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Contour-based strike zone shaping and visualization in broadcast baseball video: providing reference for pitch location positioning and strike/ball judgment

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Abstract The strike zone plays a crucial role in baseball. Pitches which pass through the strike zone count as strikes, three of which strike out the batter. Besides strike/ball judgment, the strike zone also provides the reference for positioning pitch locations, about which sports fans and professionals have an intense interest in compiling statistics. This paper presents contour-based strike zone shaping and visualization in broadcast baseball video. We first detect the home plate, which determines the vertical limits of the strike zone. Then, an efficient algorithm is designed for batter contouring and the points of curvature extremes on the batter's contour are computed to locate the dominant points which determine the horizontal limits of the strike zone. The experiments show that the proposed framework is able to shape the strike zone fairly well in various baseball sequences, needless of manual operation and additional camera setting. The proposed strike zone shaping and visualization will be able to assist in pitch analysis and statistics compiling.

Keywords Sports video · Semantic analysis · Game statistics · Visual enrichment · Object segmentation · Multimedia system

1 Introduction

With the advance in video production technology and the consumer demand, the proliferation of digital content necessitates the development of automatic systems and tools for semantic multimedia information analysis, understanding and retrieval. As important multimedia content, sports video has been attracting considerable research due to the commercial benefits and the audience requirements. Most viewers prefer retrieving the designated events, scenes and players to watching a whole game in a sequential way. Therefore, various algorithms have been developed for shot classification [9, 13, 16, 20],

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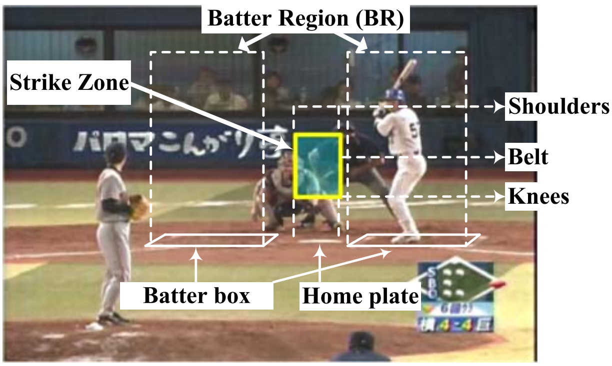
highlight extraction [2, 7, 8, 10] and semantic annotation [1, 4, 18] based on the fusion of audiovisual features and the game-specific rules.

As the multimedia processing techniques innovate, the sports fans and professionals desire to watch a sports game not only with efficiency but also with variety, profundity and professionalism. Traditional interactive sports video viewing systems for quick browsing, indexing and summarization no longer fulfill the requirements. Systems for providing informative, tactical and enriched insights into the game are undoubtedly in urgent demand. Yu et al. present a trajectory-based algorithm for ball detection and tracking in soccer video [19]. With the extracted ball trajectory, the actions of ball touching and passing are detected and the team ball possession is analyzed. Zhu et al. analyze the temporal-spatial interaction among the ball and players to construct a tactic representation, *aggregate trajectory,* based on multiple trajectories in soccer video [21]. Using the tactic representations including play region and aggregate trajectory, the tactics patterns are analyzed. Wang et al. use ball trajectory and landing position as features to classify tennis games into 58 winning patterns [17]. Luo et al. interpret and analyze human motion in sports video using video object extraction, semantic event modeling and the Dynamic Bayesian Network (DBN) for characterizing the spatio-temporal nature of the semantic objects [12]. Our previous work performs physics-based ball tracking in sports video to provide trajectory-based game analysis, such as set type recognition in volleyball and shooting location estimation in basketball [3, 6].

The *strike zone* (abbreviated to *Szone*) play a crucial role in baseball since the strike/ball judgment of each pitch must rely on the Szone. In baseball rules, the Szone is a conceptual rectangular area over the *home plate* through which a pitch must pass in order to count as a *strike* when the batter does not swing. A pitch not passing through the Szone is called a *ball* (if the batter does not swing). The top limit of the Szone is defined as the midpoint between the batter's shoulders and the belt, and the bottom limit is located at the batter's knees, as illustrated in Fig. 1. To gain strikes for striking out the batter, pitchers should acquire good mastery of the Szone.

