A Novel Color Detection Method for Robotics Soccer Image Processing

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***Abstract*—The color clusters of glossy materials always deviates from the linear model in the different brightness. For the robotics soccer game, the surface of game ball is glossy; therefore, the identification difficulty will be increased. For solving this problem, we propose a novel color detection method to improve this problem in this paper. Contrast to the traditional method use the threshold values to define the color; we create two mapping matrices based on the distribution of color cluster as the color database. Utilizing an example, one can find that the proposed method can define the target color more accurate than other traditional method. Besides, the proposed method can reduce the execution-time and increase the success rate for identifying object. Finally, some examples are illustrated to demonstrate the validity and feasibility of proposed method.**

***Keywords*—robotics soccer; vision processing; color detection**

1. INTRODUCTION

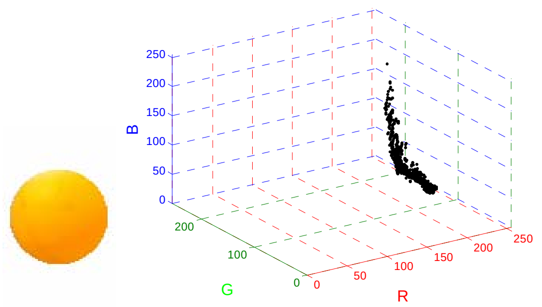
Robotic soccer is a standardized competition platform of artificial intelligence. The platform is a strong dynamic environment where robots communicate, consult and cooperate with one another to compete in games. The FIRA robot soccer game began since 1995. Due to the establishment of FIRA, it has been held annually in different countries as a world-recognized robotic festival. There are lots of categories in the FIRA game. No matter which categories, the vision system always play an important role in robotic soccer. For example, in the FIRA MiroSot and AndroSot games, a camera is hung on the top of the game field for the visual system to obtain information, as shown in Fig. 1 [1]. The vision system server is a base of robots' decision making and motion control [2]-[3]. For this reason, the vision system can work quickly and effectively will decide the result of the game [4]. Therefore, an effectiveness and precious image system is needed to identify objects instantaneously and accurately.

Fig. 1 FIRA AndroSot game panorama

In robotic soccer games, both the robots and the game ball are moving very quickly, and the vision system needs to real-timely and accurately identify the locations of both the robots and the game ball. Generally speaking, the first step to identify the game ball is through color detection, of which the accuracy will affect the result of follow-up identification. In other words, if the color detection is not accurate enough, the execution-time will be increase or even fail in the identification.

Table-tennis balls and golf balls are commonly used as the game ball in robotic soccer games. Both of they are characterized in their glossy surfaces. Such game balls bring a common problem of color detection because the glossy surface is easily affected by brightness. The problem may lead to image distortion and also affect the follow-up identification. If we want to solve the problem by increasing the range of color definition, it will result to another problem—the color definitions may overlap among different colors because there are many colors need to be identified in robotic soccer game. In the FIRA MiroSot and AndroSot games, there are two color tags set on the top of every robot, one represents its team and the other represents the robot itself. The color tags are used to identify the locations of every robot in the two rival teams. In a 3 versus 3 robotic soccer game, there are at least six colors need to be identified. Therefore, the whole visual system may not function accurately if we increase the range of the color definitions.

According to the Lambertian reflectance [5]-[7], the R, G, and B ratio of pixels have the same albedo color will be identical, that is, in the ideal situation, the distribution of color cluster will be a linearity form on RGB color space under different brightness. But unfortunately, the color clusters of glossy materials under different brightness will vary with a non-linear trend [8]. In other word, the image pixels of the same real-world color with differential brightness, the pixels values of R, G and B won't be shown a linear variation in the RGB color space under different brightness. For example, if we install a light source on the top of the table-tennis ball, then there will has a part of table-tennis ball has higher brightness, as shown in Fig. 2(a). According to the distribution of RGB color space, as shown in Fig. 2(b), we can find the color clusters of glossy materials is a non-linearity model on RGB color space under different brightness.



