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A Playfield Detection Algorithm based on Local Consistency in Sports Videos

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Abstract

A playfield detection method exploiting both color and local consistency features are proposed. Color feature is used in existing playfield detection, which does not effectively remove green pixels that do not belong in the playfield. To solve this problem, local consistency feature is introduced, and the playfield is detected using both color feature and local consistency feature. To determine the detection threshold of local consistency, a two-dimensional histogram based method and a color constrained Otsu (cOtsu) based method are proposed, which are based on the principle of color characteristic and local entropy characteristic of playfield pixels, respectively. Experiments show that the proposed method is more effective and is able to detect playfield in several typical environments.

Keywords: local consistency; broadcast soccer video; object detection; playfield detection algorithm

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1. Introduction

To present competition status, cameras need to cover certain ranges. So, in the broadcast of football videos/images, the football field area and non-field area like the stands are included. Football games are played on the competition pitch. Key semantic objects and semantic events in videos are all found from the game playground. Areas like stands basically have no aided functions on the analysis of football video content. Besides, in detecting and tracking key semantic objects in videos, removing areas that are not part of the competition field is helpful to quicken detection speed and reduce false detection. So, before analyzing the contents of competition videos, finishing detection of the competition area is required so that areas that don’t belong to the game field are omitted [1,5,10].

Field detection is a foundation of plenty of content analysis tasks. In past investigations, lots of field detection methods based on color features have been proposed. Such approaches did field detection merely depending on color characteristics [2,12]. Hence, it’s not possible to effectively exclude non-field pixels that are similar to the field pixel color. The accuracy of detection results requires further improvement. Considered the perspective of a cognition process, playground detection can correspond to the selection of eye-watching places. In the human cognition system, an eye-watching area selection is implemented through an attention mechanism. To simulate such a kind of mechanism, [3] presented a visual attention model based on significance, which examed the significant properties of image pixels through three channel colors. From the calculation model of visual significance, the selection process of the eye-staring area can merge sensory information from a variety of features. In this case, it can enhance the performance of the court detection method by fusing multiple features to that method. According to such research thinking, this paper firstly analyzes characteristics of site pixels and then presents the approach based on color and local consistency according to the difference between color and local consistency of site pixels and non-site pixels [9].

2. Feature Extraction of Local Consistency

Another feature of playground pixel is quite similar to the grey value of pixels in its neighboring area, i.e. they have a favorable local consistency. From the distribution of local grey value, the area with higher local consistency has a well-

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proportioned grey distribution; its histogram often peaks, which suggests that the area complexity is low; otherwise, the area with lower local consistency has messy grey distribution; its histogram tends to be plat, indicating that the area complexity is high. In short, the local consistency of the court pixel is high so that the local complexity is low. On this regard, the local consistency of field pixel can be measured through the complication of the local pixel value. It is shown in Figure 1.

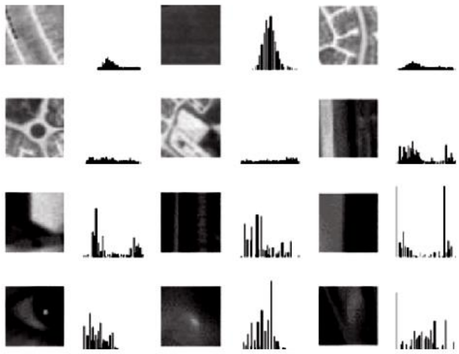


Figure 1. Examples of the local histograms of intensity

Complication of the signal is evaluated by the size of entropy. In information theory, Shannon entropy is the measurement of uncertainty. The size of the entropy value is closely related to the complexity of the signal. The more complex the signal is, the more uncertain it becomes and the relative entropy value grows bigger. On the contrary, the more orderly the system is, the lower the uncertainty maintains and the entropy value gets smaller [8]. The complexity of the image can be measured through image entropy. Image entropy was raised by Shiozaki as per the definition of Shannon entropy. Its specific calculation method is shown in Equation (1).

