Robust and Accurate Detection of Object Orientation and ID without Color Segmentation

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1. Introduction

To give optimal visual-feedback, which helps to control a robot, it is important to make its vision system more robust and accurate. In the RoboCup Small Sized League (F180), a global vision system that is robust to unknown and varying lighting conditions is especially important. The vision system, which in common use, processes an image that identifies and locates robots and the ball. For low-level vision, the color segmentation library called CMVision (J. Bruce et al., 2000) has been used to segment color and to connect component analysis to return colored regions in real time without special hardware. After color is segmented, objects are identified based on the color segmentation results, and then the robot's pose is estimated. To improve the visual system's robustness to varying light conditions, color (A. Egorova et al., 2004) must be calibrated in advance, but the system that does this requires minimal set up time.

In this chapter, we propose a robust and accurate pattern matching method for simultaneously identifying robots and estimating their orientations that does not use color segmentation. To search for similar patterns, our approach uses continuous DP matching, which is obtained by scanning at a constant radius from the center of the robot. The DP similarity value is used to identify object, and to obtain the optimal route by back tracing to estimate its orientation. We found that our system's ability to identify objects was robust to variation in light conditions. This is because it can take advantage of the changes in intensity only.

Related work and our approach are described in section 2. Section 3 describes the method for robust and accurate object identification. The experimental results are presented in section 4. Section 5 discusses some of the advantages of the proposed method. Finally, section 6 concludes the chapter.

2. Related work

In the Small Size League, one team must have 50 mm blue circles centered on the top of its robots, and the other team's robots must have 50 mm yellow circles. To detect the robot's orientation and to identify it, teams are allowed to add extra patches with up to three colors. Figure 1 shows patterns that are currently being used.

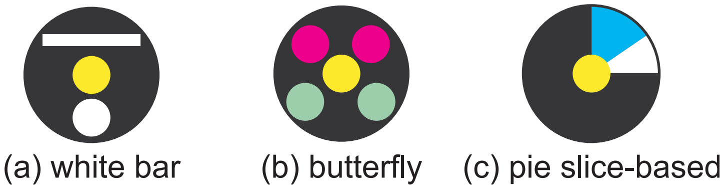


Fig. 1. Example of general identification patterns.

Pattern (a), called "white bar", is used to precisely calculate the pose of robot. The robot's orientation is calculated using a white stripe and the least squares method (K. Murakami et al., 2003) or second moment (D. Ball et al., 2004). Other sub patches are also used for identification.
Pattern (b), called "butterfly", has been reported in (J. Bruce & M. Veloso, 2003). Geometric asymmetry can be used to find the rotational correspondence for orientation estimation.
Pattern (c), called "pie slice-based", is unique and is described in (S. Hibino et al., 2002). The method that uses this patch scans the circular pattern using markers on the robot. The low angle resolution is not adequate (8 degrees).
These methods use information from color segmentation to determine a robot's identity. Such colors have problems with changes in brightness and nonuniform color intensity, including sharp shadows, over the field.

2.1 Proposed patch pattern

Our approach uses only the changes in intensity obtained by scanning at a constant radius from the center of the robot and does not use the color segmentation results. Therefore, we can paste suitably-colored patches on top of the robot, as shown in Fig. 2. This approach makes possible a large number of different patterns for identification and makes it easy to modify patch patterns. Moreover, preparing the rule-based reference table by user for object identification is no longer necessary.

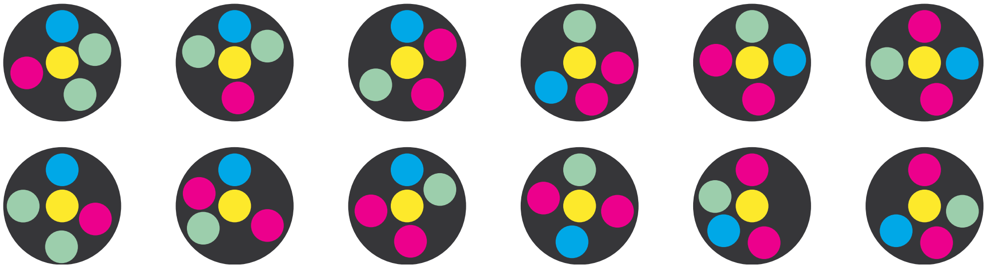


Fig. 2. Examples of our ID plates.