(a) (b)

Fig. 2 The distribution of the color clusters in RGB color space

Mostly, images are captured by means of the RGB color space, but the RGB color space is rarely used for computer vision. That is because we can not get the brightness information from RGB color space. Fortunately, through some coordinates transform, RGB color space can be transformed into other color spaces such as, $YCbCr$, YUV, YIQ, CYM, HSV and so on [9]-[11], which have been built to improve the shortcomings of RGB color space. Therefore, we can inference these color spaces that origin from the RGB color space still show a non-linear variation in the different brightness of glossy materials, too.

Motivated by above discussions, we explore a novel color image detection method. The main contributions of this paper include: i) Improving accuracy with identify colors from glossy materials with different brightness; ii) Discriminating the difference clearly between two very similar colors; iii) Reducing the execution-time and enhancing the success rate of the follow-up identifying. As a result, the image system will identify objects more real-timely and accurately.

The paper is organized as follows. In Section II, a novel color detection method is proposed to compare with the traditional method. In Section III, the process of the ball recognition is introduced. The experiment result and the analysis are shown in Section IV. Finally, conclusions are drawn in Section V.

2. THE COLOR DETECTION

The general way to detect colors is to transform RGB color space into different color space with brightness information. For $YCbCr$ space, Y, Cb and Cr represent three different dimensions, where Y is intensity, and Cb and Cr are the blue and red chroma components, respectively. There are two threshold values for each dimension. One threshold value represents the upper threshold and the other is lower threshold, as shown in Fig. 3(a). Since each dimension has 2 threshold values, there will contain 6 threshold values in $YCbCr$ color space. In addition, these threshold values can be built a cube in the $YCbCr$ color space, which is shown as Fig. 3(b). As an undefined pixel falls in the cube, the pixel will be defined as a certain color [2], [12].

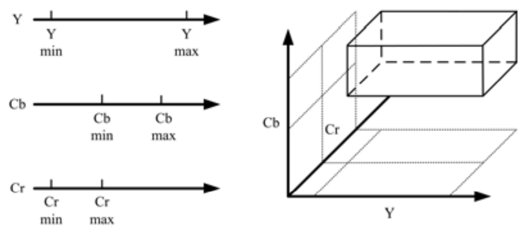


Fig. 3 Traditional color detection method

However, for a glossy-surfaced object, the different brightness will cause a non-linear variation in the color-cluster distribution. Even though the *RGB* color space is transformed into *YCbCr*, the distribution of the color clusters still vary with a non-linear trend, as shown in Fig. 4. Clearly, the non-linear variation may cause a huge error as using the cube method to detect color. These errors will cause the overlaps of color definitions in different brightness. Besides, it will cause the recognition difficult for two similar colors under different brightness.

In this section, we present a novel approach for the problems described above, and utilizing an example to demonstrate the validity of proposed method.

2.1. A novel color detection method

Firstly, target object was put into blue screen for convenience removing background. Then, few images were captured under different brightness for observing intensity trend. Secondly, the color clusters which have been transformed into 3D domain, i.e. *YCbCr* domain and then map these results into 2D planes (Y-Cb and Y-Cr matrices) for processing the noise filtering and the region filling. Finally, the data in Y-Cb and Y-Cr matrices are dilated based on the brightness trend and used as the target color data base. Through the above procedure, the color of a new pixel can easily be determined as the pixel data corresponds with the data of Y-Cb and Y-Cr of database.