$$H(p(x_i)) = -\sum_{i=1}^{n} p(x_i)\log(x_i) \tag{1}$$

Where, x_i is the grey value of the pixels in the image. $p(x_i)$ is the probability of the grey value x_i in the image. Like information entropy, image entropy can reflect the size of the information quantity contained in the image. The distribution of pixel values that constitute the image is uncertain, meaning that the information amount carried by the image is bigger and the value of $H(p(x_i))$ is bigger. Based on that feature, Kadir and Brady investigated the measuring method of image local complexity according to image entropy. According to their analysis, without domain knowledge, people are inclined to capture parts that have the structure of the image. That's why complex areas in the local mode easily draw the visual attention of human beings. Therefore, they establish the mapping between local complexity and human visual stimulation perception. An image saliency calculation method based on Shannon entropy [4] is proposed. It is shown in Equation (2).

$$H_{D,R_X} = -\sum_i P_{D,R_X}(d_i)\log_2 P_{D,R_X}(d_i) \tag{2}$$

Where, X is the current pixel point; R_X is a local neighborhood of X ; D is the range of X , $P_{D,R_X}(d_i)$ is the probability of the occurrence of d_i in the neighborhood R_X . On the basis of the above analysis, the complexity of the neighborhood of the site is lower than that of the non-site pixel. The local image has a lower entropy. Therefore, the significance of site detection is inversely proportional to the significance of Kadir and Brady. According to this feature, this paper uses local image entropy to measure the local consistency of the image. In the calculation process, the grey version of the image to be processed in Equation (2) is used in the calculation of the image D. Thus, the significant features of Equation (2) can be transformed into local image entropy. To sum up, the main steps of extracting local consistency features are:

1. According to Equation (3), the color of the image to be analyzed I into the grey image I_g.

$$I_g(x,y) = 0.298 \times r(x,y) + 0.587 \times g(x,y) + 0.14 \times b(x,y) \tag{3}$$

2. For each pixel in I_g, the neighbourhood sub-image is extracted. It is shown in Equation (4).

$$I_l = \{I_g(i, j) \mid i = x+4, j = y+4\} \tag{4}$$

3. According to (1), calculate I_l image entropy $e_{l.}$

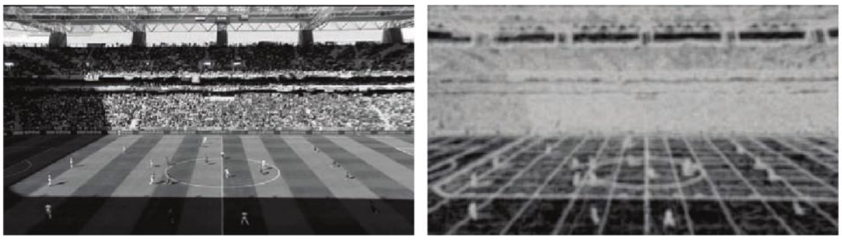
According to the properties of entropy, we can know that the maximum value of image entropy

$$H_{\max} = -\log_2(\frac{1}{256}) = \log_2(256) = 8$$

In order to facilitate the analysis, this paper will I_e zoom to the [0,255] of the grey space. Achieve the entropy image zoom according to Equation (5).

$$I_e^s = rongd(I_e \times 32) \tag{5}$$

Where round $(\times)$ is the integral function. A sample entropy image zoom is shown in Figure 2(b). As seen from the comparison of Figure 2(a), pixels in the ground area have lower local image entropy, while pixels out of the playground area have higher local image entropy. For light inconsistency, differences occur in local image entropy in different positions of the game site area. However, compared to other areas, local image entropy of play site area pixels is still smaller than that of the non-site area. From Figure 2(b), we note that local image entropy of pixels in the foreground object area is higher than game site pixels; pixels of the foreground object take a tiny portion of game site pixels, with less influence on the result of playground detection. In the meantime, in Figure 2(b), local image entropy of pixels belonging to sky area is very small, because the local consistency of its pixels is higher, and this causes wrong detection. Since the principal color of the sky is blue, this false detection can be filtered through color feature.



