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Detection of Playfield with Shadow and its Application to Player Tracking

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Abstract

Playfield detection is a key technology for content analysis in sports video, on which many semantic clue mining methods rely. However, shadow produced by substantial illumination change causes the general detection method fail and degenerate the performance of the following processing based on it. This paper presents a method for detecting playfield, which can find shadow region under the guidance of the intrinsic image proposed by Finlayson. Firstly, this method automatically finds the dominant color; secondly, according to the dominant color and the intrinsic image, it determines the playfield colors. At last, we apply it to player tracking in soccer video. Experimental results show that the proposed method can handle the problem brought by shadow and improve the performance of the application based on it.

1. Introduction

Playfield detection and player tracking are key processes for content analysis in soccer video, which can provide useful information for semantic event detection, tactics analysis and so on [1,2].

Ekin [3] first proposed to use dominant color for shot type classification, since in general playfield occupies dominant color regions in many sports videos. In [4], Xie also used the dominant color to analyze soccer video. To detect the playfield more accurately, Jiang proposed to employ GMM to model the target colors [5], and Liu extended it to learn the model on line by incremental EM algorithm [6].

Besides the application to scene classification, player detection and tracking is another important application area. Researchers [7,8] detected players by background subtraction which is based on playfield detection. In these papers, the authors focused on multiple objects tracking, and proposed new method to tackle occlusion problem in it.

It is relatively easy to detect playfield without substantial illumination change; however, this problem will become intractable when large shadow exists which may degenerate the algorithms' performance based on the detection. Compared with these methods for playfield detection and player tracking, this paper pays attention on another crucial problem in it, which is brought by suddenly illumination chang. Although HSI and CbCr space exploited [5,6] can leverage illumination issue to some extend, they appear hopeless in the case of larger shadow existing, as shown in figure 1d. In this paper we propose to exploit intrinsic image [9] to help detect playfield with shadow, and then apply it to player track.

In next section, we present the method for playfield detection, and apply it to track player across shadow region in section 3. Experimental results and discussion are given in section 4, and the paper is concluded in the last section.

2. Detecting playfield with large shadow

This section delineates a method for detecting playfield with large shadow, including candidate playfield colors detection and the true playfield colors determination via the guidance of intrinsic image.

2.1. Candidate colors detection

As pointed out in [6], the playfield colors usually correspond to one or some of the highest peaks in hue or CbCr histogram of a video sequence, as shown in figure 1. Thus, existing methods [3,6] find the color through extracting these peaks in the histograms. This paper exploits our prior proposed method in [6] to detect the main peaks in CbCr space. In short, the highest peak is extracted through connected region analysis first, and then the peak is deleted from the histogram; next, the second highest peak is detected in

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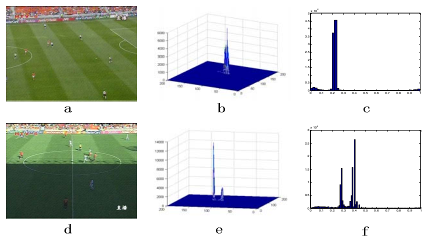


Figure 1. soccer video sequences and their accumulated histograms, in which a and d are two sample frames of two sequences; b and e are their histograms in CbCr space; c and f are their histograms in hue space.

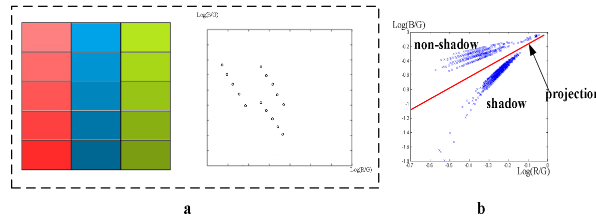


Figure 2. A is a illustation of intrinsic image, the left colum is a image of 3 color patch under 5 illuminations, and the right shows the pixels data in log-chromaticity space; b shows the distributions of shadow and non-shadow regions of playfield.

the remained histogram, and so on. Thus, some candidate colors for describing playfield are automatically found from the accumulated histogram.

In generally, the largest peak corresponds to the target color. However if there exists large shadow on playfield, new method has to be designed to tackle the problem, because we cannot determine which one or some of the peaks are corresponding to the true field colors. In the next section, a new method is presented, which can find the playfield with large shadow under the guidance by intrinsic image [9].