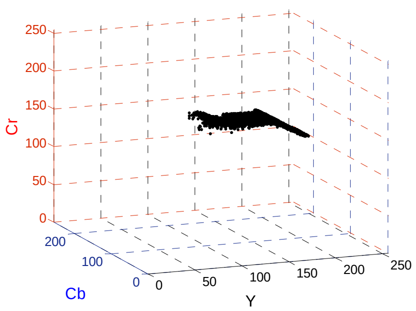


Fig. 4 The distribution of the color clusters in *YCbCr* color space

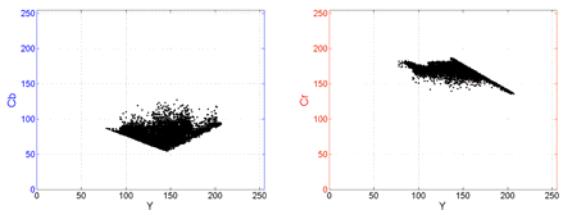


Fig. 5 The mapping matrices: Y-Cb and Y-Cr

For a game ball example, we put a game ball into blue screen and capture few images under different brightness firstly. Next, we transfer the color clusters to *YCbCr* , as shown in Fig. 4. Then, maps these color clusters into Y-Cb and Y-Cr matrices, as shown in Fig. 5, for proceeding the later noise filtering and region filling. Finally, the data of Y-Cb and Y-Cr matrices are dilated based on the brightness trend and used as the game ball color database.

By examining the noise filtering, the morphological opening operation [13] is adopted to smooth the contour of an object, breaks narrow isthmuses, and eliminates thin protrusions. In this paper, the opening process can eliminate the independent noise and smooth the main object contour of the mapping matrix. Assume that A is the image objects and B is a structuring element, the opening of set A by structuring element B, denoted $A \circ B$, is defined as (1)

$$A \circ B = (A \Theta B) \oplus B . \qquad (1)$$

Thus, the opening of A by B is erosion of A by B, followed by a dilation of the result by B.The erosion and the dilation are defined as (2a) and (2b)

$$A \Theta B = \{ z \mid (B)_z \subseteq A \} . \qquad (2a)$$

$$A \oplus B = \{ z \mid (\hat{B})_z \cap A \neq \phi \} . \qquad (2b)$$

For the region filling, we apply the conditional dilation operation to ensure the mapping matrix without any gap. Firstly, we detect the main object boundary of the mapping matrix. Next, assign a point p inside the boundary to begin, and then following procedure to fills the region as (3)

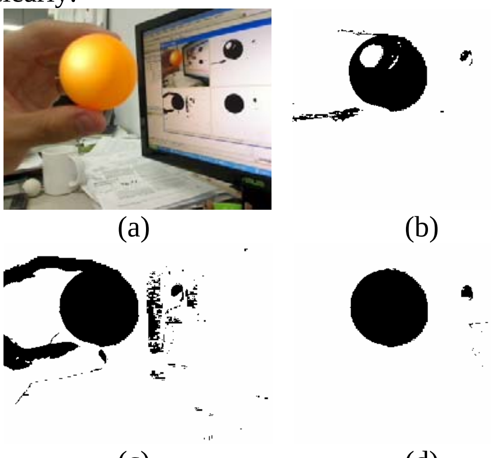
$$X_k = (X_{k-1} \oplus B) \bigcap A^c \quad k = 1, 2, 3, \cdots . \qquad (3)$$

Where $X_0 = p$, and A^c is the complement of A. The algorithm terminates at iteration step k if $X_k = X_{k-1}$. The set union of and contains the filled set and its boundary.

2.2. Example

In this subsection, a 320×240 pixels photo is illustrated for demonstrating the validity and feasibility of proposed method, which is described as Fig. 6(a). From the Fig. 6(a), we can find that the photo is a bad environment for color detection, that is, the detection object with glossy surface under the high brightness and there are many other objects with similar colors in this figure.

Firstly, we use the traditional method to detect the color of the game ball, the six threshold values set as $55 < Cb < 115$, $150 < Cr < 195$ and $90 < Y < 210$. By utilizing the traditional method to Fig. 6(a), one can obtain the Fig. 6(b). Fig. 6(b) shows that traditional method cannot detect color accurately under the high brightness. That is because that the glossy surface and the high brightness will cause the distribution of color clusters deviating from the linear model. Secondly, we increase the ranges of six threshold values for the same photo, that is, $45 < Cb < 125$, $140 < Cr < 205$ and $80 < Y < 220$. Since the threshold values haven't be defined preciously, that might cause this overlaps of this color definition with other similar color definition. From the Fig. 6(c), we can find it can detect the color in the high brightness situation, but it cannot discriminate the similar color clearly. Finally, we adopt the proposed method to detect the color. Fig. 6(d) shows that it can provide accurate color detection and discriminate color clearly.