(a) Gray image (b) Entropy image

Figure 2. An example of entropy image

In summary, the local image entropy can effectively measure the local consistency of the pixels in the field. The site area and non-site area are well differentiated. In general, the complexity of the site area is relatively low, and the local image entropy is smaller than that of the non-site area. By setting the appropriate threshold value, the distinction between the local image entropy and the non-site pixels can be obtained.

3. Selection of Local Consistency Detection Threshold

In order to achieve the result of site area detection based on local consistency, it is necessary to determine the detection threshold of local image entropy. Different game video clips are taken in different natural environments. Of them, the local image entropy does not have a certain pattern, so it is not possible to employ the fixed detection threshold. However, a detection threshold of local consistency must be chosen according to the features of the videos/images. To increase the practicability of the algorithm, the paper puts forward two kinds of selection methods for the local consistency detection threshold.

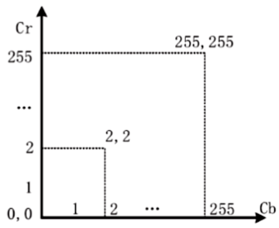
3.1. Selection of Local Consistency Detection Threshold Based on 2-Dimension Histogram

In football match videos, game field pixels play a big proportion. Since the color value of site pixels is mutually close, these pixels are located in the densest color area in the image color histogram, which is called the principal color area. According to that principle, we introduce in this part a local consistency threshold selection approach based on a 2D histogram. The basic idea of it is to detect the main color area in the image through a 2D histogram; then, from the main color area, select an area which has less interference and uses the image entropy of the area as the acquired local consistency detection threshold. Relevant researches on the field area detection reveal that in the color space $YCbCr$, the 2D histogram $CbCr$ can roughly locate the main color area in the image [6]. The color space $YCbCr$ is derived from YUV color space, where Y is the brightness component, Cb is the blue color, and Cr is the red color. Transformation relations between the $YCbCr$ color space and RGB color space are shown in Equation (6):

$$\begin{pmatrix} Y \\ Cb \\ Cr \\ 1 \end{pmatrix} = \begin{pmatrix} 0.299 & 0.587 & 0.114 & 0 \\ 0.168 & -0.331 & -0.500 & 128 \\ 0.500 & -4.187 & -0.813 & 128 \\ 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \\ 1 \end{pmatrix} \tag{6}$$

The Cb, Cr 2D-histogram is obtained by the number of [Cb, Cr] in the statistical image. The schematic diagram of the calculation process is shown in Figure 3(a). Set I_{Cb}, I_{Cr}, and the images of the Cb and Cr components, and then the two-dimensional histogram of I_{Cb} and I_{Cr} can be expressed as Equation (7).

$$H(Cb, Cr) = \sum \Pr\{\{I_{Cb} = Cb\} \cap \{I_{Cr} = Cr\}\} \tag{7}$$



(a) Schematic of 2D histogram

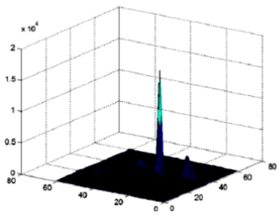

(b) Example of 2D histogram

Figure 3. Example of the 2D histogram on $CbCr$ for soccer video image

Where, $\Pr\{\cdot\}$ indicates whether the event occurred. $H(Cb, Cr)$ indicates the number of events that occur. In the 2D histogram, there are a few noticeable peak areas and colors in the image gathered around those peak areas. From the features of color distribution of competition videos/images, we know that the uppermost color value in peak areas are that of Cb, Cr to which the field area pixels correspond. To conclude, the detection method of the main color in the playground area is shown as Algorithm 1.

