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A Fine Three-dimensional Adaptive Color Segmentation Algorithm for Real-time Vision System of Soccer Robot

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***Abstract*—The aim of the vision system for small soccer robots is to recognize and track robots and soccer ball in a semi-open environment. Traditional color segmentation methods are usually sensitive to external conditions, for example light changes or uneven distribution. Machine learning-based methods usually require advanced hardware as well as huge amount of data. To overcome these limitations, we propose a fine three-dimensional adaptive color classification method in this paper. The presented method determines the thresholds in color space dynamically. For distinguishing the overlapping area in color space, Naive Bayes classifier is used to classify the color categories which obey the Multivariate Normal Distribution. Dynamic adaptive lighting is introduced to enhance the performance, and the robustness of classification is increased by combining multiple brightness separable color space. This method is embedded in a vision system for Soccer Robot to enhance the processing performance. The experiments show that the system is robust and achieves high precision. It can process the soccer video in real-time with detection rate of 99.68 % and precision of 99.92 %.**

Keywords-Vision System; Small Soccer Robot; Real Time

I. INTRODUCTION

The object of robots playing soccer is to form a team to wining against human soccer players by 2050. The small size league is held between two teams with five robots. It is a popular topic of multiagent control system in a highly dynamic environment, which can promote the development of artificial intelligence and robotics technology [2,8]. The robot plays an orange golf ball as the "football" on a 9 meters × 6 meters carpet [28]. The vision system can distinguish and recognize the small soccer robots relying on color logos of the robots.

All the objects on the field are tracked and recognized by the vision system. There are two cameras hanged on the pitch to capture the competition information. Then the data is transmitted to the computer for further processing, including identifying and localizing different objects [16,23]. The color identity of each robot is composed of the team color and character color, as shown in Fig. 1. Blue represents team b in the left and for team y is yellow. Another five different color denotes different roles of each robot, such as goal keeper or full back.

The performance of a visual subsystem for a small soccer robot is usually evaluated by the following criteria: efficiency, accuracy and robustness. The frame rate of the video can up to 60 FPS. Although high sampling rate video will provide more information in an intense competition, it is a challenging to the vision system efficiency. Accuracy is another necessary criterion. The objects are moving at high speed in the game therefore precise location information can help the control system making better strategies.

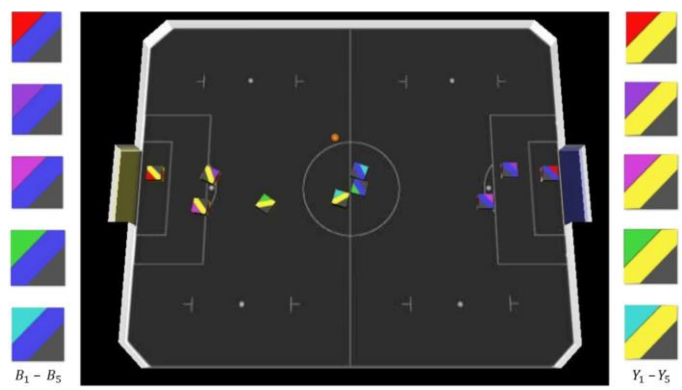

Figure 1. Color logos for small soccer robot targets. Those at the left most ($B_1 - B_5$) are for the Blue Term, while others ($Y_1 - Y_5$) for the Yellow Term.

In the match, the lighting condition on different positions of the pitch could be uneven, also it could change during the match. The change of light intensity may affect the image segmentation or even the recognition model trained offline. Therefore, the visual system needs to take certain measures to adapt different light intensity.

For obtaining accurate information in semi-open high dynamic environment, the soccer robot visual subsystem often faces the following difficulties in the real world:

(1) Uneven and unstable lighting distribution. The difference of lighting conditions might magnify the image features and defects and further affect the image quality.

(2) The efficiency of processing in a highly dynamic environment. A small size soccer robot can move up to 5m/s and the soccer ball is 15m/s. For providing accuracy information to the control system on time, high speed cameras have been gradually adopted to the competition over the years, which raises higher requirement of efficiency.

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(3) Precise position of the objects. The competition involves the collaboration of multiple agents, which requires the measurement of their positions to be as accurate as possible. However, the size of the target in a soccer robot game is relatively small compare with the frame size. In addition, the robot is moving at a high speed. Therefore, objects localization is a great challenge to the soccer robot vision system.

(4) Distortion in the image caused by the global camera. The vision sub-system usually chooses wide-angle lens to filming the game, however the images obtained by the wide-angle lenses often have barrel radial distortion, which requires further additional [9].

