Automatic Player Behavior Analyses from Baseball Broadcast Videos

Yin-Fu Huang and Zong-Xian Yang

Department of Computer Science and Information Engineering
National Yunlin University of Science and Technology
{huangyf,g9817723}@yuntech.edu.tw

Abstract. In this paper, we present a baseball player behavior analysis system by combining pitch types and swing events. We use eight kinds of semantic scenes detected from baseball videos in our previous work. For the pitch types, we use the characteristic of the ball in a pitch scene to identify the ball trajectory, and then 39 features are extracted to feed into a trained SVM for classifying pitch types. For the swing events, we use moving objects in the batter region to determine whether a swing occurs. Then, the event following the swing is detected using an HMM, based on the after-swing scene sequence. Next, the experimental results show that both pitch type recognition and swing event detection have accuracy rates 91.5% and 91.1%. Finally, we analyze and summarize player behavior by combining pitch types and swing events.

Keywords: Baseball broadcast video, player behavior analysis, pitch type recognition, event detection, SVM, HMM.

1 Introduction

In the past decade, the increasing amount of multimedia technologies has grown rapidly. With the increasing amount of multimedia information, many researchers focus on the highlight extraction, the event detection, the indexing, the retrieval and so forth on sport videos, to get the information that users want. To analyze video contents, different technologies such as pattern recognition, artificial intelligence, and computer vision are applied to videos. With the processing of sport videos, it would be convenient and effective for users to get more interesting information in a huge amount of videos.

For the processing of a baseball video, the characteristics and visual features in a baseball game were used to extract a ball trajectory in [2, 4]. Chen et al. [3] detected a strike zone utilizing shaping and visualization in a broadcast baseball video. The superimposed caption in a baseball video and rule-based decision approach [10, 12], and even the web-casting [6] were used to detect events. Furthermore, HMM could be also used to detect events, based on scene sequences [7, 8, 9]. In [11], ball trajectories were analyzed and even classified into pitch types using a random forest tree. However, player behavior has not analyzed yet.

R. Huang et al. (Eds.): AMT 2012, LNCS 7669, pp. 11–21, 2012.

In this paper, we analyze baseball player behavior by combining pitch types and swing events. First, the semantic scenes detected in the previous work are extracted. Among the detected scenes, we extract ball trajectories from pitch scenes [2]. Then, we extend and improve the method in [11] to extract the relevant features in a trajectory, and classify trajectories into pitch types. To detect swing events, a batter region should be found first and the event following the swing is detected using HMM, based on the after-swing scene sequence. Finally, we analyze and summarize player behavior by combining pitch types and swing events.

The remainder of the paper is organized as follows. In Section 2, the system overview of our baseball player behavior analysis is introduced first. In Section 3, we describe the extraction of a baseball trajectory and the relevant features, and then classify trajectories into pitch types using SVM. In Section 4, we present the swing detection and after-swing event detection using HMM. The experimental results are presented in Section 5. Finally, we make conclusions in Section 6.

2 System Architecture

In the previous work [5], we have segmented a baseball video into scenes and classified them into "pitch", "infield-hitting", "outfield-hitting", "field", "player", "running", "close-up", and "others".

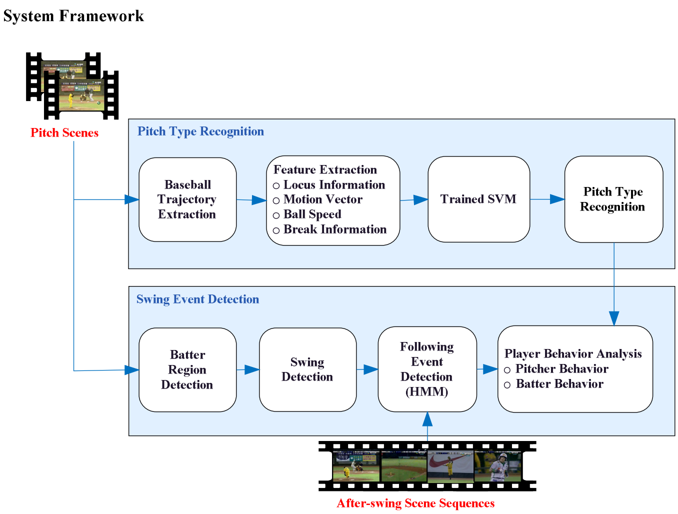

Fig. 1. System architecture

In this paper, we propose a baseball player behavior analysis system as shown in Fig. 1. The system consists of two parts: 1) pitch type recognition and 2) swing event detection. First, the pitch scenes detected in the previous work are loaded. Then, we use the characteristics of the ball in a pitch scene to extraction the ball track [2], and extract the related features such as "locus information", "motion vector", "ball speed", and "break information". Next, these features are fed into a trained SVM to classify pitch types. For the swing event detection, a batter region should be detected first. Then, we use moving pixels in the batter region to determine whether a swing occurs. Next, the event following the swing is detected using an HMM, based on the after-swing scene sequence. Finally, we analyze and summarize player behavior by combining pitch types and swing events.

