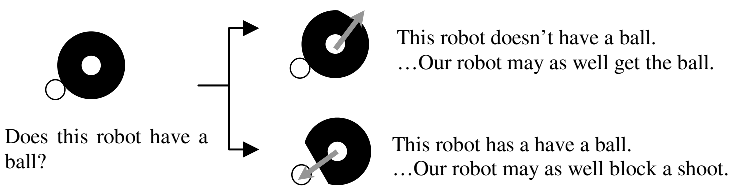

Fig. 2. Judgment of having ball

2.2 Judgment of the Shoot Course

In the penalty kick scene, for example, many teams take a strategy to prevent a shoot only by changing the direction of the robot in the same position. In this kind of scene, own robot plays more defensively based on the shoot course in Figure 3 if the orientation of the opponent robot is known.

2.3 Paying Attention to the Opponent Robots

When own robot plays with paying attention to the opponent robots, the orientations of the opponent robots are very important information. Own robot plays more offensively if the robot knows which robot among opponent team's will receive a ball.

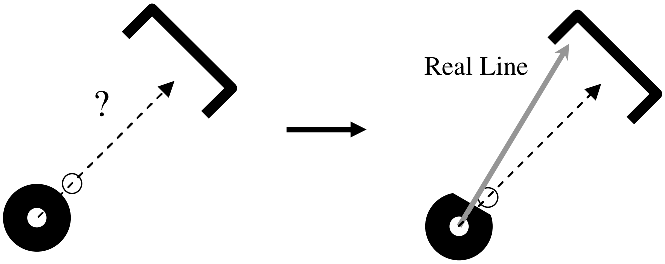

Fig. 3. Judgment of shoot course

3 Orientation Extraction and Identification of Robots

This chapter presents a method of orientation extraction and identification of opponent robots. In general, template matching technique is used to detect unknown patterns, and is a robust method to extract the most certain locus of the template from an input image, it takes much time. RoboCup's image processing system is required to work in real time, for example, 60fps performance. Since there is no information about opponent teams, we can't prepare the image processing algorithms in advance for the recognition of the opponent teams' sub-markers. Hereafter, this section explains a new method to select the most specific sub-marker attached on the top of the robot based on the features such as the size, area, and color values by using the discriminant analysis, and also presents how to extract opponent robots' orientations.

3.1 Selection of the Most Specific Sub-marker

Before the game starts, first input the opponent robots' image (sub-markers' image) and then select the most specific sub-marker, hereafter we call it 'feature marker', among N pieces of sub-markers on a robot. Both of the orientation extraction and identification of each robot is executed based on the locus or arrangement of the feature markers.

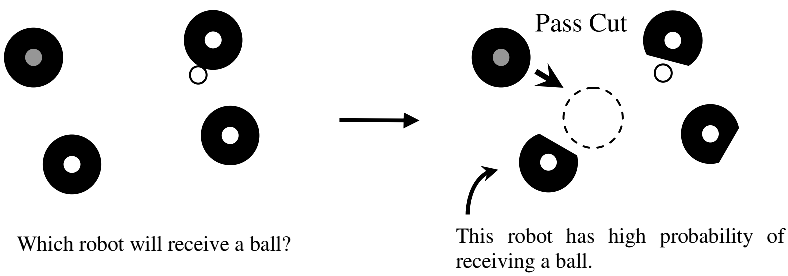

Fig. 4. Paying attention to the opponent robots

The parameter list $L^{(i)}$ of the i-th sub-marker (i=1,...N) is composed of variety of parameters such as color, area, size, the center of gravity, and so on. Let the number of them on a robot be M.

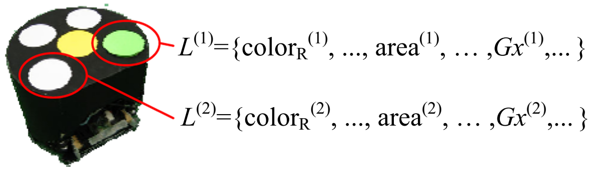

Fig. 5. Example of marker's parameters

First, make a list of each sub-marker $L^{(i)} = \{x_1^{(i)}, x_2^{(i)}, \ldots, x_M^{(i)}\}$($i = 1\ldots N$) as shown in Figure 5 and decide the 'feature marker' which has the most specific parameter value. There are many well known methods to select one of the most specific value among M, but we designed a method whose computation cost is not so high as follows.

Step-1. Make a set $F_j = \{x_j^{(1)}, x_j^{(2)}, \ldots, x_j^{(N)}\}$ of the j-th parameter (j=1,2,...,M) as shown in Figure 6.
Step-2. For the j-th parameter, apply the discriminant analysis method to the set F_j, that is, devide F_j into 2 classes and caluculate the separation ratio S_j between them.
Step-3. If each of devided classes is not composed of one element, then let S_j be 0. Repeat from Step-2 to Step-3 for all parameter j=1,2,...,M.
Step-4. Search the maximum S_j among $\{S_j; j=1,2,\ldots,M\}$ and let the number be j_{MAX} and the element's number be i_{MAX}.
Step-5. Let the sub-marker which has i_{MAX}-th and j_{MAX}-th element be the 'feature marker' G and terminate the program.

If S_j=0 in Step-4, it means that 'feature marker' could not be decided only one parameter, so we have to combine 2 or more parameters to decide 'feature marker' G.