The contributions of this paper are summarized as follows:

(1) We propose a new colour segmentation method and it can distinguish multiple colours with various colour scale simultaneously. It is also robust to illumination changes and uneven distribution. The method combines and optimizes a real time double threshold determination method and two-dimensional Gaussian model for a better segmentation performance. The boundary of colour category in HS plane is divided according to Gaussian model, and the threshold for V channel is determined by double threshold method. The brightness in HSV colour space is separated to ensure the robustness.

(2) A dynamic window is proposed and updated in each frame for narrowing the target search area to further increase the efficiency of the vision system. The influence of sampling rate and dynamic window size on system efficiency and accuracy is evaluated in the experiments. The results show that the proposed vision system overcomes the mentioned problems and it can process the soccer video in real-time with detection rate of 99.68 % and precision of 99.92 %.

II. RELATED WORK

A. *Image Segmentation*

Small size leagues vision systems typically use color-based recognition method [9,20,25] compare with HSV, YUV and RGB color Spaces. They found that RGB color space is unstable, a small change would result in significant change of the color vectors [10,14,19]. Pang combines HSV and Lab color space for image segmentation [18], while Dai unites HSV and YCbCr color space for image segmentation [2]. Their work illustrates that a single-color space is far from enough to achieve a good classification result.

For the segmentation method, Pang introduces Ostu method based on histogram and K-Means clustering method respectively on three channels of image [18], however, it is fast but not meticulous [12,15,20]. Liu and Tang apply threshold segmentation based on background subtraction and contour search, which is relatively complex and extensive [13,21]. Yang and Lu construct a fine color lookup table with adaptive threshold which has more flexibility [23].

For threshold calibration, Naughton and Shu propose a simple fast double threshold approach: the double threshold approach resulted in two extensive cubes, it may lead to one color class is divided into several different cubes and pixels in one cube belong to several different color classes [16,20].

Aiming at this problem, Lu dividedes the segmentation threshold under the UV plane based on supervised Bayesian classification method [15]. Furthermore, Li expressess the threshold value as a set of small cubes in YUV space to get a more accurate threshold model [12]. Yang and Lu use a neural network to classify each pixel in the image [23]. However, the deep learning-based methods usually demand higher computing power and has certain requirements on the hardware of the device. In fact, those deep learning-based methods probably are not suitable for a multi-task and real-time system with low hardware configuration, such as small soccer robot competition.

B. *Object Recognition*

Identifying objects is one of the most crucial parts to the soccer robot visual system. Gao distinguishes different objects by the Barnett distance of the histogram and the Hamming distance of the gray map's *dHash* values between candidate area and the target template [4]. Chen and Meng use Hough transform to distinguish football [1,17]. However, local features can be affected by random noise easily, illumination variation for example, resulting in error accumulation. As shown in Fig. 2, the basic task of the soccer robot detection and recognition are based on their color tags.

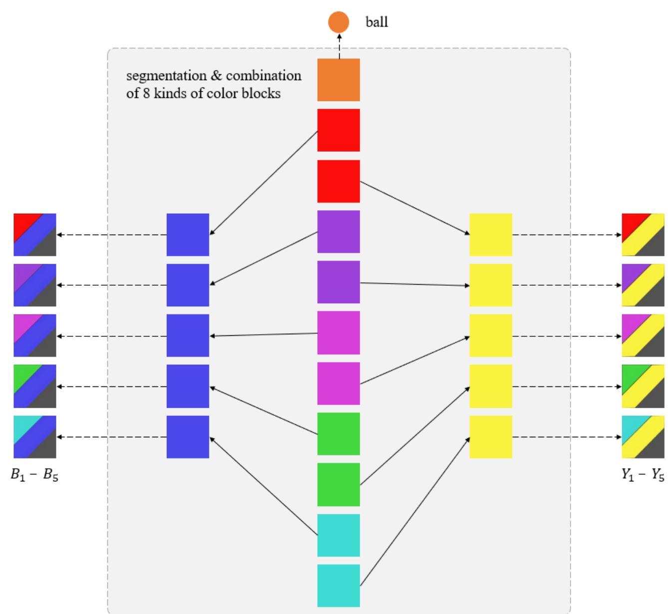


Figure 2. Target recognition process.