Algorithm 1 Domain color regions detection algorithm

Input: Image to be detected, I

Output: Main color set, R

1. According to the Equation (2), the I will be converted to $YCbCr$ color space;
2. According to Equation (3), the calculation I of the two-dimensional histogram H_{2d};
3. $P_1 = \max(H_{2d})$;
4. $sum_1 = sum(H(x_1+1, y_1+1))$;
5. If $sum_1 > 0.5$ then
6. $R = (x_1+1, y_1+1)$;
7. Else
8. $H_{2d}(x_1+1, y_1+1) = 0$;
9. $P_2 = \max(H_{2d})$;
10. $i_2 = x_2+1, j_2 = y_2+1$;
11. $R = ((x_1+1, y_1+1) \cup (x_2+1, y_2+1))$;
12. End

With the algorithm, the main color area is detected, of which the black portion is the main color area. Through analysis of the figure, we learn that the method can detect most of the site area, although certain regions are missed because of light impacts. Not all site areas can be detected, but lots of playground pixels are included in the main color area, which can be applied to determine the image entropy value of game site area. It is shown in Figure 4(a). As a result, we determine the detection threshold for local consistency by the following steps:

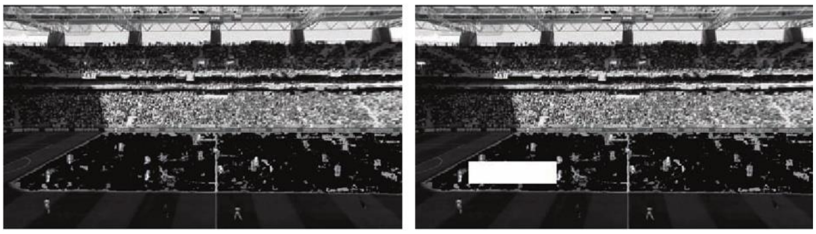
1. Input image I according to Algorithm 1 detection of the main color pixels C_d.

2. All pixels in p_i in I, if $p_i(Cb,Cr) \in C_d, p_i = 0.$

3. In I, determine a rectangular area RA.

4. Calculate RA entropy E_{RA} and set the local consistency threshold $T_e = wE_{RA.}$

The main idea of the above procedure is to select a region of minimum interference from the main color region RA. Then, the entropy of the image of the region is the detection threshold of local consistency. In this paper, the typical value of the rectangular area is RA = 20×10. The white area is the template area selected for the process in Figure 4(b). In the detection process, the first frame image of the test sequence is selected as the template image to determine the local consistency detection threshold.



(a) Domain color region (b) Template region

Figure 4. Example of domain color region and template region for threshold selection

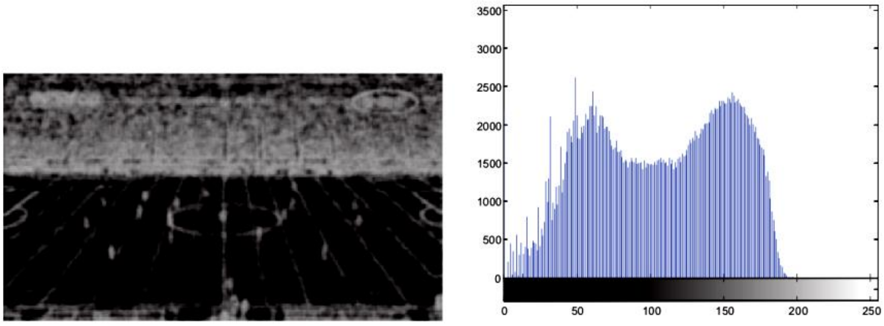
3.2. Selection of Local Consistency Detection Threshold based on the Maximum Between-Class Variance (otsu) Method of Color Constraint

