

A Robust Object Recognition Method for Soccer Robots^{*}

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Abstract - The recognition of colored objects is very important for robot vision in RoboCup Middle Size League competition. Dynamically changing light conditions can cause lots of difficulties to it. This paper describes a robust object recognition method based on our omni-directional vision system for our RoboCup Middle Size League robot-NuBot. The conditional probability density distributions of the YUV values mapping to each color are verified to be Gaussian and the means and variances are obtained by manual calibration. In the image processing, the classifying seeds are selected based on the means and variances, the object regions are grown by the principle that the colors in an object region should be similar, and then the means and variances are updated to adapt to the changing illumination. The experiment results show that the recognition method can be adaptive to light conditions when the illumination is not changed very suddenly and greatly.

Index Terms – *RoboCup, Soccer Robots, Object Recognition, Omni-directional Vision system, Changing Illumination*

I. INTRODUCTION

The Middle Size League competition of RoboCup is a standard real-world test bed for autonomous multi-robot control and it is a highly color-coded environment. Recognizing kinds of colored objects such as orange ball, blue/yellow goal, black obstacles, green field and white lines is a basic ability for robots. The final goal of RoboCup is that robot soccer team defeats human champion, so robots will have to play outdoors sooner or later. But it is still not easy for robots to recognize those objects reliably just by color under varying light conditions [1]. The traditional methods such as segmenting the image firstly and then detecting the color blobs by using color lookup table calibrated off-line can't work well when the light changes in the process of competition or the illumination is not uniform on the field. In the competition of RoboCup 2006, the changeable natural light caused much difficulty in image processing for most teams because of a glass wall near the competition field. Developing the robust object recognition method less dependent on light conditions has been a research focus in RoboCup literature.

Color constancy approaches [2, 3] have been used to adjust perceived colors to retain constancy under different light conditions, but these approaches usually have huge computational requirements, so they can not be easily applied on-line for real-time recognizing problem in RoboCup. Statistical methods are used to classify different colors in [4, 5]. Paper

[4] introduces a Bayes classifier to generate the color segmentation based on histograms. It uses shape detection to provide additional robustness and allow color recalibration. Paper [5] assumes the conditional probability of color vector as a Gaussian mixture model, classifies the color by maximum a-posteriori criterion, and updates the model parameters by EM algorithm. These two methods can work well in processing the images captured by normal camera. But in our more complex panoramic images (in figure 1), some objects such as ball are too small, so the prior probability is difficult to determine and calculate. Paper [6] supposes that the relative positions of YUV values of different colors on the color axes don't change with the light conditions, so images are segmented by the differences of YUV components relative to reference color (green field). This method is risky and inadequate for more demanding situations. Paper [7] also uses a reference color (a small green carpet on the top of robot body that always can be seen by vision system) to estimate the illumination on the field, and then determines the average values of color components according to the estimation by off-line experiments. So the different colors can be distinguished adaptive to illumination. However, the estimation can't be really consistent to the illumination, especially when the illumination is not uniform on the field.

This Paper presents a robust object recognition method for our omni-directional vision system of RoboCup Middle Size League robots [8]. In the following part, we will firstly verify the function forms of conditional probability density distribution of the YUV component values mapping to each color in section II, and then describe the recognition method in detail in section III. The experiment results and the discussions are presented in section IV, and conclusion is given in section V finally.

II. THE CONDITIONAL PROBABILITY DENSITY DISTRIBUTION OF COLOR COMPONENT

The color classification is the foundation for real-time recognizing colored objects. If we can know the conditional probability density distributions of color component values corresponding to each color, it will help to realize better color classification.