C. *Multi-Target Tracking in Dynamic Environment*

Tracking objects can preliminarily predict the possible locations of the robots so as to effectively reduce the searching area and increase the efficiency. The multi-target tracking algorithms include particle filter algorithm [5], mean shift algorithm [11,24,26] and Kalman filter method [6,7,26]. Kalman filter has solid performance with a low cost. If the interval between frame is small enough, the robots are making uniform linear motion approximately between adjacent frames.

Hence the system can easily obtain the acceleration of the target motion, thus the system can get more accurate tracking results. Therefore, we introduce Kalman filter-based target tracking mechanism into the vision system of small soccer robot.

III. METHODOLOGY

The pipeline of the small football vision system is shown in Fig. 3: we first use offline color table to classify all pixels in the image. Given a pixel whose color value is (H, S, V), we can directly look for its color class C in the pre-calculated color table. For binary images of each color category, morphological opening and closing operations are performed to filter noise (isolated points) and close the internal holes (internal missing point) in the binary images, then the connected area of the binary image obtained in the previous step is marked out. Next, we calculate the pixel area of each connected block, and filter out smaller invalid regions according to the area of the connected block.

Our vision system is based on color features, which overcomes the problem of adhesion in region of feature-based methods. The pipeline of the vision system is described as follows. The pixels' value (H, S, V) in HSV color space is classified by the offline color table first. For binary images, morphological opening and closing operations are performed to filter noise (isolated points) and close the internal holes (internal missing point). The connected area in the binary image which obtained in the previous step is marked out. The small invalid regions are filtered out according to the size of connected block.

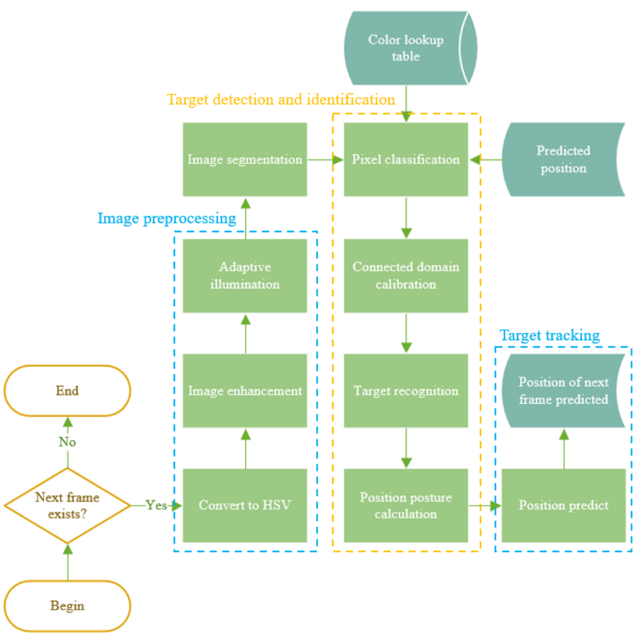
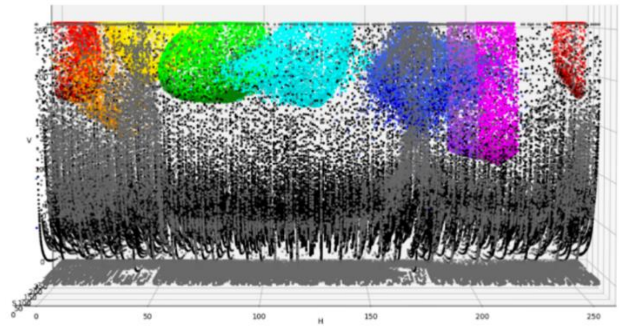
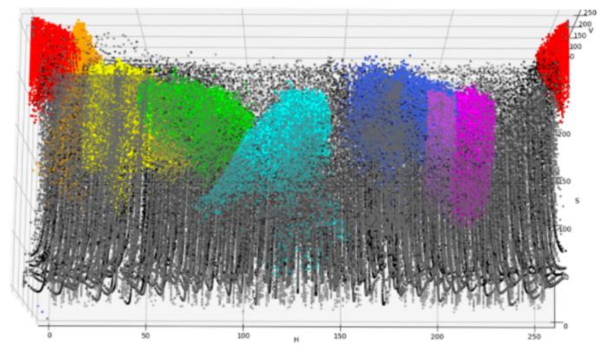


Figure 3. Flowchart of small soccer robot vision system.

The first and second moments of the color tag size, the tag center and the robot direction in the first and second frame is recorded. According to the pixel coordinates of the center between the team color logo and the players' color logo, we pair them based on minimum sum of distances method for identifying the target.



(a) Projection of pixels on HV plane.



(b) Projection of pixels on HS plane.