The selective method of local consistency threshold based on a 2-dimensional histogram makes use of a given template image to choose the threshold, relying largely on template image with limited generalization ability. In order to detect various kinds of football pitches and improve the generalized capability of the method, the paper introduces a local consistency threshold selective method that is based on the maximum between-class variance (otsu) method of color constraint. The approach can decide detection threshold with reference to distributive characteristics of entropy image with no need for a template image. It has better generalization and can be used to detect varied types of football fields in a more stable manner. The objective of the local consistency threshold selection is to divide the local entropy image into a site area and non-site area with the use of a selected threshold. When the variance between the site and the non-site areas becomes the biggest, the resultant division is the best. The maximum variance between them implies that the maximization of between-division results varies. Based on that feature, the paper applies the maximum between-class variance method, i.e. Otsu method [7], to choose the detection threshold of local consistency. Faced with the actual application scenario, it's not probable to get ideal results from the direct application of the Otsu method. To obtain better site detection results, in this part we firstly analyze features of the selected threshold by the Otsu method by referring to those of the local entropy image; then, in accordance with features of site detection, we optimize the criterion function of it; finally, we propose the maximum between-class variance method of color constraint (Color Constrained Otsu cOtsu).

The fundamental idea of the Otsu threshold-selective method is: regard between-class variance as the discriminate criterion; select grey values, which makes between-class variance the biggest partition threshold. The method has advantages of wide application, simplicity and effectiveness. It has gained extensive application in the selection threshold of image binarization. Based on Xu et al., the Otsu selected threshold has the property of t^* [11]. It is shown in Equation (8).

$$t^* = \left(\frac{1}{2}(\mu_1(t^*) + \mu_2(t^*))\right) \tag{8}$$

Where $\mu_1(t^*)$ is the grey means of the first kind of pixels after segmentation. $\mu_2(t^*)$ is the grey mean of the second kind of pixels after segmentation. t^* is the average value of two kinds of grey segmentation. Therefore, t^* in general, is located between the two peak area histogram. The higher the intraclass variance is, the more dispersed the distribution of intraclass pixels becomes, and the bigger the average distance from within-pixel to within-class expected value will be. Thus, the distance of intra-class pixel values that are close to edges is further from the intra-class expected value. So, the maximum between class variance criterion can enable t^* to keep close to the side with bigger intraclass variance. In the local entropy image, the non-site area's local image entropy is higher so its intra-class variance is smaller. However, the site area contains partial pixels that are disturbed. It is shown in Figure 5. To sum up, the above analysis, t^* locates in the place near the lower peak value between the two peaks. The utilization of that threshold to segment local entropy images may lead to false detection of pixels of some sites.



(a) Local entropy image (b) Histogram of local entropy image

Figure 5. Example of local entropy image and its histogram

The pixels in the field differ from the non-ground pixels in color and local consistency. Therefore, the local entropy image segmentation criterion should be composed of two factors of color and local consistency. Based on this idea, this paper proposes the maximum between-class variance (otsu) method of color constraint. The cOtsu method consists of three main steps, namely, the computation of the variance between classes, color constraint computation and optimal threshold selection. The paper will describe these steps in turn. First, the calculation of the interclass variance. Assume the local entropy image to be segmented by the L level is (0,1,2,..., $L-1$), and the local image entropy as the number of pixels i is f_i. It is shown in Equation (9).

$$f_i = \frac{f_i}{N}, p_i \geq 0, \sum_{i=1}^{L} p_i = 1 \tag{9}$$

According to the local image entropy, the local entropy image is divided into C_1 and C_2. Where, C_1 contains the local entropy 0 to t pixels and C_2 contains the local entropy $t+1$ to $L-1$ pixels. Therefore, the cumulative probability and mean of C_1 and C_2 are shown in Equation (10) and Equation (11).

$$w_1(t) = \sum_{i=1}^{t} p_i, \mu_1(t) = \sum_{i=1}^{L} \frac{ip_1}{w_1} \tag{10}$$

$$w_2(t) = \sum_{i=t+1}^{t} p_i, \mu_1(t) = \sum_{i=t+1}^{L} \frac{ip_2}{w_2} \tag{11}$$