We calibrate the panoramic image captured by our omni-directional vision system under certain illumination manually by human-computer interface, and collect the color value

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set $D_i = \{x_1^i, x_2^i, \dots, x_{n_i}^i\}$, where $x^i = (y^i, u^i, v^i)$ is the YUV component vector corresponding to certain color type ω_i , and n_i is the number of vectors mapping to ω_i , $\omega_i \in \{\text{orange}, \text{blue}, \text{yellow}, \text{green}, \text{black}\}$. So we can calculate the conditional probability $p(y|\omega_i)$, $p(u|\omega_i)$ and $p(v|\omega_i)$ respectively by the method of painting histograms. The histograms about green field and yellow goal are showed in figure 1, from which we find that the conditional probability density distribution function may be considered to be Gaussian approximately. Then we calculate the means $\mu_{i1}, \mu_{i2}, \mu_{i3}$ and variances $\sigma_{i1}^2, \sigma_{i2}^2, \sigma_{i3}^2$ of the three YUV component in D_i , where

$$\begin{aligned} \mu_{i1} &= \frac{1}{n_i} \sum_{j=1}^{n_i} y_j^i, \mu_{i2} = \frac{1}{n_i} \sum_{j=1}^{n_i} u_j^i, \mu_{i3} = \frac{1}{n_i} \sum_{j=1}^{n_i} v_j^i, \sigma_{i1}^2 = \frac{1}{n_i} \sum_{j=1}^{n_i} (y_j^i - \mu_{i1})^2, \\ \sigma_{i2}^2 &= \frac{1}{n_i} \sum_{j=1}^{n_i} (u_j^i - \mu_{i2})^2, \sigma_{i3}^2 = \frac{1}{n_i} \sum_{j=1}^{n_i} (v_j^i - \mu_{i3})^2, i = 1, \dots, 5 \end{aligned} \quad (1)$$

So we can get the real Gaussian functions using above means and variances as parameters to verify whether they are consistent to the histograms. The real Gaussian functions about green field and yellow goal are also showed in figure 1, from which we can find that the real Gaussian functions are approximate to the histograms.

We calibrate several other panoramic images captured under rather different illuminations, and gain the similar results. So we can consider the three conditional probability density distributions of YUV component values to be Gaussian in different light conditions and they are independent to each

other. Only the distribution parameters vary with the changes of light conditions.

Once we get the conditional probability density distribution function of YUV vector corresponding to color label: $p(x|\omega_i) = p(y|\omega_i) p(u|\omega_i) p(v|\omega_i)$, we can design Bayes classifier to determine the belonging color type $C(x)$ for each YUV vector:

$$C(x) = \arg \max_{\omega_i} p(\omega_i | x) = \arg \max_{\omega_i} p(x | \omega_i) p(\omega_i) \quad (2)$$

The prior probability $p(\omega_i)$ affects the performance of classifier greatly. But it is related to object size, and it is difficult to determine, for the ball size is too small comparing to other objects in our panoramic image. Furthermore, because panoramic image is complex, there are lots of pixels not belonging to any of the five color types. It is difficult for Bayes classifier to work well in processing our complex panoramic images, so we design a more robust object recognition method.

III. OUR OBJECT RECOGNITION METHOD

In the traditional colored object recognition methods, we usually classify each pixel of the image to a certain color type according to its color vector, and then use run length encoding or region growing algorithm to connect pixels with the same color label. But it is difficult, maybe impossible task to build an accurate pixel classifier in changeable light conditions and it is not accordant to the way that human recognize the colored objects. We should classify the pixels in the context of image, and make use of the character that the color values in