In addition to strike/ball judgment assistance, the Szone also provides the reference for positioning the *pitch location*—the relative location of the ball in/around the Szone when the ball passes by the batter. An example of the *pitch location image* which summarizes a sequence of pitch locations during a plate appearance (a turn of batting) is presented in Fig. 2a, where the thick rectangle represents the Szone, the circles mark the pitch locations and the numbers indicate the order of the pitches. After accumulating a mass of pitch locations, the statistics can be compiled and visualized as Fig. 2b, where the number in each

Fig. 1 Illustration of the strike zone definition and the pitch scene layout



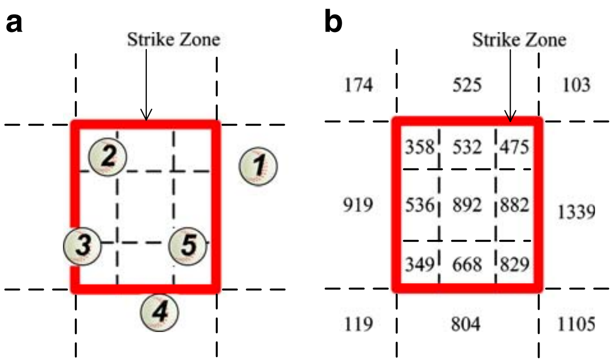


Fig. 2 Visualization of pitch locations and the Szone. **a** Pitch location image, **b** statistics of pitch locations

region is the count of pitches thrown in the region. The pitch location usually dominates the movement of the ball batted out. A batter who swings at a lower pitch has a good chance of hitting a *ground ball*, while a batter who swings at a higher pitch has a great chance of hitting the ball in the air. Since the pitch locations provide informative reference, pitch location recording has been an essential task. Sports fans and professionals have a fervent interest in the statistical information about the pitches. The current trend is to employ some workers to plot the pitch locations and compile statistics. However, manual logging is obviously labor-consuming and inefficient. To achieve automatic pitch location logging, two essential tasks are required: baseball tracking and Szone shaping. Since baseball tracking has been proposed in our previous work [5], this paper concentrates on the shaping and visualization of the Szone.

Research of Szone shaping and pitch analysis has been proposed. ESPN K Zone system outlines the Szone and extracts the trajectory of each pitch for viewers to compare with the umpire's strike/ball judgment [11]. However, an operator is required to use a specific camera and PC to locate the top and bottom limits of the Szone for each batter. UIS (Umpire Information System) tracks the pitch, measures the Szone and visualizes the 3D movement of the ball to judge the pitch is inside or outside the Szone [15]. The speed, placement and curvature of the pitch along its path are also measured. However, for Szone measurement, additional cameras specifically located low and close to the field are required.

In this paper, we design a contour-based approach for Szone shaping and visualization to provide the reference for pitch location positioning and strike/ball judgment, and furthermore to enrich the viewing experience of baseball games. Neither specific camera installation nor manual operation is required. The rest of this paper proceeds with the overview of the proposed Szone shaping framework in section 2. Section 3 describes home plate detection. Batter region outlining, batter contouring and dominant point locating are presented in section 4, 5 and 6, respectively. Section 7 reports the experimental results, and finally section 8 concludes this paper.

2 Overview of the proposed Szone shaping framework

Figure 3 depicts the overview of the proposed Szone shaping framework. Note that, for Szone shaping, we focus on the analysis of pitch scenes. Shot classification and indexing in

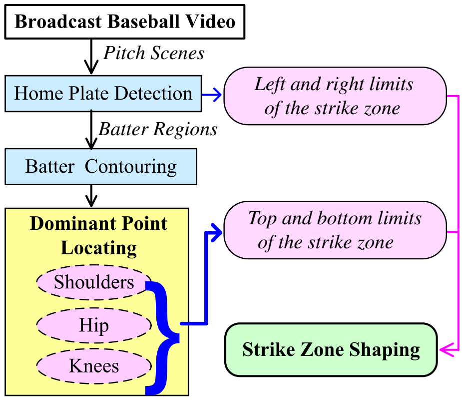
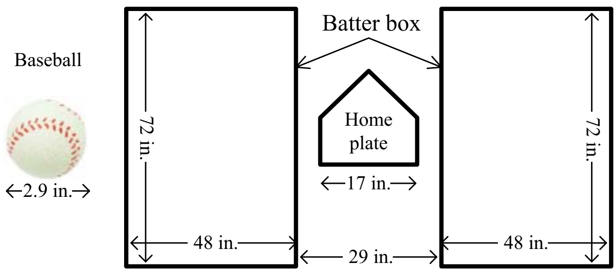


Fig. 3 Block diagram of the proposed strike zone shaping

sports video has been researched well in the literature [9, 13, 16, 20]. Thus, we adapt the existing methods for pitch scene extraction via dominant color matching, region segmentation and dominant color layout analysis.