Figure 4. Visualization of color lookup tables for different categories.

A. Adaptive threshold Color Lookup Table

The color classification method based on three-channel threshold is fast but not meticulous. In this paper, we construct a fine color lookup table with adaptive threshold. It achieves good performance on the classification of the robots' tag colors. As the color cube obtained by the fast double threshold method has color confusion therefore it cannot be recognized easily, we combine HSV and Lab color space and adopt the following method in the system.

Firstly, for each color, the mean of Lab color space (l_{mean}, a_{mean}, b_{mean}) and H channel h_{mean} of the object's color block template were calculated, and the initial Lab distance threshold $threshold_{lab}$, the H distance threshold $threshold_h$ are set up. Then, the pixels whose the value of LAB color spaceand H channel are less than the threshold are filtered as valid. Subsequently, for each valid pixel p_{valid} the projection of its HSV space coordinate value (h_{vi}, s_{vi}, v_{vi}) in HS plane is formed as a valid set $\{valid\}$. Meanwhile, the corresponding [V_{vmin}, V_{vmax}] in V channel of each valid point is recorded separately. Thus, with the increase of valid points, the shape of the point set becomes a three-dimensional closed body gradually. Lastly, applying all the operation for eight color and obtain the color table, as shown in Fig. 4.

For distinguishing the overlapping sections in the HSV color space, naive Bayes classifier is used to classify the overlapping areas of color threshold. For the overlapping color thresholds, it is more likely to judge which color category HSV value belongs to in the region according to the Gaussian model. Assuming that colors in HSV space obey multivariate normal distribution, and

H, S and V components are independent. For any color class $c \in [0, N-1]$, the probability distribution can be expressed as follow:

$$p(c|h,s,v) = \frac{1}{\sqrt{2\pi}\sigma_h\sigma_s\sigma_v} e^{-\frac{1}{2}\left[\left(\frac{h-\mu_h}{\sigma_h}\right)^2+\left(\frac{s-\mu_s}{\sigma_s}\right)^2+\left(\frac{v-\mu_v}{\sigma_v}\right)^2\right]} \quad (1)$$

where $(\sigma_h, \sigma_s, \sigma_v)$ denote the variance of HSV color space and (μ_h, μ_s, μ_v) are the mean. They can be calculated from the valid pixels. Suppose one point (h, s, v) in the initial color table belongs to multiple classes $\{c_1, c_2, ...c_n\}$, it will be classified into the most likely color category according to: $c^\star = f(h, s, v) = \mathrm{argmax}\, p(c_i\,|h, s, v)$.

In order to speed up the retrieval process, the integrated color table is stored in the three-dimensional matrix color table $[h][s][v]$.

B. Adaptive Method of Dynamic Illumination

The vision system of a small soccer robot is in a semi-open environment, the lighting distribution is uneven in different areas and it will change with time. Therefore, for accurate color segmentation, adaptive threshold for color table is adopted.

The adaptive lighting measurement used in our system takes the image subregions as the basic unit. First, the image is divided into a series of 32 × 32 blocks, then the average value of the V component brightness of each block is calculated according to the off-line image set. For processing the real time video, the average value v_{on} of the V channel in each block is calculated, and get the difference between it and the offline average value $\Delta v = v_{off} - v_{on}$. Last, the V component of the pixels belongs to the same block are fine-tuned according to (2):

$$v' = v + k\Delta v \quad (2)$$

which is essentially fine-tuning the threshold for V component dynamically in the offline color index table. k is the inhibition coefficient and it is set as 0.3 according to the empirical experiment.

C. Multi-Target Tracking Based on Kalman Filter

In the football game, the targets are in a state of intense movement and moving at a high-speed, therefore the design scheme of the visual system must put the real-time performance of the system in an important position. Our system recognizes the targets based on the dynamic window method. The dynamic window refers to the window in which the target position may be located. It is inferred from the relevance of the target between frames. Assume that the interval between the first two frames is Δt_1, the period between the following two frames is Δt_2, the parameters of the target at $(k-1)_{th}$ frame is $p_{k-1} = [x_{k-1}, y_{k-1}, \theta_{k-1}]$, and the target at k_{th} frame is $p_k = [x_k, y_k, \theta_k]$. Since the time interval between frames is small enough, it can be considered that the target is moving in a uniform straight line within the time interval of two frames, and the speed of the target movement at the k_{th} frame is calculated as (3):

$$\begin{bmatrix} v_k \\ \omega_k \end{bmatrix} = \begin{bmatrix} \frac{x_k - x_{k-1}}{\Delta t_1} \\ \frac{y_k - y_{k-1}}{\Delta t_1} \\ \frac{\theta_k - \theta_{k-1}}{\Delta t_1} \end{bmatrix} \quad (3)$$

then we can predict the parameters of the target at $(k+1)_{th}$ frame as (4):

$$p_{k+1} = \begin{bmatrix} x_{k+1} \\ y_{k+1} \\ \theta_{k+1} \end{bmatrix} = p_k + \begin{bmatrix} v_k \\ \omega_k \end{bmatrix} \Delta t_2 \quad (4)$$