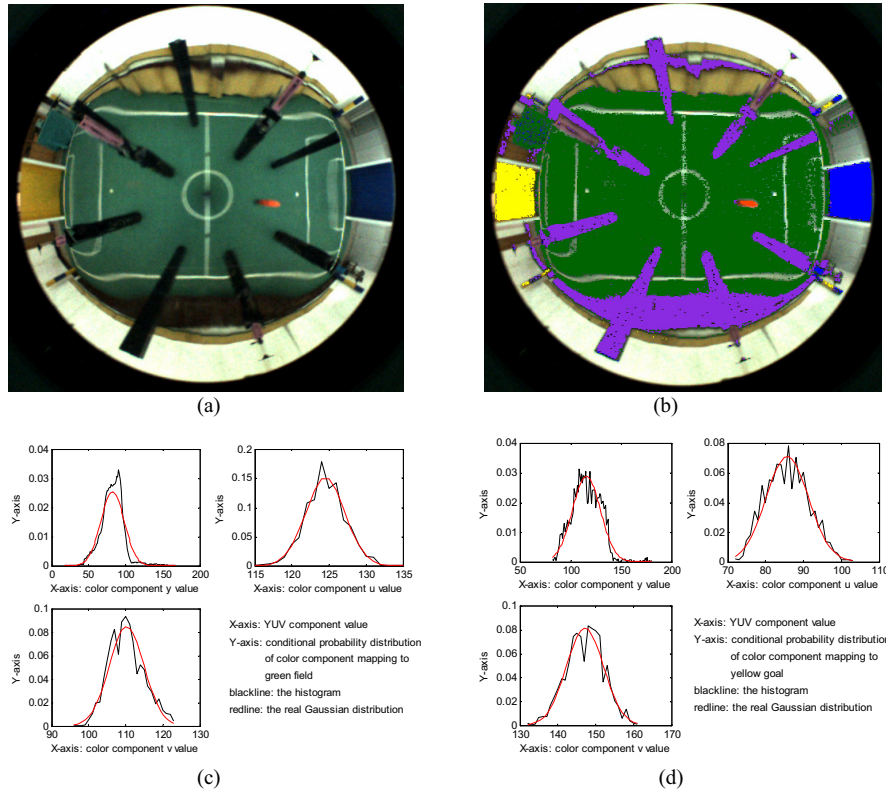


Fig. 1. (a) The panoramic image captured by our omni-directional vision system. (b) The result of color classification by manual calibration. (c)(d) The histograms and the real conditional probability of YUV component values mapping to green field and yellow goal.

an object region should be similar.

In section 2, we have verified that the conditional probability density distribution functions of color component are Gaussian, and we can get the means $\mu_{i1}, \mu_{i2}, \mu_{i3}$ and variances $\sigma_{i1}^2, \sigma_{i2}^2, \sigma_{i3}^2$ for each color type ω_i by coarse off-line calibration. We assume that the light condition changes gently, which is consistent to most of the practical situations. So when we process a new panoramic image, we can use the means and variances to classify some pixels to color label ω_i and guarantee that the classification is right, if their YUV color vector (y, u, v) satisfies:

$$\begin{cases} \mu_{i1} - \lambda_i \sigma_{i1} < y < \mu_{i1} + \lambda_i \sigma_{i1} \\ \mu_{i2} - \lambda_i \sigma_{i2} < u < \mu_{i2} + \lambda_i \sigma_{i2}, \text{ where } 0 < \lambda_i \leq 1, i = 1, \dots, 5 \\ \mu_{i3} - \lambda_i \sigma_{i3} < v < \mu_{i3} + \lambda_i \sigma_{i3} \end{cases} \quad (3)$$

These pixels are considered as the classifying seeds. Because color values of pixels in the same object region are similar to each other, we use region growing algorithm to grow new pixels to form a series of regions from these seeds. If the Euclidean distance between YUV values of the new pixel and the closest seed encountered in the growing process is smaller than threshold γ_i , the new pixel belongs to the region:

$$(y - y_s)^2 + (u - u_s)^2 + (v - v_s)^2 < \gamma_i^2, \quad (4)$$

where (y, u, v) and (y_s, u_s, v_s) are the YUV values of the new pixel and the closest seed encountered in the growing process.

The color label of the growing region is the same as the seeds from which the region is grew. These regions are candidate object regions, and then we choose the biggest one of the regions with the same color label (orange, blue, yellow) as the real ball and goal region. All of the regions with the color label green are green field. The regions with the color label black are considered to be black obstacles if their sizes are not too small and they are not too far from the robot. So we can recognize the orange ball, blue goal, yellow goal, green field, and black obstacles. We also can get the new color value set D_i corresponding to each color ω_i , and use equation (1) to calculate the new means $\mu_{i1}, \mu_{i2}, \mu_{i3}$ and variances $\sigma_{i1}^2, \sigma_{i2}^2, \sigma_{i3}^2$. If objects are not detected in current image, the old means and variances will be saved. These parameters are used to process the next frame image, so the object recognition can be adaptive to the changeable light conditions.