3. Object Identification

DP matching calculates the similarity between a reference pattern and an input pattern by matching the intensity changes of the robot's markers. After the DP matching has been done, a similarity value is used to identify the robot. Correspondence of the optimal route obtained by back tracing is used to determine its orientation. The flow of the proposed

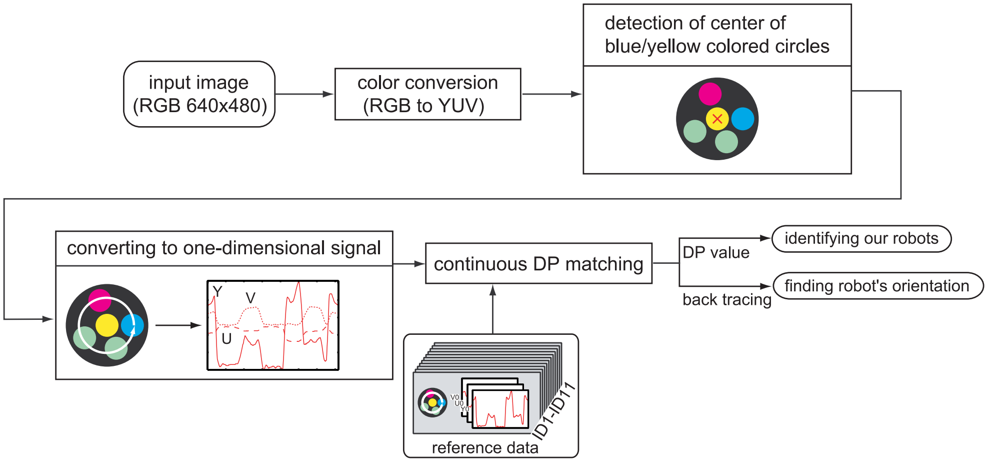


Fig. 3. Overview of our vision system.

method is as follows and shown in Fig. 3.

1. Color conversion (RGB to YUV)
2. Detection of the center of blue/yellow colored circles
3. Converting to one-dimensional signal by scanning at some constant radius from the center of the robot
4. Identifying our robots by continuous DP matching
5. Finding the robot's orientation by back tracing

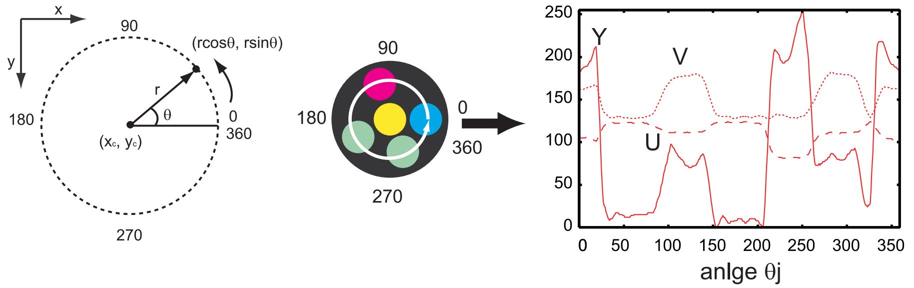
3.1 Detection of the center of blue/yellow colored circle

It is important to detect the center of the blue/yellow circle because our approach uses this center position to convert to one-dimensional signals for object identification. The following describes an algorithm used to determine the center of a circle given three points on a plane. The three points determine a unique circle if, and only if, they are not on the same line. The relationship of these three points is expressed as:

$$(x_c - x_i)^2 + (y_c - y_i)^2 = (x_c - x_j)^2 + (y_c - y_j)^2 = (x_c - x_k)^2 + (y_c - y_k)^2, \tag{1}$$

where (x_c, y_c) is a center coordinate and three points on the image are (x_i, y_i) (x_j, y_j) (x_k, y_k). Equation (1) is a linear simultaneous equation. Thus, (x_c, y_c) is determined by Gaussian elimination using the following steps:

Step1 Detect blue/yellow colored circle.
Step2 Extract contour points of the circle.
Step3 Randomly select three points from the contour points and calculate center position $(x_c, y_c)$by equation (1).
Step4 Increment a count in the accumulator at point (x_c, y_c).
Step5 Repeat Steps 3 and 4 100 times.
Finally, the spot with the most votes is determined to be the center of the main marker.



(a) scanning at a constant radius (b) converting to one-dimensional signal

Fig. 4. Converting to one-dimensional signal.