To determine the vertical limits of the Szone, we first detect the home plate based on the visual characteristics: location, intensity and shape. In baseball, the layout and specifications of the field and equipments are strictly defined in the rules, as shown in Fig. 4. Thus, we can proportionally estimate the in-frame width of the home plate from the in-frame ball diameter (computed by ball tracking [5]) to facilitate home plate detection. To reduce the processing area of batter contouring, we outline the *batter region* above each *batter box* (see Fig. 1 for the layout) utilizing the relative locations and sizes of the home plate and the batter boxes, as presented in Fig. 4. Then, an efficient algorithm is designed to contour the batter in the batter region. To determine the top and bottom limits of the Szone, we locate the dominant points on the batter's contour: the hip, shoulders and knees, using the curvature extremes. The hip is located instead of the belt, because the belt is not obvious and the top of the hip has about the same y-coordinate as the belt. With the home plate detected and the dominant points located, the Szone finally takes shape.



Diameter of baseball (S_{ball}) : 2.9 in.
Width of home plate (S_{HP}) : 17 in.
Width of batter box (S_{box}) : 48 in.
Length of batter box : 72 in.
Distance between two batter boxes: 29 in.

Fig. 4 Specifications of the baseball, home plate and batter boxes

Fig. 5 Procedure of home plate detection. **a** Original frame of a pitch scene, **b** pixels with high intensity around the frame center, **c** detected home plate

3 Home plate detection

In the pitch scene, the home plate shows in the form of a short horizontal line segment in a light gray color close to white, as shown in Fig. 1. Besides, the home plate is mostly located around the frame center, because the best presentation of the pitch vs. batter can be provided in this viewpoint. Based on these visual properties, we design a compute-easy yet effective algorithm for home plate detection. The procedure is presented in Fig. 5.

We remove the pixels with low intensity, and then retain only the pixels in the center quarter region of the frame, as shown in Fig. 5b. Objects are formed from the remaining pixels by region growing. Utilizing the specifications of the baseball and the home plate defined in the rules (see Fig. 4), the in-frame width of the home plate W_{if} can be proportionally estimated from the in-frame diameter of the baseball (computed by ball tracking [5]). Thus, the object in the form of a short horizontal line segment with the width closest to W_{if} (the estimated in-frame width of the home plate) is extracted as the home plate, as shown in Fig. 5c.

4 Batter region outlining

The batter is restricted (by rules) to stand in one of the batter boxes when he is preparing to bat. To reduce the processing area of batter contouring for efficiency and accuracy, we outline the *batter region* above each *batter box* (see Fig. 1) based on the relative locations and sizes of the home plate and the batter boxes, as presented in Fig. 4. The in-frame width of the batter box W_{box} can be proportionally estimated from the width of the detected home plate W_{hp} by Eq. (1).

$$W_{box} = \mathrm{S}_{\mathrm{box}} \times W_{hp} / \mathrm{S}_{\mathrm{HP}} \tag{1}$$

$\mathrm{S}_{\mathrm{box}}$ and S_{HP} are the standard widths of the batter box and the home plate, respectively. Then, the batter region (BR) is outlined above each batter box with the height H_{region} computed by Eq. (2).

$$H_{region} = H_{batter} \times W_{hp} / \mathrm{S}_{\mathrm{HP}} \tag{2}$$

We roughly set H_{batter}=78 in. (about 200 cm) so that the BR could cover almost all batters. Whether the batter is right-handed or left-handed, that is, whether the batter stands in the right or left BR can be judged by the intensity difference between frames within each BR. The BR with the batter would have larger intensity difference.

5 Batter contouring

After batter region outlining and the recognition of the BR with the batter, we are able to contour the batter within a specific region efficiently. To extract the moving edges of the batter, we adopt the algorithm in [12], which incorporates the spatial edge information in the motion detection stage by exploiting double-edge map derived from the difference between two successive frames. Here we give a brief review of the algorithm with the example presented in Fig. 6. First, the edge map E_n of current frame I_n (gray level image) is calculated as Eq. (3):

$$E_n = \Phi(I_n) \tag{3}$$

where $\Phi(.)$ is the Canny edge detector and n is the frame sequence number. The difference edge map DE_n is calculated by applying the Canny edge detector to the luminance difference image $|I_n - I_{n-1}|$ of successive frames, as defined in Eq. (4). The Gaussian convolution included in the Canny operator suppresses the noise in the luminance difference.

$$DE_n = \Phi(|I_n - I_{n-1}|) \tag{4}$$

Finally, the moving edge map ME_n is generated by selecting the edge pixels in E_n with at least one neighboring pixel in DE_n, i.e.

$$ME_n = \{e \in E_n | \exists\, p \in DE_n, e \text{ and } p \text{ are neighboring pixels}\} \tag{5}$$

The procedure of batter contouring is illustrated in Fig. 7. We extract the rightmost moving edge points along the y-direction as the *contour points* of the right half contour. The x-coordinate x_k of each contour point forms a one dimensional discrete function $R(k)=x_k$, where k is the vertical index of each contour point [see Fig. 7b]. Similarly, the contour points of the left half contour are extracted from the leftmost moving edge points along the y-direction, and the x-coordinate of each contour point forms a one dimensional discrete function $L(k)$.