For achieving accurate self-localization for soccer robots, the white lines or line points on the field should be detected. The traditional method is to search the green-white-green transition pixel as the line points after classifying each pixel with a color label. For detecting white line points robustly, we should reduce the dependence on pixel classification as much as possible. We scan the panoramic image by 72 scan lines arranged radially around the center of the image, which is similar to the method in [9]. The color variations are measured by Euclidean distance in YUV color space. If a variation along the scan line is more than a threshold, a color transition is found. Two consecutive color transitions are considered to be a possible line point if they are close to each other along

the scan line and the color variation of the pixel before the first transition and the pixel after the second one is small. Finally we confirm the possible line points to be real ones if the color vector (y, u, v) of two pixels before the first transition and after the second one satisfies the following condition:

$$\begin{cases} \mu_{41} - 4\sigma_{41} < y < \mu_{41} + 4\sigma_{41} \\ \mu_{42} - 4\sigma_{42} < u < \mu_{42} + 4\sigma_{42}, \\ \mu_{43} - 4\sigma_{43} < v < \mu_{43} + 4\sigma_{43} \end{cases} \quad (5)$$

where $\mu_{41}, \mu_{42}, \mu_{43}$ and $\sigma_{41}, \sigma_{42}, \sigma_{43}$ are the Gaussian parameters of the conditional probability distribution functions of color component values mapping to green field. So the false detection rate of white line points can be reduced effectively.

IV. EXPERIMENT AND DISCUSSION

We design two experiment scenes to test our object recognition method. The first one is that the robot is stationary on the field, and the illumination is changed gradually by us. The second one is that the illumination is not uniform on the field, and robot, ball and obstacles can move.

A. Experiment one

In this experiment, we localize the robot on the center of the field, and then turn off a few lights on the ceiling every time. Finally, we get five panoramic images under the weaker and weaker illumination. We calibrate the first image manually and get the color lookup table and the initial means and variances. Then we process the five images by the traditional method based on static color lookup table and our method respectively. The processing results of the first, the third and the fifth image are showed in figure 2.

From the figure 2, we can find that the performance of traditional method become worse and worse as the illumination changes more and more greatly. For example, when the illumination is weakest, the yellow goal and lots of white line points can't be recognized, and parts of green field are recognized as the black obstacles wrongly. But our new method can recognize all the objects with good accuracy even when the illumination changes greatly.

B. Experiment two

In this experiment, we turn off more and more lights from yellow goal to blue goal on the field, so the illumination is not uniform. We move robot from yellow goal to blue goal by remote control. So a series of images can be captured. We also calibrate the first image (captured when robot is on the front of yellow goal) manually and get the color lookup table and the initial means and variances. Then we process the images by the traditional method based on static color lookup table and our method respectively, as in the experiment one. The processing results of images when robot on the front of yellow goal, the center of field and the front of blue goal are showed in figure 3. From the figure, we can find that the objects especially white line points can be recognized with better accuracy by our method. For example, less and less white line points are detected by the traditional method when robot moves from yellow goal to blue goal.