3 Pitch Type Recognition

In this section, we derive a baseball trajectory using the algorithm proposed by Chen et al. [2]. Then, we extract the features in a trajectory, some of which are extended from those used by Takahashi et al. [11]. Finally, a trained SVM is used to classify trajectories into pitch types.

3.1 Baseball Trajectory Extraction

According to the characteristics and visual features in a baseball game, the framework to derive a baseball trajectory can be depicted in Fig. 2. First, the moving objects of each frame are located in pitch scenes. The ball candidates of each frame are detected in terms of position, color, size, and compactness filters. The motion of a ball may be a parabolic curve, due to the gravitational influence in a trajectory. Therefore, we utilize this physical characteristic to track a ball on the distribution of X-axis and Y-axis. Finally, a baseball trajectory is identified.

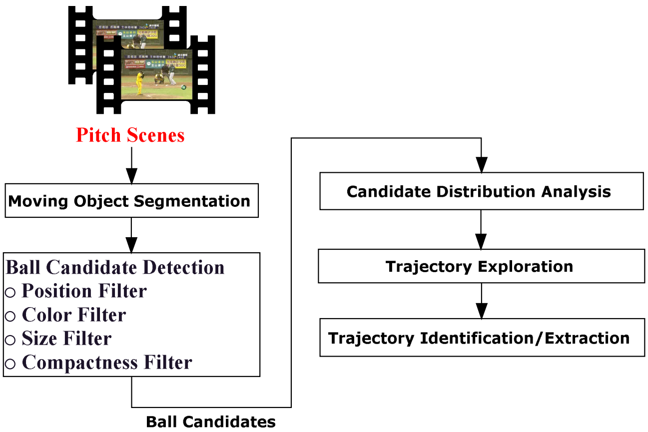

Fig. 2. Process of baseball trajectory extraction

3.2 Feature Extraction

The shape of a ball trajectory varies with its pitch type. Not only the locus information is included, but also the motion vectors, ball speed, and break information in the trajectory are selected as features in the system. Totally, 39 features are extracted from the ball trajectory as follows.

- Locus slop and locus curvature (i.e., first-order differential coefficient and second-order differential coefficient): Entire, first, second, third, and last parts
- Motion vectors (for horizontal and vertical): Last 12 frames in the ball trajectory
- Speed ratio of the first part to the second part
- Ball speed
- Break length
- The frame number with the break point
- The distance between the release point and the break point

We divide the ball trajectory into four parts, and the slope and curvature of each part are calculated, respectively. Since the closer a ball is to a home plate and the more movement a ball varies, the motion vectors in the last 12 frames are collected. Besides, the speed ratio is obtained from the ball speeds calculated from the motion vectors for the first and second part of the trajectory. The ball speed can be derived using the trajectory length expressed with total frame number. For the distance between the pitcher mound and home plate 18.44 m, and a video with 30 frames/sec, the ball speed can be calculated as follows:

$$Ball\ speed(km/h) = \frac{0.01844\ (km)}{(Trajectory\ length/30/3600)(h)} \tag{1}$$

Finally, the break length is the greatest distance between the trajectory and the straight line from the release point and the front of a home plate.

3.3 Support Vector Machines

The number of pitch types to be recognized depends on a pitcher, and the trajectory, movement, speed, and position of a pitching ball could vary with different pitchers. Hence, in our system, a classifier was created for each pitcher. Although there are various types of pitches in professional baseball, we could classify pitch types into nine types by using support vector machines (i.e., libSVM toolkit [1]). In the training phase, the radial basis function (i.e., RBF) was selected for the kernel function and five-fold cross validation was conducted on the training data.

4 Swing Event Detection

For the swing event detection, a batter region is detected first. Then, the moving objects in the batter region are used to determine whether a swing occurs. Next, the event following the swing is detected using an HMM, based on the after-swing scene sequence.

4.1 Batter Region Detection

Since a pitch scene is always taken by a fixed camera, we can consider two batter regions are also fixed. To detect a batter is right-handed or left-handed, the intensity differences between frames within each batter region are used. In other words, the batter region occupied by a batter would have larger intensity differences between frames than another batter region.