3.2 Converting to one-dimensional signal

The intensity values of YUV on the top of the robot are obtained by scanning at a constant radius (r=10 pixel) from the detected center of the circle, as shown in Fig. 4. It is impossible to obtain the 359 points (1 degree each) on the circle's perimeter because of the low-resolution of the image. To solve this problem, we apply the bilinear interpolation to estimate the robot's orientation with sub-pixel accuracy.

Image coordinate (x, y) for an angle θ is obtained by

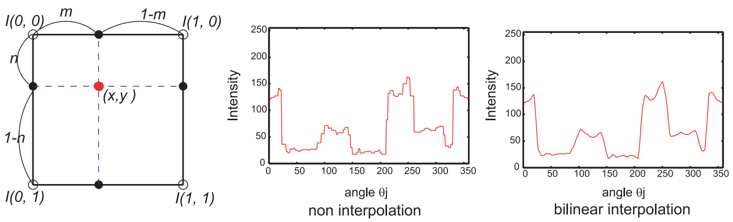
$$x = r\cos\theta + x_c, \quad y = r\sin\theta + y_c, \tag{2}$$

where (x_c, y_c) is the center position on the image coordinate. Since the values of (x, y) are real numbers, the intensity value $I(x, y)$ is interpolated by the bilinear interpolation method used for two-dimensional operations, for instance magnifying an image. The interpolated intensity value is calculated as shown in Fig. 5 (a).

$$I(x,y) = (1-n)((1-m)I(0,0) + mI(1,0)) + n((1-m)I(0,1) + mI(1,1)), \tag{3}$$

Figure 5 (b) shows the interpolated intensity values of Y. This can be useful in estimating the orientation angle with sub-pixel accuracy. Finally, the intensity values of Y normalized to 0-255, U and V are obtained as a one-dimensional signal from the circle patches on the robot as shown in Fig. 4 (b), and these values are expressed as:

$$I(\theta_j) = I(r\cos\theta_j, r\sin\theta_j) \quad j = 0, \cdots, 359. \tag{4}$$



(a) bilinear interpolation (b) example of interpolation

Fig. 5. Bilinear interpolation.

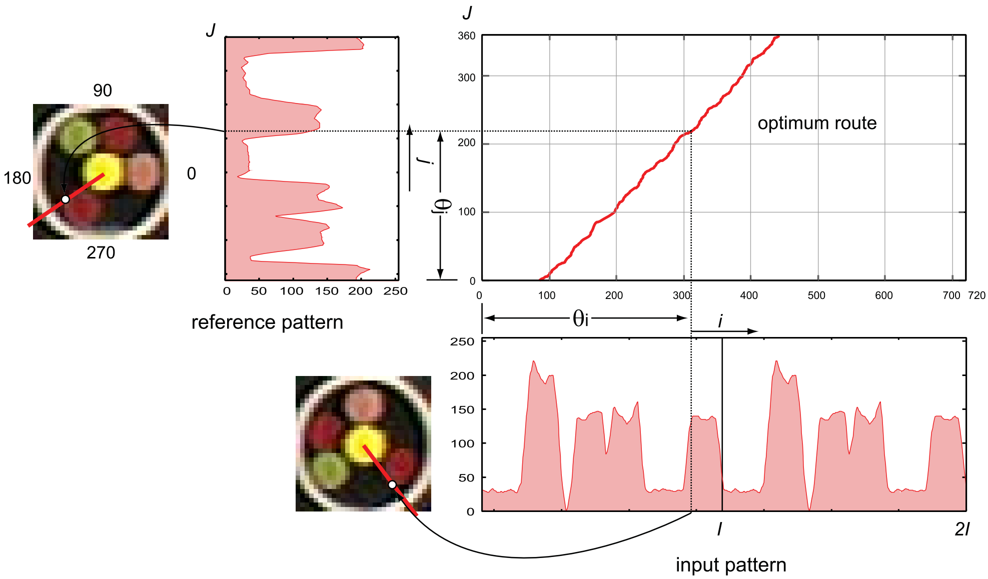


Fig. 6. Example of back tracing.