Assuming that the side length of the circumscribed rectangle of the robot target is R, the dynamic search window in the next frame is a rectangular area centered on (x_{k+1}, y_{k+1}), with the side length of R.

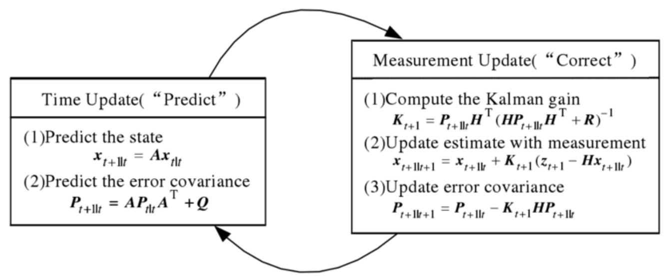


Figure 5. Status update diagram of Kalman filter.

The Kalman filter is a low-cost recursive filter for linear systems, which includes two stages: the stage of predicting the next state and the stage of updating the current state, as shown in Fig. 5, the continuous alternation of prediction and correction improves the prediction during the iteration.

D. Objects Identification

The vision system of a small soccer robot in this paper involves 5 robots in each team and a football, there are 11 targets need to be identified. The identification of these 11 goals relies on 8 different colors on the top: 2 colors denote the team, 5 colors for the roles and one for football. After using the color index table to classify all pixels and mark the connected domains, 21 connected domains will be obtained, as shown in Fig. 2. It contains 5 colors for player roles and each forming 2 connected domains. Two teams' color form 5 connected domains each, and one football color forming one connected domain. Then there are $(5!)^2 \cdot 2^5 = 460800$ possible solutions.

The color blocks are combined by minimizing the sum of distances between them. The areas of players' tag and the team's are determined according to their colors. The first-order moments are calculated for all areas, as well as the first-order and second-order moments for the team logo area. The first-order moment is utilized to find the position of the regional centroid, and the second-order moment is for finding the deflection angle of the region. The deflection angle of the team logo denotes the orientation of the robot.

For the two connected domains formed by the player color, calculate the distance between the connected domains of the players' identifications as well as the centroids of the connected team tags domains. Compare and obtain the blue and the yellow with the minimum European distance from the two connected domains formed by each team color. For example, taking the two connected domains r_1 and r_2 formed by the red player, calculate the blue team logo area and the yellow team logo area with the smallest distance to r_1, r_2. Assume that the blue area with the smallest distance to r_1 is bl_1, and its distance is $dist_1$. The yellow area (the other team color) with the smallest distance to r_1 is y_1, the distance is $dist_2$. The smallest distance of blue area with r_2 is bl_2, and its distance is $dist_3$. The smallest distance between yellow and $r2$ is $y2$. Its distance is $dist_4$. If $dist_1 + dist_4 < dist_2 + dist_3$, then r_1 and bl_1 are combined recognized as a combination of $target_2$, r_2 and y_2 are recognized as $target_7$, otherwise, r_1 and y_1 will be combined together forming $target_7$, r_2 and bl_2 will form a combination of $target_2$. After identifying the target, the centroid and orientation of the target can be calculated by calculating the moment of the color patch. If we define the center of gravity coordinate of the image as (x_c, y_c):

$$\begin{cases} x_c = \dfrac{M_{10}}{M_{00}}, \\ y_c = \dfrac{M_{01}}{M_{00}}. \end{cases} \tag{5}$$

$$\begin{cases} M_{00} = \sum_I \sum_J V(i,j) \\ M_{10} = \sum_I \sum_J i \cdot V(i,j) \\ M_{11} = \sum_I \sum_J j \cdot V(i,j) \end{cases} \tag{6}$$

Even if there is external noise interference, (5) and (6) ensure that the calculated centroid will not deviate too much.