4.2 Swing Detection

Next, the moving objects in the detected batter region are used to determine whether a swing occurs. In general, the more moving objects the batter region has, the more likely a swing occurs. When a ball is close to a home plate (i.e., the last three frames in the trajectory), if the batter swings a bat, the number of the moving objects in the batter region would be more than a threshold Ts.

4.3 Following Event Detection

Here, five kinds of after-swing events are identified using an HMM method. As shown in Fig. 3, five trained HMMs representing different events are used to detect after-swing events. We feed each of these HMMs with after-swing scene sequences, and each HMM would produce the probability of the corresponding event. Finally, the detected event of the scene sequences would be what the HMM with the maximal probability represents.

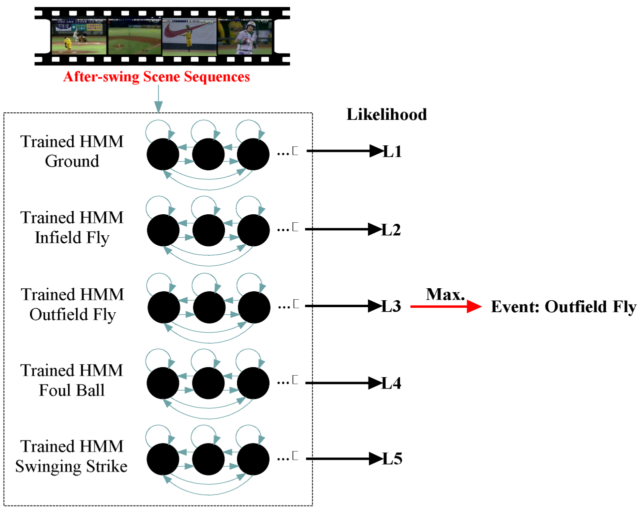

Fig. 3. HMMs used to detect after-swing events

5 Experimental Results

In the experiments, the training/test videos were recorded from the broadcast TV programs of “Chinese Professional Baseball League”. These games include different teams, pitchers, baseball fields, and all the videos are compressed in the MPEG-1 format with frame size 352*240 and frame rate 29.97fps. Two performance measures of precision and recall were applied to analyze the accuracy of the pitch type recognition and swing event detection.

$$\text{Precision} = \frac{N_C}{N_C + N_F} \tag{2}$$

$$\text{Recall} = \frac{N_C}{N_C + N_M} \tag{3}$$

$$\text{Accuracy} = \frac{\text{total}_c}{\text{total}} \tag{4}$$

where NC is the number of pitch types (or swing events) that were retrieved and correctly detected, NF is the number of pitch types (or swing events) that were retrieved but falsely detected, and NM is the number of missed pitch types (or swing events), totalc is the number of all pitch types (or swing events) correctly predicted, and total is the number of all pitch types (or swing events).

5.1 Pitch Type Recognition

The recognition results of seven pitchers are presented in Table 1. Their dominant arms include left and right, each pitcher has four or five pitch types, and the number of pitches for each pitcher is more than 300. The total accuracy for all the pitch type recognition is 91.5%. Besides, we also show the detailed recognition results for pitcher A in Table 2. For pitcher A, two-seam fastball accounts for over 60% of all pitched. Two-seam fastball is better recognized than fastball or breaking ball so that it has high precision and recall. Changeup ball has low recall caused by limited training data (accounting for only 2% of all pitched).

Table 1. Precision and recall for each pitcher

Pitcher	Dominant arm	Number of pitch types	Number of pitches	Accuracy
A	right	4	469	93.8%
B	left	4	335	91.9%
C	right	5	389	91.8%
D	right	5	342	88.0%
E	right	4	327	90.2%
F	left	5	312	91.3%
G	left	4	343	92.7%
Total	right/left	9	2517	91.5%

Besides, we also compare the recognition results between the Takahashi et al. method [11] and our method, as shown in Table 3. In this paper, we extend the feature extraction model used by Takahashi et al., and use a different classification method, thereby achieving significant accuracy.

Table 2. Results for pitcher A

	Two-seam Fastball	Slider	Circle-changeup	Changeup	Recall
Two-seam Fastball	280	0	4	0	98.6%
Slider	11	90	1	0	88.2%
Circle-changeup	5	5	63	0	86.3%
Changeup	3	0	0	7	70.0%
Precision	93.6%	94.7%	92.6%	100.0%	

Table 3. Comparisons between two methods

	Number of pitch types	Number of pitchers	Number of pitches	Number of features	Methods	Accuracy
Takahashi et al.	9	5	1538	36	Random forest	88.7%
Ours	9	7	2517	39	SVM	91.5%

5.2 Swing Event Detection

Here, the 4-state HMM is used to detect five after-swing events. The datasets used to train and test the HMM are shown in Table 4. In the experiments, five kinds of after-swing events could be detected, including “Ground”, “Infield Fly”, “Outfield Fly”, “Foul Ball”, and “Swinging Strike”.