In the subsequent process, we have to locate the dominant points for the horizontal limits of the Szone. Due to the human kinematic constraints, the sharp turns on the body contour

a I_n **b** E_n **c** $|I_n–I_{n-1}|$ **d** DE_n **e** ME_n

Fig. 6 Example of moving edge extraction (within the BR). **a** Gray level image I_n, **b** Edge map E_n, **c** luminance difference image $|I_n - I_{n-1}|$, **d** difference edge map DE_n, **e** moving edge map ME_n

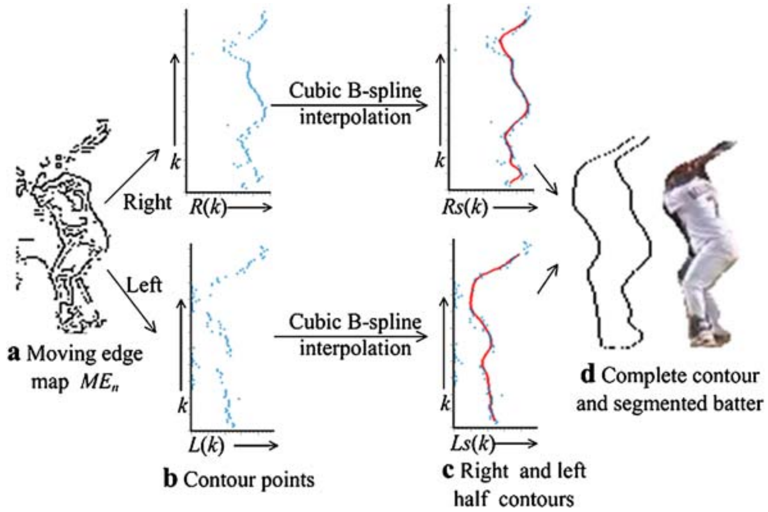


Fig. 7 Procedure of batter contouring

are usually at the joints. Hence, points of curvature extremes are good candidates for the dominant points. The contour curvature can be obtained via computing the partial derivatives on the extracted contour. However, the zigzag contour due to the imperfect moving edge extraction may result in false alarms of curvature extremes. Thus, to achieve spatial continuity and ignore fragments, the cubic B-spline interpolation [14] is used to transform the discrete contour to a continuous one, as shown in Fig. 7c. The complete contour is finalized by combining the smoothed right and left half contours, as shown in Fig. 7d, and the points of curvature extremes can be easily obtained by computing the second order partial derivatives on the parameterized contour.

6 Dominant point locating

To determine the top and bottom boundaries of the Szone, a curvature-based method is designed to locate the dominant points on the batter's contour: the hip, shoulders and knees. In the following, the terms *back contour* and *front contour*, as depicted in Fig. 8, are used to avoid the confusion of the left or right half contour for a left- or right-handed batter.

We compute the NMC (negative minimum curvature) and PMC (positive maximum curvature) points of the contour, as shown in Fig. 9a. Each NMC (or PMC) point on the back contour is linked to the nearest PMC (or NMC) point on the front contour, and vice versa, as shown in Fig. 9b and c. Two points which are bi-directionally linked are deemed as a *pair*, as shown in Fig. 9d. In the following, we use the term "NP point" to denote the midpoint of the pair of a NMC point on the front contour and a PMC point on the back contour, and the term "PN point" to denote the midpoint of the pair of a PMC point on the front contour and a NMC point on the back contour.