According to Equation (10) and (11), for any t value, Equation (12) was established:

$$w_1(t) + w_2(t) = 1 \tag{12}$$

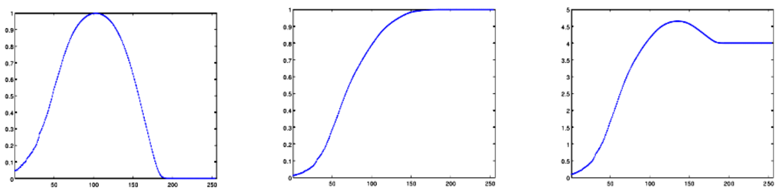
After calculating the variance of the class, the color constraint of the image to be analyzed is calculated. According to the characteristics of the site pixel, this paper defines the green constraints $\tau(t)$ as shown in Equation (13).

$$\tau(t) = \frac{Count(P_d(t))}{Count(P_g)} \tag{13}$$

In this paper, we study the optimal threshold selection of local consistency. As mentioned above, the local consistency threshold selection process should take into account both the color constraints and the maximum interclass variance constraints. According to the characteristics of the field detection, this paper proposes the maximum class variance criterion function, which is shown by Equation (14).

$$\xi(t) = \sigma_b^2(t) + \beta\tau(t) \tag{14}$$

In the cOtsu criteria shown in Equation (10), $\sigma_b^2(t)$ reflects the degree of satisfaction of the largest class of variance constraints. $\tau(t)$ reflects the degree of satisfaction of color constraints. The greater the value of $\sigma_b^2(t)$, the more $\xi(t)$ is bound to meet the maximum between-class variance. The greater the $\sigma_b^2(t)$ value is, the more satisfied the color constraint $\xi(t)$. The relative weights between $\sigma_b^2(t)$ and $\tau(t)$ are regulated by β. Its typical value is β = 4. Figure 6 shows an example of the change in $\sigma_b^2(t)$, $\tau(t)$ and $\xi(t)$. The maximum value of $\xi(t)$ is slightly higher than that of $s_b^2(t)$.



(a) Change example of $\sigma_b^2(t)$ (b) Change example of $\tau(t)$ (c) Change example of $\xi(t)$

Figure 6. Change example of $\sigma_b^2(t)$, $\tau(t)$ and $\xi(t)$

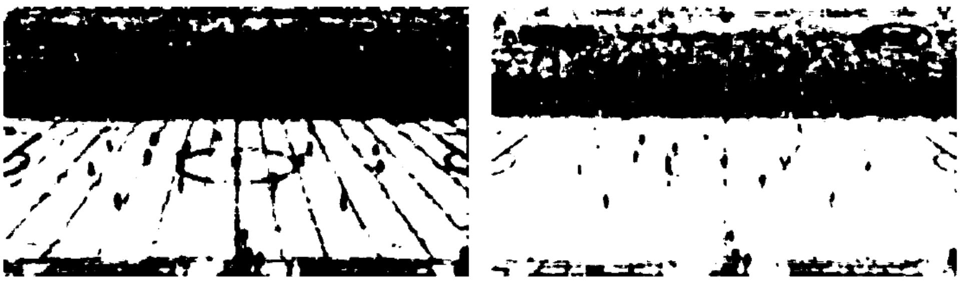
According to the characteristics of $\xi(t)$, use Equation (15) to determine the optimal threshold t^*.

$$t^* = \arg\max_{1<t<L}\{\xi(t)\} \tag{15}$$

In general, the local image entropy of the site pixel is smaller than that of the non-field pixel. Therefore, this paper, based on the local consistency of Equation (16), carried out the local consistency of the site detection.

$$M(x,y)e = \begin{cases} 1, ifE(x,y) < t^* \\ 0, ifE(x,y) > t^* \end{cases} \tag{16}$$

The local consistency of the results is obtained from Equation (16). It is shown in Figure 7. The cOtsu method proposed in this paper can be more effective in reducing the false detection of the pixel in the field.