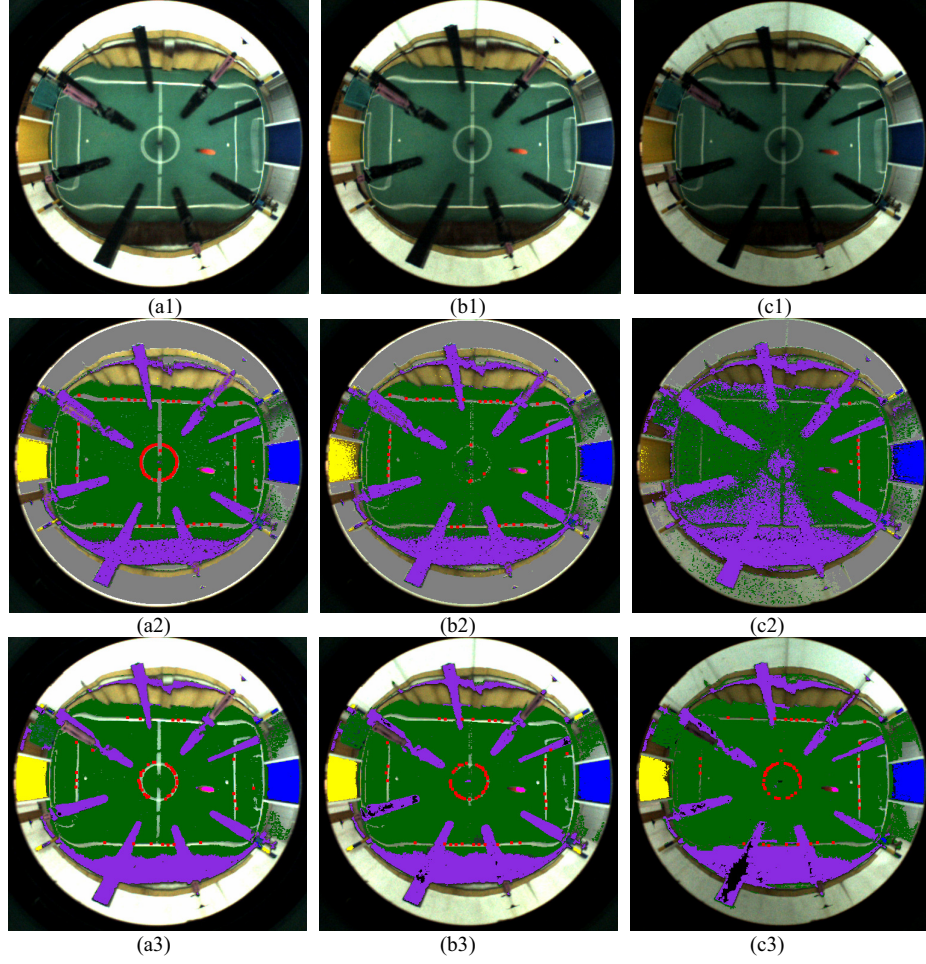


Fig. 2. The processing results of panoramic images under different illumination. (a1)(b1)(c1) The first, the third and the fifth image captured under weaker and weaker illumination. (a2)(b2)(c2) The processing results of the three images by traditional method based on static color lookup table. (a3)(b3)(c3) The processing results of the three images by our new method. The red points are the detected white line points.

C. Discussion

In our object recognition method, we take the context of image into account and use the character that the color values in an object region should be similar, which is more accordant to the way human recognize the colored objects than traditional methods. Once the omni-directional vision system is calibrated off-line manually, we can select the classifying seeds based on the Gaussian parameters of the conditional probability density distributions, recognize the objects by region growing algorithm and update the Gaussian parameters. We also search the white line points by scanning the color variations and confirm them based on the Gaussian parameters corresponding to green field. So our method can be robust and adaptive to the changes of light condition, which can be verified by the above two experiment results.

However, our method can work well only when the assumption that the light condition changes gently is satisfied and furthermore, coarse off-line calibration is needed. If the illumination is changed too suddenly and greatly, the formula (3) can't ensure the right selection of classifying seeds and

wrong objects may be recognized. To overcome these limitations, we must combine our method with the self-calibration method [10, 11] to let object recognition be adaptive to the sudden changes of light condition and can work well even when into a new competition field for needing not any off-line calibration manually.

RoboCup Middle Size League competition is a highly dynamic environment, so robot must process its sensor information as soon as possible. We also test the running time of our object recognition algorithm. Our computer is equipped with 1.73GHz CPU and 512M memory and the resolution of our panoramic images is 500*492. Our algorithm takes about 35ms to process each panoramic image and the region growing algorithm takes the most of running time. Furthermore, green field is not the object we need to use directly, so we could recognize the green field once in every 10 or 20 frame images. So the running time can be reduced to about 22ms when not recognizing the green field. Our method doesn't need extra processing time comparing to color constancy approaches and can meet the real-time requirements of RoboCup Middle Size League competition.