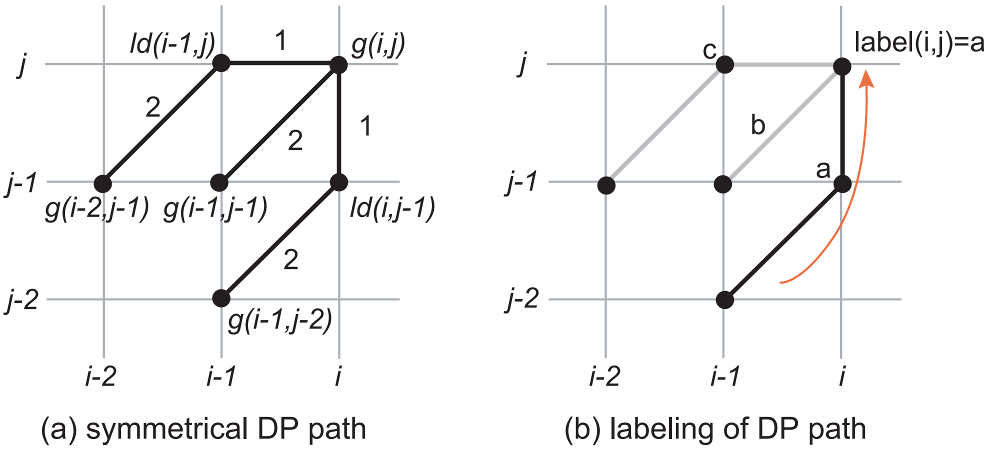


Fig. 7. Symmetrical DP path.

3.3 Identifying our robots by the continuous DP matching

To uniquely distinguish a robot, the intensity values $I(\theta_j)$ as a reference pattern for each robots, are registered initially by clicking with a mouse on points in the direction of the robot's front to help to assign an ID to each robot. Continuous DP matching is done to calculate a similarity between the reference patterns and the input pattern of the current image.

Continuous DP matching DP matching has been used in various areas such as speech-recognition (H. Sakoe et al., 1978). DP matching is a pattern matching algorithm with a nonlinear time-normalization effect. Timing differences between two signal patterns are eliminated by warping the axis of one, so that the maximum coincidence is attached as the minimized residual distance between them. The starting point of the input pattern provided by scanning, as described in section 3.2 is not at the same position as the reference pattern. Therefore, continuous DP matching can be useful in computing the similarity distance by considering the lag of each starting point. The input pattern is repeated twice as ($1 < i < 2I$) and this handling is shown in Fig. 6.
In this implementation, the symmetrical DP path, shown in Fig. 7 (a), is used. Minimum accumulated distance is calculated by the following equations. Let the vertical axis represents reference pattern frame j, and the horizontal axis represents input pattern frame i. Initial conditions are given as:

$$\begin{cases} g(i,0) = 0 & (i = 0,1,\ldots,I) \\ g(0,j) = \infty & (j = 1,2,\ldots,J) \end{cases}, \tag{5}$$

where I and J are the lengths of the patterns. The minimum accumulated distance $g(i, j)$ on the i frame and j frame are calculated by:

$$g(i,j) = \min \begin{Bmatrix} g(i-1,j-2) + 2 \cdot ld(i,j-1) : (a) \\ g(i-1,j-1) + ld(i,j) \quad : (b) \\ g(i-2,j-1) + 2 \cdot ld(i-1,j) : (c) \end{Bmatrix} + ld(i,j) . \tag{6}$$

Local distance $ld(i, j)$ on the point of (i, j) is computed as:

$$ld(i,j) = (I_t(\theta_t) - I_{t-1}(\theta_j))^2 . \tag{7}$$

The length for the optimal route:

$$c(i,j) = \begin{cases} c(i-1,j-2) + 3 \mid if\,(a) \\ c(i-1,j-1) + 2 \mid if\,(b) \\ c(i-2,j-1) + 3 \mid if\,(c) \end{cases}, \tag{8}$$

is used to obtain the normalized accumulated distance by:

$$G(i) = \frac{g(i,J)}{c(i,J)} . \tag{9}$$

Object ID recognition The continuous DP matching is done to calculate similarity distances for each reference pattern, when a robot's blue/yellow circle is detected. The identity of the robot is determined by selecting the reference pattern which is given the minimum value of G.