(a) Detection example of the Otsu (b) Detection example of the cOtsu

Figure 7. Examples of local consistency detection result

Sum up the above description. The main objective of this paper is to propose a method based on cOtsu for local consistency detection:

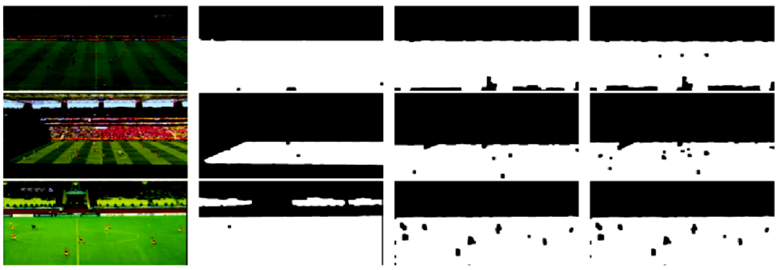
1. Reads in the image to be analyzed and converts to grayscale images;
2. According to Equation (6), calculate the entropy of image I_e^s;
3. According to Equation (9), calculate the entropy $\sigma_b^2(t)$ in different image segmentation thresholds;
4. According to Equation (10), calculate the image color constraint $\tau(t)$;
5. According to Equation (11), calculate $\chi(t)$;
6. According to Equation (12), obtain the optimal threshold t^*.

4. Experimental Design and Discussions

The major challenge of football field detection is variations of pixel pattern caused by different environments. So, the evaluation of site detection method should consider the effect of different environmental factors. Typical environmental conditions to be considered in field detection include uniformly illuminated surroundings, shadowy circumstances and green regions of audience stand areas. Here we'll validate the effectiveness of the proposed method from the above 3 conditions. To be specific, #1 is the video of an evenly illuminated site; #2 is the video of a shadowy site; #3 is the video of a vast green pixel area of audience stands. #1 and #2 are respectively videos of competition between Netherlands and Spain and between Honduras and Chile in the 2014 World Cup, which last 99 frames and 93 frames; #3 is the video of Spartacus and Žilina in the UEFA Europa League 2014, which lasts 52 frames. The size of videos adopted for the experiment is adjusted to 720x404. In the field detection method based on color, Hung et al. recently showed a color clustering method that made fine detection effects. So, in this paper, we use that method to compare detection results. Color clustering method and the proposed method both acquire initial detection results by removing smaller falsely detected areas of the results through morphological close operations, small area deletion and open operations.

4.1. Visual Contrast of Field Detection Results

Visual contrast compares detection results of field detection methods through visual observations. It's simple and intuitive, which can qualitatively compare the detective performances of such methods. Therefore, in this paper, first of all, the visual comparison of the results of the field test is carried out. Figure 8 shows the sequence from the top-to-bottom area from #1 to #3 video detection results. Where, the color clustering method, the 2D histogram threshold method, and the cOtsu threshold method are presented in this paper. They are shown in Figure 8(b), Figure 8(c) and Figure 8(d).



(a)Video images (b)Color Cluster (c)Threshold by two-dimensional histogram (d) Threshold by cOtsu

Figure 8. Visual comparison of the playfield detection results

In the case of fine illumination, field detection results by each method are shown in the first row in Figure 8. As observed carefully, each method can find most field pixels. The color clustering method, the proposed 2D histogram thresholding method and the Otsu method achieved identical detection results without significant differences. Through in-depth comparisons, we find detection results by each method differ slightly only in the foreground object area. On the whole, such a difference is acceptable and has little impact on other content analysis tasks. The detection results by each method in the shadowy condition are put in the second row in Figure 8. From them, we note that a big range of missing detection occurred in the detection result by the color clustering method; that's because the luminance value of pixels in shadowy areas are lower; the color clustering method regards pixels of it as part of a grey area. Comparatively, the method of merging color and local consistency in this paper describe more thoroughly features of site pixels; no wide scope of missing detection is found in the detection result. Detection results of green pixels beyond the football pitch are listed in the third row in Figure 8. As seen clearly, the color clustering approach doesn't effectively eliminate green pixels of the competition site. Green pixels beyond the pitch and those on the pitch are approximate to the green color. The color clustering method utilizes merely a color feature so it hardly removes those green pixels from the detection result. On the contrary, the proposed solution here employs color feature and local consistency, and it better differentiates green pixels in the pitch area and others; so, a fewer number of pixels are falsely detected in the detection result.