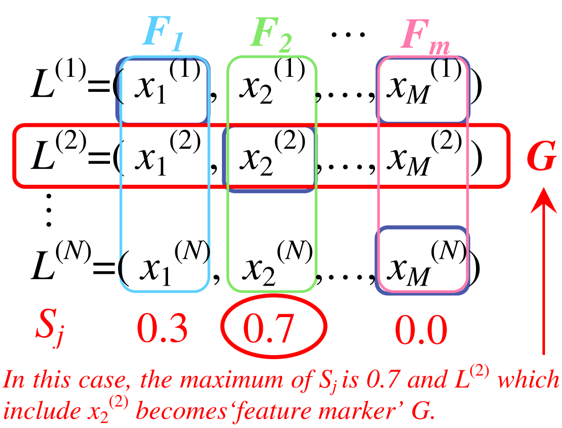

Fig. 6. Example of deciding feature maker

3.2 Identification of the Robot and Orientation Extraction

The robot is identified by matching the parameter lists (*i.e.* $\cos\psi$□0.95, here, ψ is the angle between two vectors corresponding to the lists in M dimensional space. 0.95 is obtained by some experiments).

As shown in Figure 7, the orientation of the robot is calculated by using the ‘feature marker’ G. If the real front orientation ϕ_0 and the angle θ_0 of the ‘feature marker’ G are known in advance, the front orientation ϕ during the game is obtained by

$$\phi = (\theta - \theta_0) + \phi_0 \tag{1}$$

where, θ is the angle of the ‘feature marker’ G. This angle θ is easily calculated by

$$\theta = \tan^{-1}\frac{y_T - y_G}{x_T - x_G} \tag{2}$$

where, (x_T, y_T) and (x_G, y_G) are the centers of gravity of team marker T and the ‘feature marker’ G, respectively.

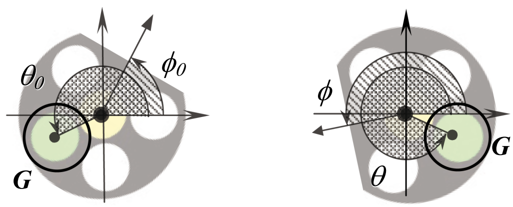

Fig. 7. Feature marker and the definition of the orientation

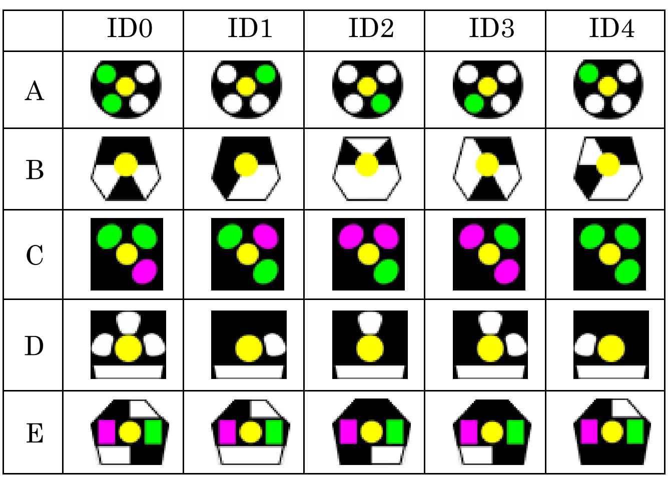

Fig. 8. Marker set of opponent robot’s

4 Experiments and Discussions

In order to confirm the effectiveness of the proposed method, we experimented by using several typical sets of sub-markers used in the past games in RoboCup competitions. Figure 8 shows examples of the sub-markers, and Table 1 shows the experimental results. A, B, ...in the figure denotes the team and ID is the identification number of each robot. Orientation error in Table 1 is the difference between the real and measured angles.

Table 1. Identification rate and orientation extraction error

Set of markers	A	B	C	D	E
Identification Rate [%]	100.0	99.44	100.0	100.0	100.0
Maximum of Orientation Extraction Error [deg]	9.818	98.44	7.275	178.01	7.967
Minimum of Orientation Extraction Error [deg]	0.093	0.108	0.040	0.192	0.000
Average of Orientation Extraction Error [deg]	2.956	7.157	2.183	9.729	3.199

From the experiments, there appear some errors in the orientation extraction, especially for B and D team's sub-markers. The differences of size of sub-markers for team B's and the differences of shape, rectangle and circle sub-markers, for team D's are the main causes of the errors.

We compared calculation time with several conventional methods, template matching etc. Here, 'calculation time' is measured only foe the orientation extraction and the identification processes just after the main-marker extraction process. The results are shown in Table 2. As a result of the experiment, the accuracy of the individual identification rate was about 99.8%, and error for the orientation extraction is about 4.95 degrees.

Table 2. Comparison of calculation time

	Calculation Time [msec]	Orientation Extraction Error[deg]
proposed method	0.15	4.95
nearest neighbor method	207	
bi-linear method	214	2.0
bi-cubic method	417	

5 Conclusion

This paper described a new method to select the most specific sub-marker attached on the top of the robot based on the features such as the size, area, and color values by using the discriminant analysis. This method realized a strategic planning of the robots based on the locus and the direction of the opponent robots.

Although the proposed method shows the effectiveness, there remain some subjects to be solved. It is necessary to add and increase the menu of the shape measures such as the complexity of the sub-markers. Since the robot doesn't always kick a ball to the front direction, it is also important to introduce the learning mechanism from image sequences of the game in order to recognize real front orientation of the robot. These are future works.

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