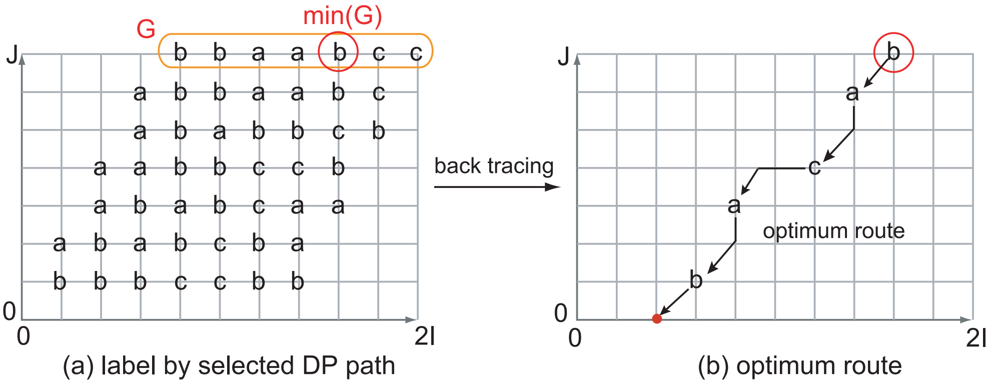


Fig. 8. Back tracing.

3.4 Object orientation estimation by back tracing

To detect the robot's orientation, back tracing, i.e., computations of local corresponding points of input and reference patterns by reference to the selected DP path, is done as follows:

1. DP matching and labelling of the selected DP path
   While computing the minimum accumulated distance, the path selected by equation (6) is memorized with label a/b/c as shown in Fig. 7 (b).
2. Back tracing
   After normalizing minimum accumulated distance, the minimum value of $G(i, J)$ is selected as a starting point for the back tracing as shown in Fig. 8 (a).

$$i' = \arg\min_{(J/2 \le i \le 2I)} G(i, J) \ . \qquad (10)$$

The optimum route is tracked by referring to the label, either 'a', 'b', or 'c' at each node as shown in Fig. 8 (b). The DP path labelled 'a' means insert, and 'c' means delete.

Path 'b' means that frame i and j are a pair of corresponding points. When path 'b' appears on the optimum route, the orientation of the current robot θ is estimated by:

$$\theta = \theta_i - \theta_j \ , \qquad (11)$$

where θ_i is the orientation angle of input pattern, and θ_j is reference pattern. This process is finished when the route, by back tracing, reaches the end point (j = 0), and the angle θ points at the robot's orientation are averaged (front direction).

As we mentioned above, object orientation and ID are determined by the continuous DP matching and not by color segmentation.

Noise	Proposed method		General method	
	SSD	DP	Least-squares method	Second moment
0	0.30	0.76	0.85	1.08
1	1.71	1.10	-	-
2	4.20	1.75	-	-

Table 1. Average of absolute errors of orientation estimation in simulation experiments [degree].

	Proposed method		General method	
	SSD	DP	Least-squares method	Second moment
White bar	0.30	0.76	1.17	0.96
Patch pattern	1.71	1.10	-	-

Table 2. Average of absolute errors of orientation estimation in real experiments [degree].

4. Results

The robustness and accuracy performance of the proposed method in varying light conditions was evaluated by simulation as well as by experiments.

4.1 Results for orientation estimation

Simulation results To determine the accuracy of the orientation estimation, the estimated angle using the proposed method is compared to ground truth. Table 1 shows the simulation results simulation experiments from evaluations of 360 patterns (1 degree each). Our method more accuracy estimates orientation than general methods based on the least-squares method (K. Murakami et al., 2003) and the second-moment method (Ball D. et al., 2004) using the white bar ID plate.

The accurate center position of the blue/yellow colored circle for main marker can not be obtained, when there is noise in the circle's perimeter. In this case, we evaluated the robustness of our method using the pattern in which the center positions of the circle translate to its neighbors. Noise 1 in Table 1 is an area of 3x3 pixels, except for the center. Noise 2 is an area of 5x5 pixels, except for the center and noise 1. Five pixels represent 25 millimeters. The SSD in Table 1 indicate the method of linear matching using the sum of squared differences to estimate the orientation. The SSD method is more accurate than the proposed method when a very accurate center position (noise 0) is obtained. However, our method is effective with respect to errors in the center position of the circle because the DP warping function can obtain the optimum correspondence against the gap.

Experimental results Table 2 shows results for experiments using the real vision system, in which a camera is mounted at a height of 4,000 mm. It can be seen that our method performs almost as well as the general method, and that it works well with respect to the white bar. This shows that our method can determine which way the opponent robot is facing. This information is useful for intercepting a ball that is being passed.