Table 4. Events in the training set and test set

	Training set	Test set
Ground	70	35
Infield Fly	11	6
Outfield Fly	59	29
Foul Ball	83	41
Swinging Strike	48	24
Total events	271	135

We present the swing event detection results as shown in Table 5. The total accuracy for all the swing event detection is 91.1%. From the results, we found that an outfield fly event has high accuracy owing to its salient scene sequence. However, an infield fly event has low accuracy since its scene sequence is very similar to a ground event and only 17 events exist in the dataset.

Table 5. Precision and recall of event detection

	Ground	Infield Fly	Outfield Fly	Foul Ball	Swinging Strike	Recall
Ground	31	4	0	0	0	88.6%
Infield Fly	3	3	0	0	0	50.0%
Outfield Fly	0	0	29	0	0	100.0%
Foul Ball	0	0	0	37	4	90.2%
Swinging Strike	0	1	0	0	23	95.8%
Precision	91.2%	37.5%	100.0%	100.0%	85.2%	

5.3 Behavior Analysis

In this section, we summarize and analyze player behavior by combining the pitch type recognition and swing event detection. Table 6 presents the pitch result distribution for pitcher A. We observed that two-seam fastball causes major foul ball events (40.2%) and ground events (28%); slider/circle-changeup causes major swinging strike events (35.8%/39.3%). Changeup even causes complete swinging strike events (100%) although the number of changeup is only 10 as indicated in Table 2.

Table 6. Pitch result distribution for pitcher A

	Ground	Infield Fly	Outfield Fly	Foul Ball	Swinging Strike	Swing rate
Two-seam Fastball	28%	3.4%	20.5%	40.2%	7.7%	39.3%
Slider	22.6%	3.8%	15.1%	22.6%	35.8%	47.3%
Circle-changeup	10.7%	14.3%	10.7%	25.0%	39.3%	45.9%
Changeup	0.0%	0.0%	0.0%	0.0%	100.0%	37.5%

In general, the majority of pitch types in a baseball game is fastball. Table 7 and Table 8 present the summarize results of two kinds of fastball. In the summarization, we observed that two-seam fastball causes more ground events than four-seam fastball. But, four-seam fastball causes more outfield fly events than two-seam fastball, especially for pitcher D (30.8%) and F (32.0%).

Table 7. Two-seam fastball summarization

Pitcher	Ground	Infield Fly	Outfield Fly	Foul Ball	Swinging Strike	Swing rate
A	28%	3.4%	20.5%	40.2%	7.7%	39.3%
C	27.1%	2.3%	13.5%	45.1%	12.0%	46.5%

For batter part, Table 9 presents the swinging result distribution for batter 1. We observed that four-seam fastball and knuckle curve cause more outfield fly events (45.0% and 50.0%), and it indicates batter 1 can grasp these pitch types easily. On the contrary, slider causes more swinging strike (50.0%), and it indicates batter 1 cannot grasp this pitch type. Besides, according to the swing rate, we found that batter 1 prefers two-seam fastball (54.5%), knuckle curve (66.7%), and split-finger (60.0%) to the other pitch types.

Table 8. Four-seam fastball summarization

Pitcher	Ground	Infield Fly	Outfield Fly	Foul Ball	Swinging Strike	Swing rate
B	22.3%	3.2%	24.5%	42.6%	7.4%	42.0%
D	12.1%	1.1%	30.8%	40.7%	15.4%	67.9%
E	23.2%	2.4%	24.4%	42.7%	7.3%	40.4%
F	21.3%	5.3%	32.0%	40.0%	14.7%	41.4%
G	22.8%	4.3%	15.2%	44.6%	13.0%	37.5%

Table 9. Swinging result distribution for batter 1

	Ground	Infield Fly	Outfield Fly	Foul Ball	Swinging Strike	Swing rate
Four-seam Fastball	10.0%	0.0%	45.0%	40%	5.0%	42.6%
Two-seam Fastball	16.7%	8.33%	25.0%	33.3%	16.7%	54.5%
Slider	12.5%	0.0%	0.0%	37.5%	50.0%	47.1%
Curve	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Changeup	0.0%	0.0%	33.3%	50.0%	16.7%	35.3%
Circle-changeup	0.0%	0.0%	50.0%	0.0%	50.0%	40.0%
Knuckle Curve	0.0%	0.0%	50.0%	50.0%	0.0%	66.7%
Fork	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Split-finger	33.3%	0.0%	0.0%	33.3%	33.3%	60.0%

Table 10 presents the swinging result distribution for slider. In the results, batter 1 has more swinging strike event (50.0%); batter 2 and batter 3 have more ground event (38.5% and 37.5%). Besides, batter 4 grasps slider easily whereas batter 1 cannot. In summary, the swing characteristic of each batter can be obtained, which a coach can use to arrange in a baseball game.