2.2. Playfield colors determination

Substantial illumination change will cause the playfield with the same reflectance characteristics to appear different color. From e and f in figure 1, it can be found that the colors of shadow and non-shadow region in playfield cluster into two peaks, despite the fact that CbCr and hue spaces are invariant to luminance change to some extend. In order to further eliminate the negative effect, which may confound many methods in computer vision, researchers try to devise new image feature independent of illumination.

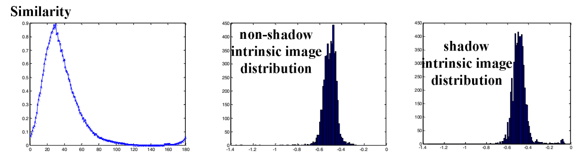
The intrinsic image proposed in [9] is such an image. Different from most researchers, they make it through physical rather than image processing approach. Based on the assumptions of Lambertian reflectance, approximately Planckian lighting and narrowband camera sensors, they derived a formula which implies the pixels of a surface (with the same reflectance properties) under different illumination lie on a line in log-chromaticity space which is constructed by taking logarithm of {R/G, B/G}. Figure 2a gives a diagram for it, in which data of different patches under different illumination spread along a set of parallel lines. That is to say, if these data in log-chromaticity space are projected along the parallel line, illumination invariant image can be acquired. For more details, readers can refer to [9].

In generally, the projection direction is calibrated in lab, but it is unrealistic for broadcast video. Although [9] gave a method for the calibration by entropy minimization, it cannot work stably in this situation. Fortunately, we find that data of the region with similar color approximately obeys **normal distribution**, as illustrated in figure 3 (b) and (c). Thus, the projection direction is roughly calibrated, which can result in a more like normal distribution. The procedure is briefly described in procedure 1. We found that this method can give a close result, which is enough for determining the playfield colors. For example, the results produced by the data of shadow and non-shadow in figure 2 are 30 and 69 which are close to accurate calibration (in next section). In our experiments, we regard the result with the most like normal distribution as the projection direction, which is 30.

Procedure 1: Intrinsic image projection direction rough calibration

1. Select one candidate playfield color cluster;
2. For each degree from 1-180
   a) Project the cluster data;
   b) Compute the similarity between the projected data distribution and normal distribution through formula (2);
3. Return the degree with the maximal similarity.

The proposed system automatically determines the playfield colors from the candidate clusters detected in CbCr space using the algorithm in procedure 2. Once the playfield colors are determined, GMM is used to model the playfield in CbCr space [6]. Figure 5 shows some results of playfield detection and player segmentation based on the proposed method.



a b c

Figure 3. A is the similarity between shadow distribution and non-shadow distribution obtained by projecting data in figure 2b along 0-180 degree respectively; b and c are their distributions obtained by projection along the direction with the best similarity.

Procedure 2: Playfield color determination

1. Set the maximal cluster in CbCr as one of the playfield colors, named dominating color;
2. Compute the distribution of each candidate cluster projected along the calibrated direction;
3. Compute the similarity by formula (2) between the distribution of dominating color and the one of any other candidate cluster.
4. If the similarity is more than T (=0.5) and the region corresponding to the candidate cluster is connected to region corresponding to the dominating color, the candidate color is set as another playfield color.
5. Return all the determined playfield colors.

3. Application for player tracking

As pointed in preceding section, robust playfield detection paves the way for application based on it. Here, we focus on player track. First, players are segmented through region analysis, and readers can refer to [6] for details duo to space limitations. Figure 5 shows an example for player segmentation. Then the players are tracked based on appearance template using intrinsic image feature.

To alleviate the negative effect of shadow, appearance template is set up on intrinsic image. Although we have roughly calibrate the intrinsic image projection direction, more accurate calibration should be performed to acquire better representation of player appearance. Since the shadow and non-shadow color clusters in CbCr space, we can calibrate the intrinsic image projection direction by maximizing their distributions' similarity when these two cluster are projected from 1 to 180 degree, which is computed according to formula (1) and (2)

$$\theta^* = \arg\max_{\theta}(sim(H(\mathbf{I}_1(\theta)), H(\mathbf{I}_2(\theta))), \quad (1)$$

$$sim = \sum_{i=1}^{L} \min(H_1^i, H_2^i), \quad (2)$$

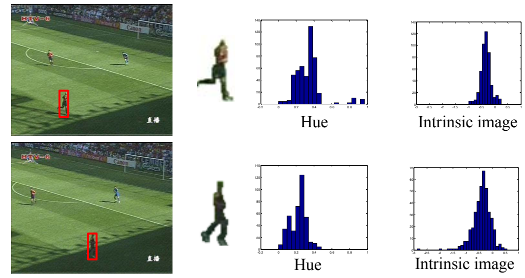


Figure 4. A player's histograms of hue space and intrinsic image space under different illumination.