(a) (b) (c) (d)

Fig. 6 (a)Original image (b)Traditional method (c)Traditional method (extending the thresholds) (d)Novel color detection method

3. THE BALL RECOGNITION

After detecting the color in Section II, now we will explore how to apply the algorithms for recognizing the game ball. And the detail procedure of the game ball recognition can be shown in Fig. 7.

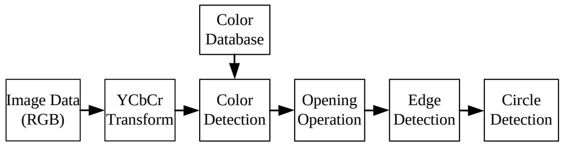


Fig. 7 The procedure of the ball recognition

Firstly, we transform the data of *RGB* color space into *YCbCr* color space from capture images. In this, we use a modified transformation equations [14], as shown in (4), and its computation cost is lower than the standard equations.

$$\begin{cases} Y = (9798R + 19235G + 3736B) >> 15 \\ Cb = 18514(B - Y) >> 15 + 128 \\ Cr = 713(R - Y) >> 15 + 128 \end{cases} \quad (4)$$

Utilizing the modified equation, all of the floating point operations are replaced by integers operations, and the division operations are replaced by shift-right operation , which will shorten the running time than standard equation. Next, we use the color database to detect the ball color, and utilize the result to execute opening operation. After the opening processing, we apply the Sobel edge detection for detecting the edge to obtain a group coordinates of these edge points. Finally, we adopt the group coordinates and the typical circle detection method: RCD (Randomized Circle Detection) algorithm [15]-[17] to detect the circle. The RCD algorithm random to find three non-collinear edge points: $p_1(x_1, y_1)$, $p_2(x_2, y_2)$, $p_3(x_3, y_3)$ at first, and these three points can represent a candidate circle form, follow (5a)-(5c)

$$a_{123} = \frac{\begin{vmatrix} x_2^2 + y_2^2 - (x_1^2 + y_1^2) & 2(y_2 - y_1) \\ x_3^2 + y_3^2 - (x_1^2 + y_1^2) & 2(y_3 - y_1) \end{vmatrix}}{4((x_2 - x_1)(y_3 - y_1) - (x_3 - x_1)(y_2 - y_1))}, \quad (5a)$$

$$b_{123} = \frac{\begin{vmatrix} 2(x_2 - x_1) & x_2^2 + y_2^2 - (x_1^2 + y_1^2) \\ 2(x_3 - x_1) & x_3^2 + y_3^2 - (x_1^2 + y_1^2) \end{vmatrix}}{4((x_2 - x_1)(y_3 - y_1) - (x_3 - x_1)(y_2 - y_1))}, \quad (5b)$$

$$r_{123} = \sqrt{(x_i - a_{123})^2 + (y_i - b_{123})^2}. \quad (5c)$$

Where a_{123} and b_{123} are the center point of the circle, and r_{123} is the radius, respectively. Then, keep calculating the distance between the circumference and the other edge points. If the distance is smaller than the designate threshold value T_d, then the votes of the candidate circle will be added one. Finally, if the votes of the circle exceed a certain ratio threshold T_r, this candidate circle is identified as a real circle, otherwise the number of failures add one. In contrast, if the numbers of failures achieve the threshold T_f , then the RCD algorithm will declare that there in no circle in this image. Hence, the threshold T_d and T_r can be regarded as the sensitivity of the circle detection. After a series of processing, we can identify the location and size of the game ball from an original image.

4. The Experiment Results and The Analysis

In this section, we illustrate some examples to demonstrate the feasibility and effectiveness of proposed method. Besides, the evaluation performance is also addressed in this section. In this section, all experiments are implemented by using the Pentium D personal computer with 3.4 GHz and the C programming language.