Due to the kinematic constraints of body joints and the balance of the gravity center during the batting action, the trunk and knees tilt forward as the hip is pushed backward. Since the hip forms a salient curve at about half of the batter's height, we choose the NP point closest to the midpoint of the contoured batter's height as the *hip point*. Then, the PN

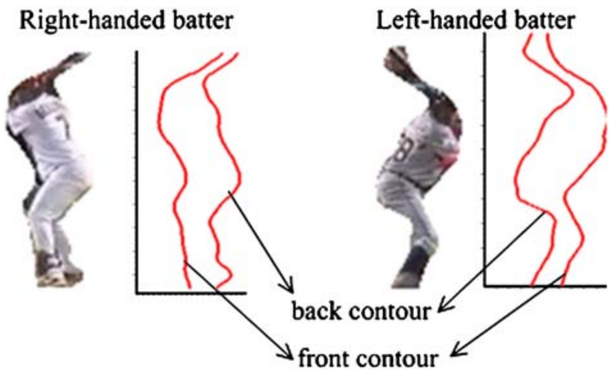


Fig. 8 Back and front contours for right- and left-handed batters

point under the hip point and with the longest horizontal distance to the hip point is chosen as the *knee point*, while the PN point above the hip point and with the longest horizontal distance to the hip point is chosen as the *shoulder point*. Figure 10 demonstrates sample results of the extracted pairs (the red lines) and the located dominant points (the solid red circles).

With the home plate detected and the dominant points located, now we are ready to shape the Szone. The left and right limits of the Szone are vertical lines at both sides of the detected home plate. The top limit is the horizontal line located at the midpoint between the batter's hip and shoulders, and the bottom limit is located at the batter's knees. Sample results of Szone shaping and visualization for a right-handed batter and a left-handed batter are presented in Fig. 11. More demonstrations are given in the next section.

7 Experimental results

The methods elaborated in the previous sections support contour-based Szone shaping needless of manual operation and additional camera setting. For performance evaluation, the proposed scheme has been tested on the broadcast baseball videos (352x240, MPEG-1) of MLB (Major League Baseball), JPB (Japan Professional Baseball) and CPBL (Chinese Professional Baseball League) captured from various channels, including ESPN of USA,

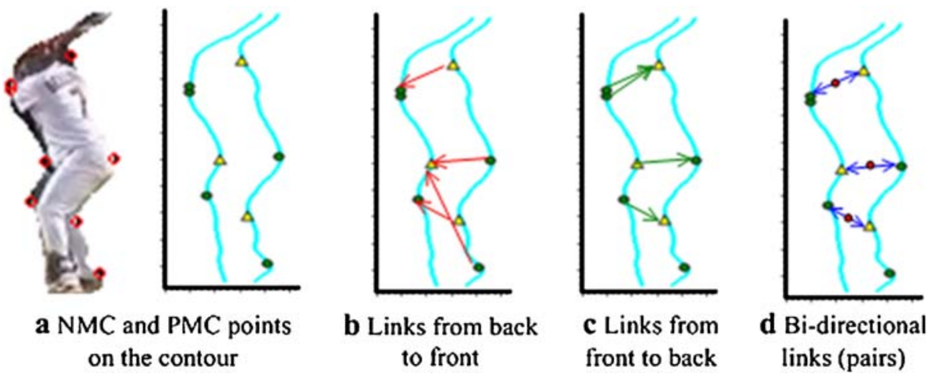


Fig. 9 Dominant point locating using the points of curvature extremes

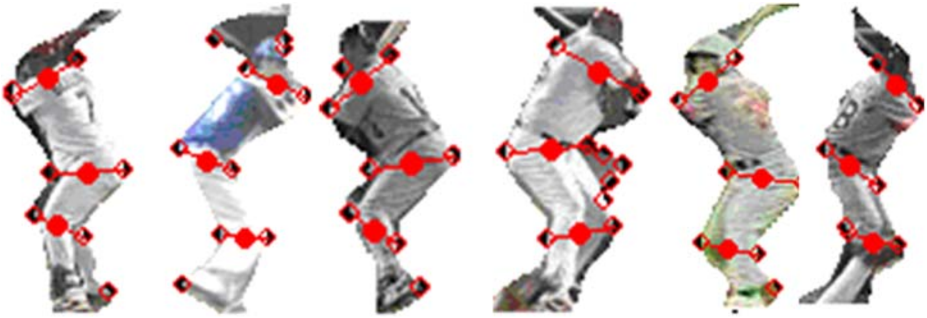


Fig. 10 Sample results of dominant point locating

BS-hi and NHK of Japan, VL sports and PT of Taiwan. Note that only pitch scenes are processed.

7.1 Results of home plate detection

The results of home plate detection are presented in Table 1, which lists the correct, missed and false detections. The home plate can be correctly detected in most clips. Only two misses occur as the home plate is stained with soil and is not clear in the frame. For the clarity of strike/ball decision, the plate umpire has the responsibility to clean the home plate when the home plate is stained. Therefore, the home plate is clear in most of the sequences. On the other hand, there are seldom objects similar to the home plate in the center region of the pitch scene. Thus, we achieve a fairly good performance in home plate detection.