If the orientation of the object is defined as θ:

$$\theta = \frac{1}{2}\arctan\left(\frac{2b}{a-c}\right), \theta \in [-90°, 90°] \tag{7}$$

where a, b, c are calculated as:

$$\begin{cases} a = \dfrac{M_{20}}{M_{00}} - x_c^2 \\ b = \dfrac{M_{10}}{M_{00}} - x_c y_c \\ c = \dfrac{M_{02}}{M_{00}} - y_c^2 \end{cases} \tag{8}$$

M_{20}, M_{20}, M_{20} are second-order moments for the area:

$$\begin{cases} M_{20} = \sum_I \sum_J i^2 \cdot V(i,j) \\ M_{02} = \sum_I \sum_J j^2 \cdot V(i,j) \\ M_{11} = \sum_I \sum_J i \cdot j \cdot V(i,j) \end{cases} \tag{9}$$

IV. EXPERIMENTS

In the experiments, the frame rate of the input video is 30 FPS. By balancing the sampling distance between frames and the width of the dynamic window, the real-time performance requirements are basically meet for processing every 4 frames and a dynamic window width of 200 pixels. For accuracy, we construct a three-dimensional irregular and a fine color look-up table to classify pixel colors, the accuracy reaches 99 %.

In addition, the system also uses the Laplacian Filter to sharpen the V channel of the frame in HSV color space. Based on the method used in this paper, we processed and analyzed the image with a sampling interval of 4 frames under the video input of 30 FPS. Experimental results will be illustrated in the next section.

A. Color Lookup Table Construction

Distribution of Color Block Pixels in HSV Color Space. Considering of the robustness to the lighting condition and the distinction between the color types of different color codes, HSV color space is selected in this paper. It can basically meet the first point, but as shown in the Fig. 4. The close distribution of some colors brings difficulties for recognition. Therefore, it is necessary to combine the Lab color space.

Visualization of Color Lookup Table. HSV and Lab color space are combined to construct a three-dimensional fine color lookup table and it is visualized in HSV color space, as shown in Fig. 4. In the experiment, recognizing blue purple and rose red have to be combined with $threshold_h$. As it is hard to distinguish yellow and sky blue in HSV space therefore we combine HSV color space and Lab color space.

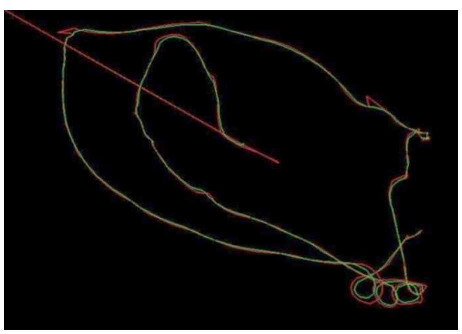
TABLE I. THE IMPACT OF SAMPLING FRAME DISTANCE AND WINDOW WIDTH ON THE TIME CONSUMPTION OF EACH MODULE.

Frame Step-Window Width	3-50	3-100	3-200	2-200	4-200
Time(s)	20.15	20.73	21.49	30.18	**15.4**
Detected Frames	148	149	149	221	111
Global Search Frames	7	**5**	**5**	9	6
Dynamic Window Frames	146	147	147	**219**	109
Fail Frames	5	**3**	**3**	7	4
Failure Frame Rate	0.03	**0.02**	**0.02**	0.03	0.035
Success Frame Rate	0.97	**0.98**	**0.98**	0.97	0.97

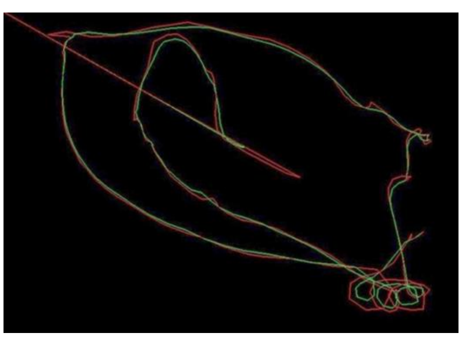
B. Kalman Filter

Trajectory prediction can reduce the range of the dynamic window and improve the real-time performance of the system. When the sampling rate between frames is small enough, it can be considered that the target is moving in a uniform linear motion between adjacent frames. The state transition equation of the Kalman filter can be obtained by using a simple formula of uniform linear motion displacement and velocity. If the interval is relatively long, the trajectory is unlikely to be a uniform straight line. Therefore, for obtaining an accurate tracking result, the external control quantity (the acceleration of the robot wheel) needs to be incorporated into the state transition equation, which requires the football robot controller system coordination. In Fig. 6 the green line denotes the measured value, and the red line represents the predicted value. The prediction error of the Kalman filter increases with the increase of frame distance.