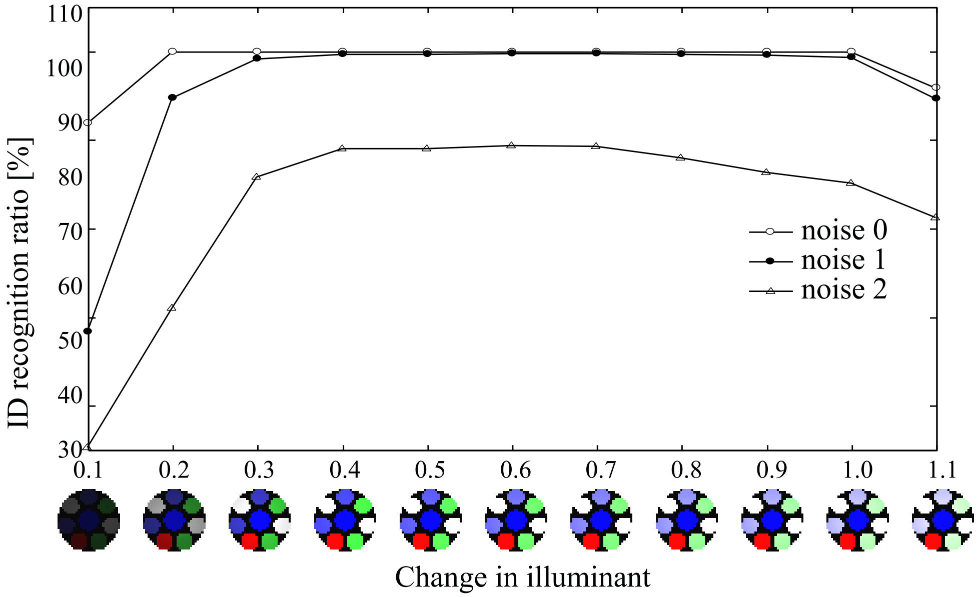


Fig. 9. Results for ID recognition in simulation experiments.

4.2 Results for object identification

Simulation results To determine our methods robustness to variations in light condition, we created a model of illuminant and the marker using CG. We varied the pixel intensity of the input image by changing the illuminant. Figure 9 shows ID patterns under illuminant changes in the simulation and identification performance with 11 unique robots. Our system's performance is stable against the change in lighting conditions. However, recognition performance suffers at noise 2. When there is an error of two pixels in the center, the center is near the edge of the main marker. Therefore, it is difficult to calculate the one-dimensional signal, and the recognition ratio decreases.

Experimental results Figure 10 shows images captured at illuminance ranging from 100-to-2,900 lux. In the experiment, we evaluate 330 images for 11 unique robots in varying light conditions (100 ~3,000 lux). Figure 11 shows object identification ratios for the 330 images. Note that here, general method means color segmentation-based object identification (adjusting the threshold to obtain high performance for lighting condition between 600 to 1,000 lux). On the other hand, for reference patterns of our method, only images captured under 1,000 lux light are registered. It is clear that our method performs better performance with respect to varying light conditions, because our approach is not based on color segmentation but on matching using changes in intensity obtained by scanning at a constant radius from the center of the robot.