7.2 Results of Szone shaping

The *ground truth* of the Szone is established by manually pinpointing the two sides of the home plate and the batter's shoulders, hip and knees. To evaluate the proposed Szone shaping approach, two degrees, P and R, are defined to measure the overlapping between the computer-generated Szone and the ground truth, as represented in Eq. (6) and Eq. (7), respectively.

$$P = A_{ov} / A_{cg} \tag{6}$$

Fig. 11 Szone shaping and visualization. **a** Right-handed batter, **b** left-handed batter

Table 1 Performance of home plate detection

Video	#Seq	#Correct	#Missed	#False
MLB	33	32	1	0
JPB	33	33	0	0
CPBL	34	33	1	0
Overall	**100**	**98**	**2**	**0**

$$R = A_{ov} / A_{gt} \tag{7}$$

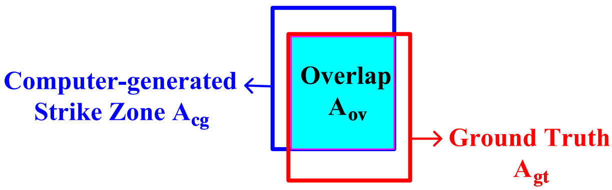
A_{cg} is the area of the computer-generated Szone, A_{gt} is the area of the ground truth and A_{ov} is the area of the overlapping between the two, as shown in Fig. 12. The degree P indicates what percentage of the computer-generated Szone is correct, and the degree R indicates what percentage of the ground truth Szone is contained in the computer-generated Szone. Both P and R should be assessed for performance evaluation, because, for example, a very small computer-generated Szone located within the ground truth Szone will have a high P but a very low R, while a very large computer-generated Szone which covers the whole ground truth Szone will have a high R but a very low P.

The P-R distribution of the 98 sequences with the home plate detected correctly is presented in Fig. 13, where each point represents a testing sequence, the horizontal and vertical axes indicate the P and R degrees, respectively. Table 2 reports the average P and R degrees. It can be seen that the computer-generated Szone has great overlapping with the ground truth in most sequences. Overall, both the average P and R degrees are over 0.9. The demonstration of Szone shaping and visualization in Fig. 14 makes it convincible that the proposed framework is able to shape the Szone fairly well, no matter whether the batter is right- or left-handed and no matter what color of uniform the batter is dressed in.

Inspecting the error cases, we find that the misshaped Szone is mainly caused by improper batter contouring. The dynamic advertising board, the plate umpire, the audience moving or other noises behind the batter might lead to faults in batter contouring. An example of the error case is shown in Fig. 15, where the change of the dynamic advertising board behind the batter affects the batter contouring so that the dominant points cannot be located accurately. Figure 16 shows another example of improper Szone shaping in the case when the batter and the plate umpire wear the clothes in the same color and the view angle causes the two persons overlapped. Our contour extraction is based on the difference between frames. Therefore, if the batter's uniform has the same color as the background or the person behind the batter, the proposed method may not be able to extract the batter's contour correctly.

Strictly speaking, the computer-generated Szone may differ from the umpire-assumed Szone due to the different viewpoints and the subjectivity. However, our experimental

Fig. 12 Illustration of A_{cg}, A_{gt} and A_{ov}



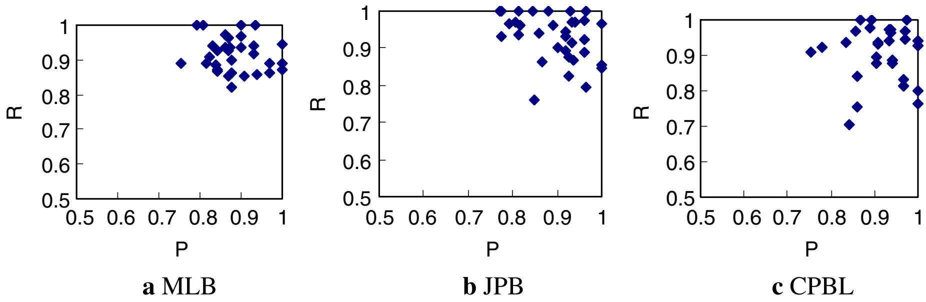


Fig. 13 P-R distributions for evaluating Szone shaping. **a** MLB, **b** JPB, **c** CPBL

results show that the proposed contour-based method is able to shape the Szone satisfactorily to provide the reference for pitch location positioning and strike/ball judgment.

7.3 Discussion and comparison

The experiments are conducted on an IBM ThinkPad X60 notebook computer (CPU: Intel Core Duo T2400 1.83 GHz, RAM: 1 GB). Table 3 presents the average computing time of each process stage: home plate detection, batter contouring and dominant locating. Overall, we achieve the computing time of about 21 ms/frame on average. That is to say, the proposed approach is able to shape and visualize the Szone *in real time* as soon as a pitch scene is detected.