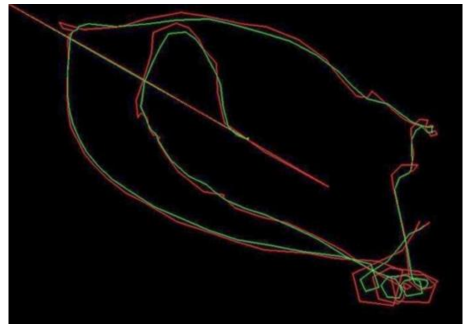
The sampling rate of the Kalman filter and the width of the detection window have significant influence to the accuracy and efficiency of the system. Therefore, the parameters set in the system have to balance accuracy and time consumption. TABLE I shows the impact of sampling frame distance and dynamic window width on the time-consuming and success rate of the vision system. TABLE I shows that when the sampling frame distance is fixed, the consuming time is increasing with the dynamic window width. The increase of the dynamic window can reduce the failure frame rate to a certain extent. After the dynamic window width exceeds to a certain value, the failure frame rate will no longer decrease with the increase of the window width. When the dynamic window width is fixed, the system time consumption decreases with the increase of the processing interval due to the reduce of frame number. However, the accuracy of the pose estimation will decrease with the increase of sampling rate.



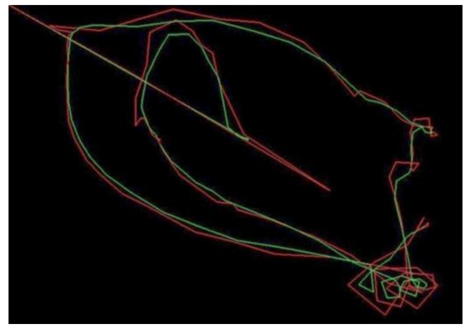
(a) Frame distance is 1.



(b) Frame distance is 2.



(c) Frame distance is 3.



(d) Frame distance is 4.

Figure 6. Comparison of Kalman filter effects under different sampling frame distances.

TABLE II. THE EFFECT OF DYNAMIC WINDOW SEARCH METHOD ON THE TIME-CONSUMING (MS) OF EACH MODULE.

	w/ Dynamic Windows	w/o Dynamic Windows
Pretreatment Time	**17.3**	19.1
Pixel Classification Time	**96.4**	107.4
Recognition and Pose Calculation Time	**15.0**	15.4
Target Tracking Time	**0.5**	0.6
Total Time	**130.2**	141.8

In the experiment, the sampling frame distance is set as 4 and dynamic window width is set as 200 in TABLE II. The real-time performance of the vision system has been improved after the dynamic window mechanism introduced. TABLE II shows that among the various steps of target recognition, the most time-consuming module is looking up table and pixel classification. The fastest module is Kalman filter. The system processes and analyzes one frame at a sampling interval of every four frames in a 30 FPS video. The success detection rate is 99.68 % and the accuracy is 99.92 %, which can meet the requirements of small soccer robot vision system.

V. CONCLUSIONS

The soccer robot competition is an interdisciplinary topic and can be used as a comprehensive test platform for various theories and algorithms in many fields such as artificial intelligence. There exist various problems that affect the vision system's performance. Among them, the illumination condition is a particular intractable problem. Aiming at this issue, we put forward a fine three-dimensional adaptive color classification method in this paper. The method combines and optimizes a real time double threshold determination method and two-dimensional Gaussian model for a better colour segmentation performance. The boundary of colour category in HS plane is divided according to Gaussian model and the threshold for V channel is determined by double threshold method. The brightness in HSV colour space is separated to ensure the robustness. Based on the proposed colour segmentation method and various optimization, our vision system can process the soccer videos steadily in real-time with high precision.

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REFERENCES

[1] Z. Chen, "Application of Random Hough Transform in Ball Recognition of Robocup," Industrial Control Computer, vol. 29(05), pp. 95–97, 2016.

[2] T. Dai, J. Cai, H. Zheng, H. Lin, Y. Yang, and M. Yan, "Multi-color Space Joint Adaptive White Blood Cell Threshold Segmentation Method," Journal of Fujian Computer, vol. 27(09), pp. 102–104, 2011.

[3] A. Ferrein and G. Steinbauer, "20 Years of Robocup," KI-K¨unstliche Intelligenz, vol. 30(03), pp. 225–232, 2016.