4.2. Quantitative Comparisons of Football Pitch Detection Results

Unlike visual contrast, the quantitative comparison can more precisely find the differences in detection results by those methods. Hence, we calculate the quantitative values of each method's detection results. Before our job, we annotate pitch pixels in tested videos; then, we compare the marked competition areas and detection results by each method; lastly, we get quantitative comparative indicators of detection results. Here, we use precision and recall rate to do quantitative appraisal and comparison of detection results. The calculation methods are shown in Equations (17) and (18).

$$\Pr ecision = \frac{tp}{tp + fp} \tag{17}$$

$$\operatorname{Re} call = \frac{tp}{tp + fn} \tag{18}$$

The accuracy and recall rate of the test results are obtained by using the above method. In this paper, the fusion color and local consistency of the site detection method are proposed to obtain better detection results.

Table 1. Quantitative comparison of the playfield detection results

Video Number	Color clustering method		2D histogram threshold method		cOtsu threshold method	
	Accuracy	recall	Accuracy	recall	Accuracy	recall
#1	94.92%	99.83%	95.96%	99.58%	98.15%	94.67%
#2	92.00%	56.12%	97.65%	92.76%	96.96%	94.33%
#3	84.80%	99.99%	94.30%	96.34%	95.39%	98.92%
mean value	90.62%	83.34%	96.61%	97.22%	96.93%	96.01%

The first row has quantified values of game site detection results computed by the use of video clip #1. In the condition of even illumination, the color clustering method and the proposed one fusing color and local consistency both realize benign detection results. In the tested video, each detection method achieves higher detection accuracy and recall rate. The Otsu thresholding method gets a lower recall rate in spite of higher detection accuracy. The reason is that pixels in a small part of a playground are undetected. Hence, a tiny difference occurs in the quantitative results. The second line is the quantification of field detection results with the use of video clip #2. Based on our observations, we see color clustering has a lower recall rate of detection because it easily regards pixels of lower brightness falsely as grey pixels, resulting in missed detection of field pixels in shadowy areas and thus, reducing the recall rate of its detection result. Conversely, the proposed method detects more precisely pitch pixels in shadows and maintains a higher level of both precision and recall rate. The third line is quantified detection results attained through video clip #3. The color clustering method's precision degree is slightly lower than the proposed approach, which merges color and local consistency. The reason for that is the former method mistakes green pixels of some non-pitch areas as pitch pixels, leading to partial wrong detection in the results. The proposed detection method blends color and local consistency, which better removes green pixels of non-pitch areas, so incorrect detection is less and accuracy is higher.

5. Conclusions

In this paper, the problem of field detection in soccer video content analysis is studied. The current site detection methods use the color feature in the location of image pixels and cannot effectively distinguish between the venue and outside the venue with similar color pixels. To solve this problem, this chapter proposes a new method based on color and local consistency. First of all, the characteristics of the appearance of the site pixels were analyzed, and the differences of the color and local consistency between the pixel and the non-site pixels were summarized. Based on these differences, the color features of the green ratio and the local consistency of the local image entropy based on the green ratio are extracted, and the two kinds of features were used to detect the site area. Threshold selection method based on two-dimensional histogram is proposed in order to determine the detection threshold of local consistency. In order to reduce the dependence on the threshold value of the selected template image, a selection method of local threshold color consistency constraints was produced based on Otsu. The automatic selection of the threshold of local consistency detection is realized. Finally, the color and local consistency of the site detection results are fused, and thus, the final detection of the site area is obtained. The experimental results show that the proposed method can improve the accuracy of the site detection method when compared with the color clustering method.

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