4.1. The first experiment

The first experiment is carried out on four 320×240 real images, which shown at Fig. 8, for justifying the performance of the proposed method. In Fig. 8(a)-(d), the image comprises a game ball in the normal background. In Fig. 8(b), the image comprises a game ball and some objects, which color is similar to the game ball. In Fig. 8(c), the game ball and these same objects are laid in a high brightness circumstance. In Fig. 8(d), the similar color overlaps with the game ball in a high brightness circumstance. After the color detecting, we detect the circle by these edge points, so the integrity of edge will affect execution-time and accuracy of circle detection directly. Therefore, we execute the color detection, opening operation and Sobel edge detection for these images.

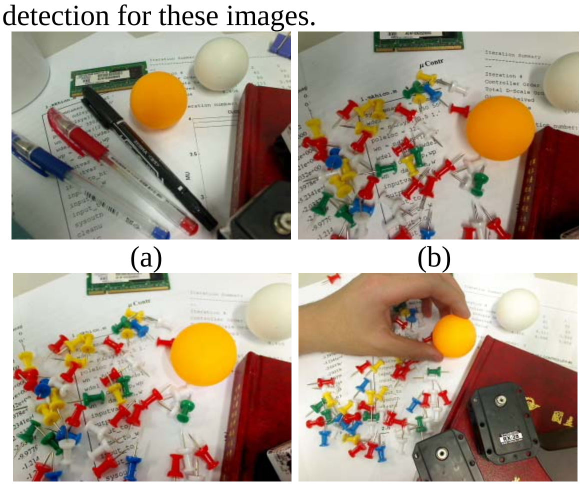


Fig. 8 Four different interference environments

Firstly, for the part of color detection we adopt the traditional method firstly, the six threshold values set as $50 < Cb < 120$, $145 < Cr < 200$ and $85 < Y < 215$, as show in Fig. 9. From Fig. 9(a)-(d), one can find that there are two problems, if one adopts the traditional method. i) Fig. 9(b)-(d) show that the traditional method cannot discriminate clearly for the similar color, such as the orange ball, the yellow thumbtack and skin tone hand. ii) From Fig. 9(c) and 9(d), one can discover the edge of pseudo-round is contained in the true ball edge; therefore, it means the traditional method cannot detect the distortion color under the high brightness circumstance. For avoiding the first problem, we narrow the range of threshold values, but that will make the second problem more aggravate. In contrast, if we increase the range of threshold values for avoiding the second problem, the first problem will be highlighted.

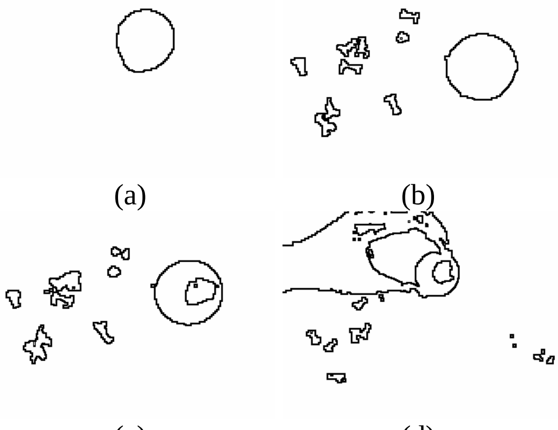


Fig. 9 Traditional color detection, opening operation and edge detection for Fig. 8

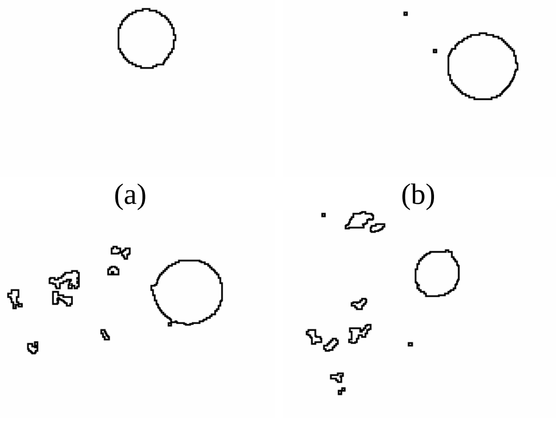


Fig. 10 Our proposed color detection, opening operation and edge detection for Fig. 8