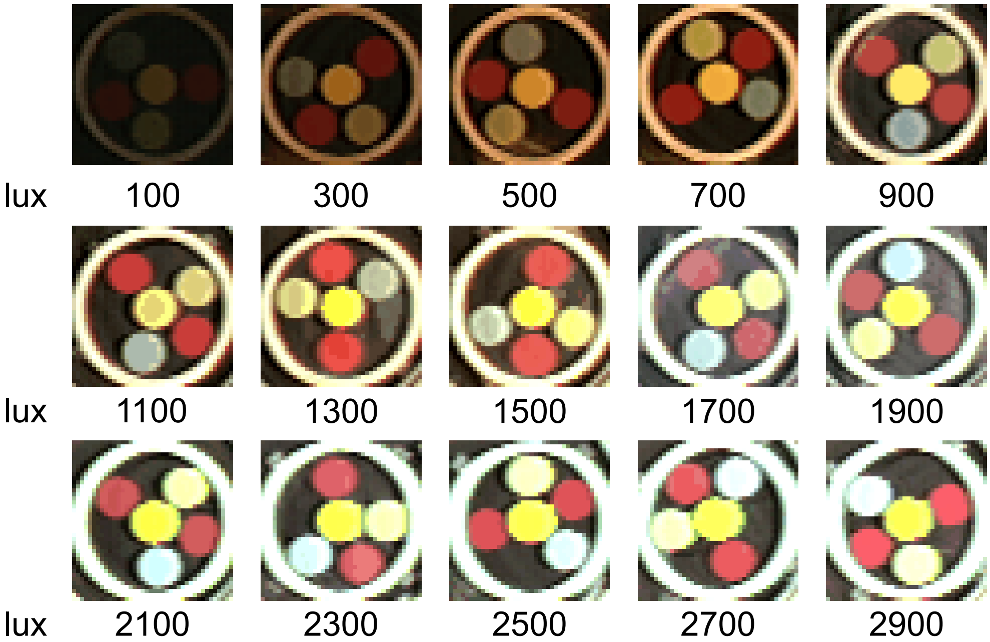


Fig. 10. Images captured at the illuminance from 100 to 2,900 lux.

5. Discussion

This section describes some of the benefits of the proposed method.

- Easy set up
  To register reference patterns for each robot's ID, orientation is obtained by clicking on the fronts of the robots to assign an ID to each one. There is no need to make a rule-based reference table to identify objects.
- Easy patch modification
  Since the white bar is used to estimate the robot's orientation in the general method, there is less space in which to paste sub-marker patches. This means that our method allows for more space on the top of the robot and it is very easy to modify the patch pattern because of its easy set up.
- Robustness with respect to varying light conditions
  There is no perfect color segmentation. Even if the lighting conditions change, because of the weather, our method can work well because the changes in intensity are used to detect a robot's orientation and identity.
- Determining the direction of an opponent robot
  Our method for estimating the robot's orientation works well with any shaped-patch patterns such as white bar or butterfly. Therefore, it is possible to know which way the opponent robot is facing. This means that our robot can intercept a ball being passed between opponent robots.

Our method has a disadvantage associated with conversion to a one-dimensional signal. If

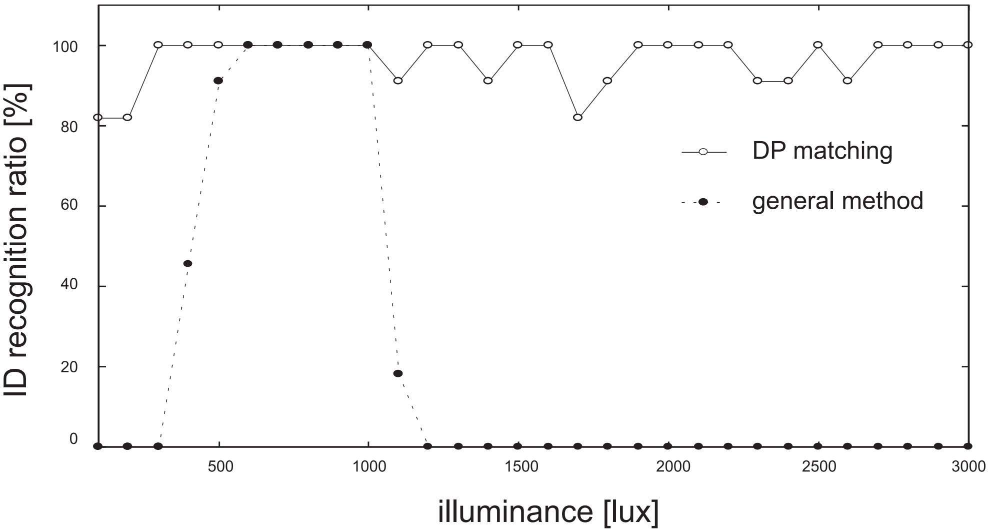


Fig. 11. Experimentals ID recognition results.

the center of the circle cannot be accurately calculated, it is difficult to accurately convert to it to a one-dimensional signal. To calculate accurately, the object's identity and orientation must be known, so that the error of the center position within two pixels can be suppressed. Moreover, when determining the ID, it is necessary to compare the input pattern to all reference patterns. Therefore, as the number of robots increases the computational cost is increases.

6. Conclusion

This chapter describes a novel approach to detecting orientation and identity of robots without color segmentations. We showed that the proposed method more accurately estimates orientation than the general method, that it is robust to varying light conditions. The system using the proposed method runs in real time on a Xeon 3.0 GHz PC, so the system can be completely setup in a short amount of time by a single operator.
Future works will focus on more automation in the reference pattern registration procedure.

7. References

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