It is difficult to perform a head-to-head comparison with other systems since the proposed Szone shaping works on the single-view broadcast baseball video, whereas other systems [11, 15] work on the baseball video captured from the camera(s) specifically located around the field. K zone system [11] outlines the Szone in such a way that an operator uses a specific camera and PC to locate the upper and lower boundaries of the Szone. That is, special camera setting is necessary, and manual manipulation is required for each batter and each pitch. In UIS (Umpire Information System) [15], two cameras are placed low and close to the field for measuring the batter's strike zone. K zone system and UIS have been used in official games and they are motivated to provide strict information for assisting the umpire in strike/ball judgment. Thus, their demanding accuracy necessitates the extra cost of special camera setting and manual efforts. In this paper, the proposed approach aims at shaping and visualizing the Szone automatically in broadcast baseball video. Hence, neither specific camera setting nor manual operation is required, and the proposed approach can be generally used. Even though the accuracy is not as high as

Table 2 Performance of Szone shaping

Video	Sequence	Avg. P	Avg. R
MLB	32	0.884	0.914
JPB	33	0.895	0.928
CPBL	33	0.923	0.904
Overall	**98**	**0.901**	**0.915**

Fig. 14 Example results of strike zone determination

that of K zone system or UIS, the proposed Szone shaping and visualization can provide entertainment effects and statistical information.

As discussed in section 7.2, we can find that batter contouring (object segmentation) plays an important role in Szone shaping. Hence, we use our contour extraction method to

Fig. 15 Improper strike zone shaping caused by the dynamic advertising board

compare against the video object segmentation (VOS) algorithm in [12], which performs well for human motion analysis in sports videos. Note that we implement the VOS algorithm without the background edge map, since the background edge map can not always be obtained and their method of providing background edge map by manually deleting moving edges of target objects does not fulfill the requirement of automation.

Now we briefly describe the procedure of the VOS algorithm. With the moving edge map, as shown in Fig. 17a, the horizontal candidates of VOP (video object plane) are declared to be the region inside the first and last edge points in each row [see Fig. 17b] and the vertical candidates for each column. After obtaining horizontal and vertical VOP candidates, intersection regions [see the black regions in Fig. 17c] through logical AND

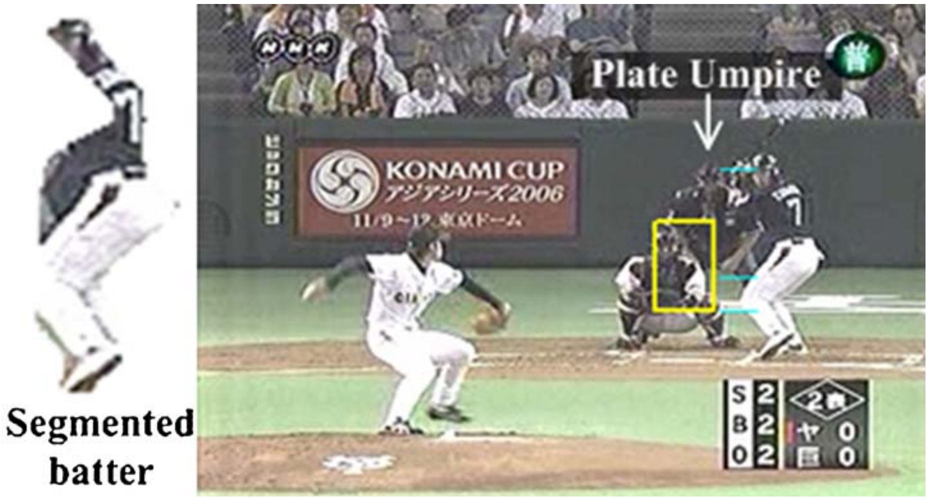


Fig. 16 Improper strike zone shaping when the batter and the plate umpire wear the clothes in the same color and the view angle causes the two persons overlapped

Table 3 Average computing time of each process stage

Process stage	Average computing time
Home plate detection	6.54 (ms per frame)
Batter contouring	8.16 (ms per frame)
Dominant point locating	6.13 (ms per frame)
Overall	20.83 (ms per frame)

operation are processed by morphological operation and the moving object is segmented, as shown in Fig. 17d.

