Advanced Science and Technology Letters
Vol.111 (NGCIT 2015), pp.138-142
http://dx.doi.org/10.14257/astl.2015.111.26

Offensive strategy in soccer video

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Abstract. A novel Real-world trajectory based tactic analysis method is proposed, which can automatically analyze the offensive tactics of soccer game from the perspective of professionals. First, a real-world trajectory extraction method is proposed, and then an offensive pattern recognition method is described based on the definition of the ball states.

Keywords: Video content analysis, Scene analysis, offensive strategy

1 Introduction

Semantic analysis of sport videos is an important aspect of general video content parsing. Sport videos gain very high audience ratings and huge commercial values. Thus more and more researches change to focus on sport video analysis. [1-2] pointed out that semantic analysis includes event detection and strategy analysis. Event detection aims to find out hot shots or focal events such as “shooting”, “corner kick”, “penalty kick” etc. in football sport videos [3-4]. In that case, users can retrieve interesting or informative scenes and view quickly the whole video stream. Unlike event detection, strategy analysis is to discover and identify strategic modes of the match. We take football game for example. Through strategy analysis, it’s possible to reveal threatening cooperative mode of offence and figure out effective defensive modes [5-6]. Based on event detection, it provides useful information to players as for them to improve skills and for coaches to improve team tactics. For footballers, they need to search out rapidly shots relating to one strategy mode [7-8], so that they summarize and find out main factors leading to successful offensive and main reasons for the failure of offensive [9]. For coaches, they need to dig out offensive mode of one player or team. They need a system to retrieve all related shots of offensive by one player or team to one strategy mode [10]. The proposed system in the paper can organize properly video database from the perspective of strategy analysis, convenient for effective retrieval. Moreover, the detected strategy mode can be used for the application with artificial intelligence demands like robot football [11-12].

ISSN: 2287-1233 ASTL

2 Segmentations of ball's real track

2.1 Ball's states

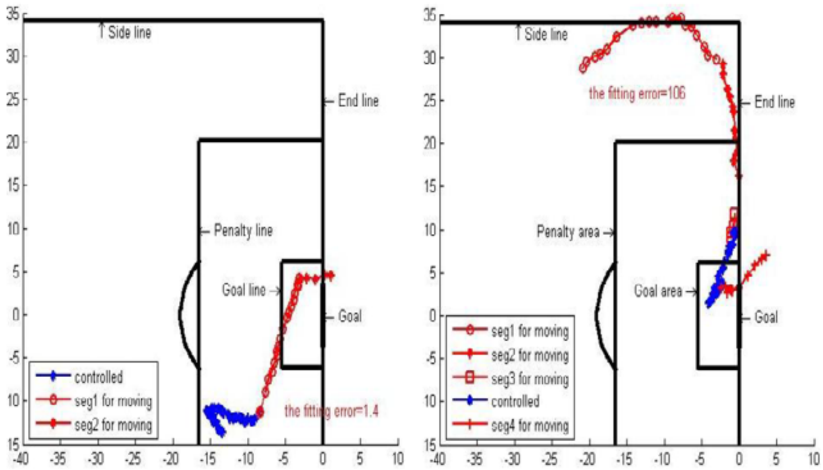
Leather ball is a key object in the football game. Both its trace and state contain lots of information. Normally, the ball has two states in the match: control state and pass state. The former describes the leather ball is being controlled by a player; the latter shows the ball being passed from one to another player. Further on, pass state includes volley pass state and ground pass state. Strictly in all, the ball has three states like: control state, volley pass state and ground pass state (Table 1). Knowing better features regarding ball's states and track is very conducive to analyze semantic information of football game, particularly the information about offensive modes. To be specific, football's state suggests a manner in which the offence is organized. We see if the football is mostly in volley pass state, the organizing way of the offensive is formed by in-the-air pass; if the football is mostly in ground pass state, the offense is formed by ground pass; if it's mostly under control, the offensive is completed by only one player.

Table 1. Football state, trajectory characteristics and semantic information

State		Trajectory characteristics	Semantic information
Control		The ball is moving very slowly Next to the players	Dribbling
Trans fer	The ground	Track segment makes up of line segments	Ground cutting
	In the air	The path has a curve	Over the top or the air pass

2.2 Recognition of ball's states

In different states, the ball's path has different features. When the ball is being controlled, its movement speed is very slow; and its path overlaps with that of the controller. The feature can help us discriminate control state and other states before thinking about how to distinguish volley pass and ground pass. As mentioned above, homography transformation is obtained by estimation of the relationship between image plane in image coordinate system and the pitch plane in real coordinate system. The transformation can map correctly graphical trail of objects moving in the pitch plane onto that in real coordinate system. When the ball is passing on the ground, with the mapping relationship, we can acquire correctly the ball's real track. Now, ball's 3-dimensional trajectory are straight lines on the pitch planar. Its real track is also a straight line. As seen in Fig. 1(a), if rubber ball is rolling on the ground among several teammates, its real trail is composed of some straight lines. If it flies in the air, its 3-dimensional trail is a parabola, not within the pitch plane. For now it's impossible to get the projection (i.e. a straight line) of its 3-dimensional trajectory on the plane by the said transformation. On the contrary, the directly calculated path is a curved line like Fig. 1(b). This feature can help discern volley pass state and ground pass state.



(a) the ground offensive (b) the air offensive

Fig. 1. Analysis of the soccer state and track

4 Experiment Design and Discussion

To prove the effectiveness of the proposed solution, we experimented on video data of FIFA World Cup 2012 goals. The data were collected from totally 64 sessions of matches tallied on radio and television. It's MPEG-2 compression format at 704*576 DPI.

We used those data for the experiment it's because scoring a goal is the most attractive event in the football match. In FIFA World Cup 2012 final stage, there were totally 168 goals. Setting apart goal events from broadcast videos is fundamental to the analysis of offensive modes. We split manually broadcast video data according to a certain standard, which is to keep the complete process of the whole event as long as possible. To get truthful analysis results about ball's states and offensive modes from those events, we invited experts to remark ball's states and offensive modes of goal events. For the correctness, we invited five experts to do independently. We used majority results as truthful analysis results.

Table2 shows the statistics of true analysis results of totally 168 scoring events: 55 ground offensives, of which 45, 8 and 2 events belong to mode IV, V and VI; 61 air offensives, of which 23, 24 and 14 events belong to mode I, II and III; the rest 52 events belong to other modes like penalty kick, place kick and long drive.

Table 2. annotation statistics of offensive mode manual

Offensive mode		The number of events	Percentage (%)
Air-offensive	AP-I	23	13.7%
	AP-II	24	14.2%
	AP-III	14	8.3%
Ground-offensive	AP-IV	45	26.8%
	AP-V	8	4.7%
	AP-VI	2	1.2%
Penalty		30	17.8%
Long shots		12	7%
Other		10	6%

4 Conclusion

This paper used the analysis method based on real trajectory. According to the analysis of the real trajectory, football strategy can more effective and appropriate expression. This paper first gives a field ground tracking algorithm, and then gives the true trajectory extraction algorithm.

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