[4] Y. Gao, "Color-shape Based Target Recognition and Localization with Omnidirectional Camera in Mobile Robot," Master's thesis, Chongqing University, 2017.

[5] S. Hu, "Research on Visual Recognition and Tracking of Soccer Robot Based on Robocup," Master's Thesis, Harbin Engineering University, 2018.

[6] Z. Huang, L. Chen, J. Li, Y. Wang, Z. Chen, L. Wen, J. Gu, P. Hu, and R. Xiong, RoboCup 2018: Robot World Cup XXII, Lecture Notes in Computer Science, Springer, 2019.

[7] L. Huo, "Research on Template Matching and Probability Data Association in Video Tracking with Kalman Filter," Master's thesis, Liaoning Normal University, 2011.

[8] H. Kitano, M. Tambe, P. Stone, M. Veloso, S. Coradeschi, E. Osawa, H. Matsubara, I. Noda, and M. Asada, The Robocup Synthetic Agent Challenge 97, Heidelberg: Springer Berlin Heidelberg, 1998.

[9] C. Li, "Research and Design of the Vision Sub-system in Small Size Soccer Robot," Master's thesis, Dalian University of Technology, 2007.

[10] F. Li, W. Jin, W. Chen, Y. Cao, X. Wang, and L. Wang, "Global Color Image Enhancement Algorithm Based on Retinex Model," Journal of Beijing Institute of Technology, vol. 30(08), pp. 947–951, 2010.

[11] J. Li, "Research on Image Processing and Path Planning for Soccer Robot," Master's thesis, Southwest Jiaotong University, 2017.

[12] S. Li, "Vision Based Self-localization of Humanoid Robot," Master's thesis, Zhejiang University, 2013.

[13] J. Liu, "Construction of Robocup Small Size Soccer Robot Vision System," Master's thesis, Zhejiang University, 2007.

[14] J. Liu, "A research of Color Image Enhancement Technology Based on Retinex Theory," Master's Thesis, Xi'an Institute of Optics and Precision Mechanics, Chinese Academy of Sciences, 2015.

[15] L. Li, L. Wanchun, and L. Ling, "Robust Object Recognition based on Color Segmentation in Robot Soccer Domain," Computer Engineering and design, vol. 25(11), pp. 2093–2095, 2004.

[16] M. McNaughton and H. Zhang, "Color Vision for Robocup with Fast Lookup Tables," in IEEE International Conference on Robotics, Intelligent Systems and Signal Processing, vol. 3(1) pp. 399-404, 2003.

[17] X. Meng, L. Li, and L. Luo, "The Identification of Target Red Ball and the Fast Ball Finding Strategy of Nano Robot in Robocup," Computer Knowledge and Technology, vol. 9(24), pp. 5515–5519, 2013.

[18] X. Pang, Z. Min, and J. Kan, "Color Image Segmentation Based on HSI and LAB Color Space," Journal of Guangxi University: Nat Sci Ed, vol. 36(06), pp. 976–980, 2011.

[19] J. Ren, "Research and Implementation of Color Image Enhancement Algorithms," Master's thesis, Wuhan University of Technology, 2013.

[20] J. Shu, "Research and Design of SSL Vision System," Master's thesis, Hubei University of Technology, 2009.

[21] F. Tang, J. Li, F. Xie, and J. Han, "Soccer Robot Target Recognition Based on Conversion of Multi-color Models," Journal of Fujian Computer, vol. 33(01), pp. 34–35, 2017.

[22] E. Torres and A. Weitzenfeld, "Robocup small-size league: Using neural networks to learn color segmentation during visual processing," in 2008 IEEE Latin American Robotic Symposium, pp. 14-19, 2008.

[23] X. Yang and Y. Lu, "An Adaptive Threshold for Color Image Segmentation and Object Recognition," Computer Digital Engineering, vol. 34(08), pp. 15–17, 2006.

[24] L. Zhang, "Dynamic Image Object Identification and Tracking Research," Master's thesis, Xi'an University of Science and Technology, 2011.

[25] Y. Zhang, "The Recognition of Field Features Based on Vision System of Humanoid Soccer Robot," Master's thesis, Jilin University, 2013.

[26] H. Zhao, "Object Detection and Tracking Algorithm Based on Blob," Master's thesis, Harbin Institute of Technology, 2017.

[27] S. Zickler, T. Laue, O. Birbach, M. Wongphati, and M. Veloso, SSL-Vision: The Shared Vision System for the Robocup Small Size League, Heidelberg: Springer Berlin Heidelberg, 2010.