Table 10. Swinging result distribution for slider

Batter	Ground	Infield Fly	Outfield Fly	Foul Ball	Swinging Strike	Swing rate
Batter 1	12.5%	0.0%	0.0%	37.5%	50.0%	47.1%
Batter 2	38.5%	0.0%	15.4%	46.2%	0.0%	54.2%
Batter 3	37.5%	0.0%	12.5%	12.5%	37.5%	57.1%
Batter 4	0.0%	0.0%	33.3%	66.7%	0.0%	37.5%
Batter 5	22.2%	0.0%	22.2%	33.3%	22.2%	47.4%
Batter 6	0.0%	0.0%	33.3%	33.3%	33.3%	42.9%

6 Conclusions

In this paper, we propose a baseball player behavior analysis system using both pitch types and swing events. For the pitch types, we extract the features from ball trajectories including locus information, motion vectors, ball speed, and break information, and then classify them into nine pitch types. For the swing events, we use the moving objects in the batter region to determine whether a swing occurs, and then a swing event is detected using an HMM, based on the after-swing scene sequence. The experimental results show that both pitch type recognition and swing event detection have high accuracy (i.e., 91.5% and 91.1%). Finally, the pitch types and swing events are combined to analyze player behavior, and this information will be useful for coach to arrange in a baseball game.

Acknowledgments. This work was supported by National Science Council of R.O.C. under Grant NSC100-2218-E-224-011-MY3.

References

1. Chang, C.-C., Lin, C.-J.: LIBSVM: a library for support vector machines (2001), software available at `http://www.csie.ntu.edu.tw/~cjlin/libsvm`
2. Chen, H.-T., Chen, H.-S., Hsiao, M.-H., Tsai, W.-J., Lee, S.-Y.: A trajectory-based ball tracking framework with visual enrichment for broadcast baseball videos. Journal of Information Science and Engineering 24(1), 143–157 (2008)
3. Chen, H.-T., Tsai, W.-J., Lee, S.-Y.: Stance-based strike zone shaping and visualization in broadcast baseball video: providing reference for pitch location positioning. In: Proc. IEEE International Conference on Multimedia and Expo, pp. 302–305 (2009)
4. Chu, W.-T., Wang, C.-W., Wu, J.-L.: Extraction of baseball trajectory and physics-based validation for single-view baseball video sequences. In: Proc. IEEE International Conference on Multimedia and Expo, pp. 1813–1816 (2006)
5. Huang, Y.-F., Tung, L.-H.: Semantic scene detection system for baseball videos based on the MPEG-7 specification. In: Proc. ACM Symposium on Applied Computing, pp. 1–9 (2008)
6. Huang, Y.-F., Chen, L.-W.: An event-based video retrieval system by combining broadcasting baseball video and web-casting text. In: Proc. ACM Symposium on Applied Computing, pp. 846–852 (2011)
7. Huang, Y.-F., Huang, J.-J.: Semantic event detection in baseball videos based on a multi-output hidden Markov model. In: Proc. ACM Symposium on Applied Computing, pp. 929–936 (2011)
8. Lien, C.-C., Chiang, C.-L., Lee, C.-H.: Scene-based event detection for baseball videos. Journal of Visual Communication and Image Representation 18(1), 1–14 (2007)
9. Mochizuki, T., Tadenuma, M., Yagi, N.: Baseball video indexing using patternization of scenes and hidden Markov model. In: Proc. IEEE International Conference on Image Processing, pp. 1212–1215 (2005)
10. Su, Y.-M., Hsieh, C.-H.: Semantic events detection and classification for baseball videos. In: Proc. IEEE International Symposium on Industrial Electronics, pp. 1332–1336 (2009)

11. Takahashi, M., Fujii, M., Yagi, N.: Automatic pitch type recognition from baseball broadcast videos. In: Proc. the 10th IEEE International Symposium on Multimedia, pp. 15–22 (2008)
12. Zhang, D., Chang, S.-F.: Event detection in baseball video using superimposed caption recognition. In: Proc. the 10th ACM International Conference on Multimedia, pp. 315–318 (2002)