where $I_1(\theta)$ and $I_2(\theta)$ are the sets of pixels in shadow and non-shadow regions projected along degree θ respectively. sim is the similarity of two distribution, and H_j^i is the i^{th} bin of the histogram j. The bin width is computed as (3).

$$bin\_width = 3.5std(\mathbf{I}_1(\theta) \cup \mathbf{I}_2(\theta))(N_1 + N_2)^{-\frac{1}{3}}. \quad (3)$$

Here, N_i is the number of elements in the i^{th} set. Figure 4 shows a calibration result and the intrinsic image distributions of shadow and non-shadow.

When players run into shadow region, the tracking method based on non-illumination invariant appearance template will fail to track the object. Here, intrinsic image is used for setting up appearance template. Figure 4 shows a player's appearance histograms of hue space and intrinsic image space under different illumination. According to the formula in (2), the player's histogram in hue space change more dramatically than the one in intrinsic image, and their similarities are 0.51 and 0.75 respectively.

Once players are detected, the minimal boxes around them are set as templates, these objects are tracked by Kalman filter, and sum of squared differences (SSD) is exploited to measure difference between candidate area and template. Different from standard SSD, we anticipate the criteria for best matching can strengthen object and restrain background. By this idea, the best matching area is determined via (4)

$$Area_{best} = \arg\min_{Area} \frac{SSD_{Obj-Area}}{SSD_{Bak-Area}}, \quad (4)$$

where $SSD_{Obj-Area}$ is the SSD between the object and candidate matching area, and $SSD_{Bak-Area}$ is the SSD between the background (playfield) and candidate matching area.

4. Experiments

To validate the proposed methods, we give two experiments including playfield detection and players tracking in the condition of with large shadow.

4.1 Playfield detection

In this experiments, playfield with large shadow in soccer video is detected based on the proposed the method. Figure 5 shows some detection results given by the proposed method. From the figure, we can see that intrinsic image effectively help tackle the problem brought by shadow while the traditional method can only detect the first dominant color (non-shadow or shadow region).

Figure 5. Results of playfield detection and player segmentation.

4.2 players tracking by intrinsic

To test effectivity of the players tracking method based on intrinsic image which is acquired by the calibration method proposed in this paper. In this experiment, we compare three appearance templates based on RGB, CbCr, and intrinsic image respectively. In the experiment, the method based intrinsic image can stably track the players running across shadow and non-shadow regions, while the other two methods will lose objects soon in this situation. Figure 6 shows the results obtained by the three methods, in which, columns a and b are results using RGB and CbCr space, and column c is the result by intrinsic image. As it shows, the player dressed white sport suit is lost when he run from non-shadow region into shadow region, in contrast, the proposed method can track him well whether he is in non-shadow, shadow, or across these two regions. More of this tracing result video can be downloaded from http://nclab.hit.edu.cn/liuyang~/.

5. Conclusion

The proposed method based on intrinsic image can automatically detect playfield with large shadow region, and it can also enhance the performance of player detection and tracking.

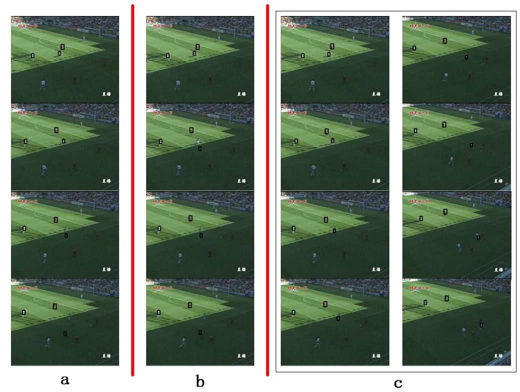


Figure 6. Result comparison among the based on three different appearance templates, including RGB (a), CbCr (b) and intrinsic image (c).

Acknowledge

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