As presented in Fig. 17e, the VOS algorithm may produce fragments in the segmented object or discontinuities on the contour, while our method is able to extract a smooth

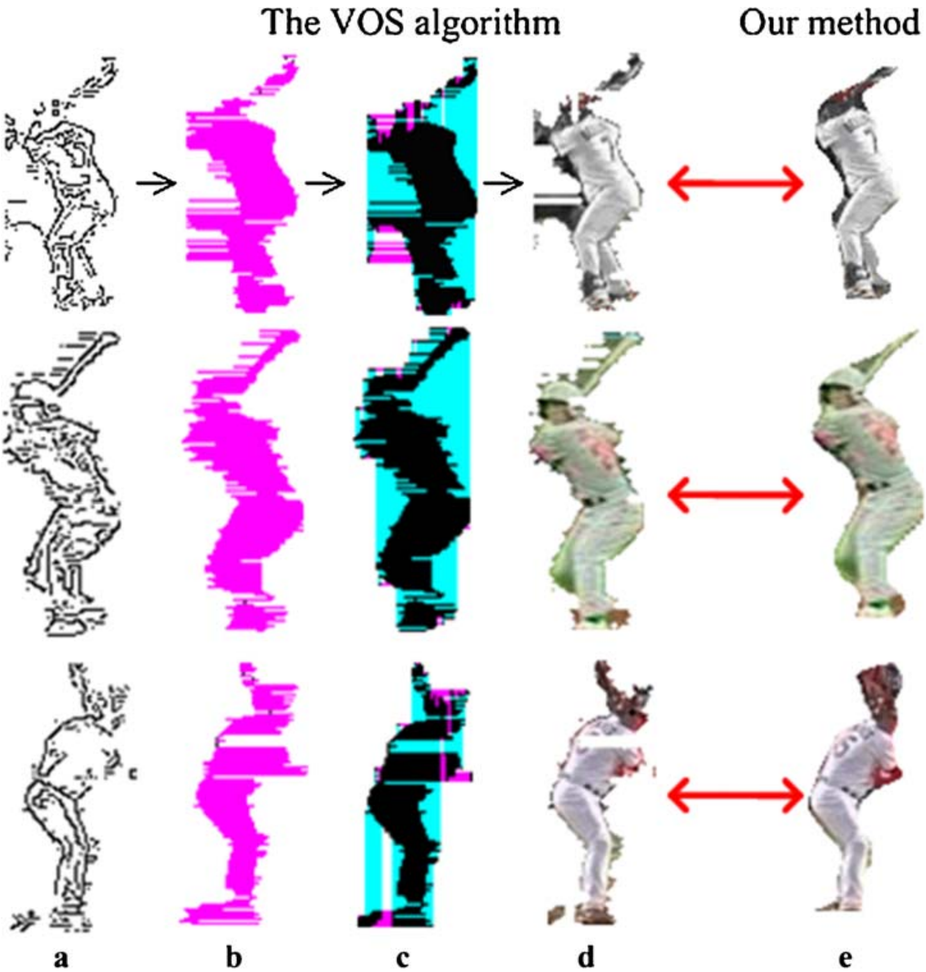


Fig. 17 Comparison between the VOS algorithm and our method. **a** Moving edge map, **b** horizontal candidates, **c** logical AND (black areas) of horizontal and vertical candidates, **d** extracted VOP after morphological operations, **e** segmented object by our method

contour, which plays an important role in curvature extreme calculation for dominant point locating. The comparison shows that the proposed method performs better in object contouring when the background edge map cannot be obtained.

8 Conclusions

The pitch content dominates the situation on the baseball field. As an important role in each pitch, the Szone not only supports the strike/ball judgment but also provides the reference for pitch location positioning. In this paper, we design a contour-based Szone shaping scheme which integrates efficient algorithms of home plate detection, object contouring and dominant point locating. The Szone can be shaped and visualized to enrich the viewing experience of baseball games, needless of additional camera installation and manual efforts.

There are several avenues for future research work. One direction is to adapt the batter contouring approach (in section 5) for object segmentation and contouring in other types of videos. With the bounding boxes of moving objects computed, we will be able to segment and contour people, vehicles or other moving objects appropriately and smoothly. The object-based or contour-based applications are manifold, such as human action recognition, behavior analysis, video content understanding, and object-based manipulation of bit-streams. Another direction is to refine the proposed Szone shaping method to handle live streaming video in real time and to research on the spatial and temporal relationship of the batter contour and the shaped Szone. Furthermore, we will integrate the proposed Szone shaping with our baseball trajectory extraction [5] and batting content abstraction [4] into a powerful baseball exploration system, analyzing the entire process from pitching to batting. Thus, content abstraction, pitch-bat strategy analysis and statistics compiling can be achieved automatically.

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