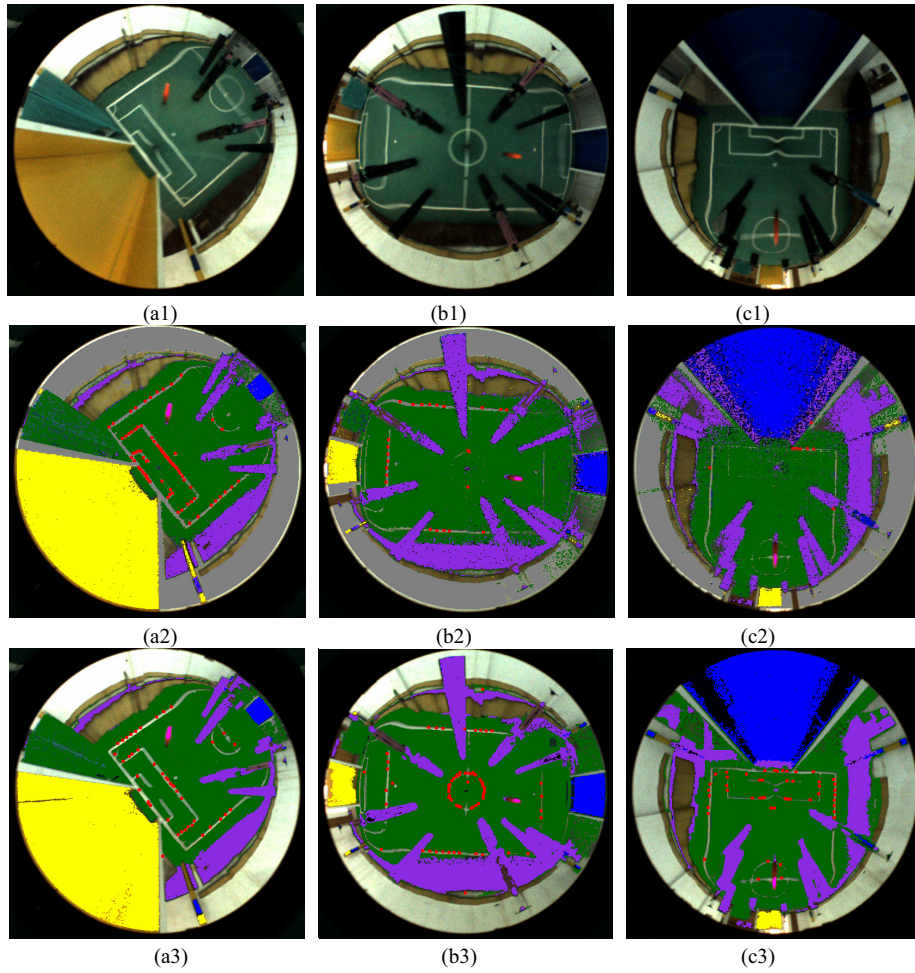


Fig. 3. The processing results of panoramic images when robot is on different pose of the field with not uniform illumination. (a1)(b1)(c1) The panoramic images captured on different pose. (a2)(b2)(c2) The processing results of the three images by traditional method based on static color lookup table. (a3)(b3)(c3) The processing results of the three images by our new method. The red points are the detected white line points.

V. CONCLUSION

In this paper, we firstly verify that the conditional probability density distribution of the YUV values mapping to each color is Gaussian, and then present a robust object recognition method based on our omni-directional vision system for RoboCup Middle Size League robots. In the method, classifying seeds are selected based on the Gaussian parameters of the conditional probability density distribution, object regions are grown from these seeds using region growing algorithm by the principle that the colors in an object region should be similar, and then the Gaussian parameters are updated to adaptive to new light conditions. We also detect white line points by scan the color variations to reduce the dependence on the pixel classification. Experiment results show that our method can recognize the orange ball, blue/yellow goal, green field, black obstacles and white line points with good accuracy and it can be adaptive to the changeable light conditions when the illumination is not changed too suddenly and greatly.

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