Secondly, for the part of color detection, we use our proposed method and the result is shown in Fig. 10. In Fig. 10(b), it shows that our proposed method can discriminate color clearly. Besides this, from Fig. 10(c) and 10(d), one can find that the performance of discriminate color becomes more wane, but it still can detect the distortion color under the high brightness. Notably, from Fig. 9(a) and 10(a), we can find that two color detections methods haven't conspicuous difference under low interference environment. However, our method can provide a better performance under many interference environments than traditional method, and the result can be shown at Fig. 9(d) and 10(d).

4.2. The second experiment

In this experiment, we carry out on the same images, and the experimental results are utilized to compare the success rate and the execution-time with the traditional method and proposed method, the results are shown in Table I and Table II. The execution-time can be figured out from obtaining an original image to finish the location and size identifications of the game ball, and its measured unit is milliseconds.

While executing the RCD for the four images, the thresholds T_f, T_d, and T_r are set as 30000, 3, and 70%. The thresholds T_f denotes the number of failures that we can tolerate. When it is larger, it might not miss to identify the possible circle. On the contrary, it will waste more execution-time when there is no circle in an image. The threshold T_d and T_r can be regarded as the sensitivity of the detection, when these threshold values are tighter, it will can identify the location and size of the circle more accuracy. But however, this movement will increase the execution-time of detection image.

TABLE 1
SUCCESS RATE COMPARISON

	Image			
	Fig.8 (a)	**Fig.8 (b)**	**Fig.8 (c)**	**Fig.8 (d)**
Traditional method	100%	100%	99%	84%
Proposed method.	100%	100%	99.5%	99.5%

Table 1 shows that the comparison result between the traditional method and our proposed method. From the three column (Fig. 8(a)-(c)) of Table 1, we can find the success rate hasn't conspicuous difference in low interference environment, and their gap of success rate is less then 1%. But in high interference environment (Fig. 8(d)), the success rate gap increases to 15.5%. The main reason is there is more noise overlap with circle edge, which will cause the identification difficult. For Fig. 8(d), if we adopt the traditional method, the failure rates will up to 16%. There are 10% failure rate raised by the number of failures achieve the threshold T_f. In other word, the system will recognize there doesn't exist in any circle in this image. Besides, wrong identification of the system will be 6%.

TABLE 2
EXECUTION-TIME COMPARISON

	Image			
	Fig.8 (a)	**Fig.8 (b)**	**Fig.8 (c)**	**Fig.8 (d)**
Traditional method	15.6685	29.6849	36.3281	139.439
Proposed method.	15.5379	15.7159	18.8536	19.0212
Improvement rate	0.0083	0.4706	0.4885	0.8636

Improvement rate = (Traditional method – Proposed method) / Traditional method

In the Table 2, one can clearly know that the traditional method and proposed method have almost the same execution-time under low interference environment. However, in high interference environment, such as Fig. 8(d), the execution-time improvement rate is up to 86.36%. Table 2 shows that our proposed method can improve the success rate and shorten the execution-time.

5. CONCLUSIONS

In this paper, we present a novel color detection method. Different from the traditional method, our proposed method can identify colors more accurately from glossy materials in different intensity of light. Besides, our proposed method can also discriminate very similar colors clearly, and then enhances the speed and success rate for later image processing. Furthermore, it can more accurately determine the non-linear variation in the color-cluster distribution. According to the experimental results, it is demonstrated that our proposed method can help robot soccer image system to identify object by increasing the execution-time improvement ratios and higher success rate. Further improving the real-timely and correctly of image system for identify object.

ACKNOWLEDGMENT

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