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Analysis of 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. Our experiments on user study by soccer professionals demonstrate that the defined offensive patterns can be used to analyze soccer tactics effectively in terms of conciseness, clarity and usability.

Keywords: *Video content analysis, Scene analysis, offensive strategy, Tactic analysis*

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].

In general, especially for football game, strategy analysis has the two approaches according to the idea if target trajectory is utilized or not: track driven and non-track driven method [13-14]. Here we discuss the first method. Football game strategies can be often described by player's behaviors and ball's states. The track of both players and the rubber ball can reflect meaningfully their actions. So the trajectory-based method is visual and effective for the analysis of strategies [15].

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2. Analysis of Football Offensive Strategies

2.1. Segmentations of Ball's Real Track

2.1.1. 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
Transfer	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

2.1.2. 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 is straight lines on the pitch planar. Its real track is also a straight line. As seen in Figure 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 Figure 1(b). This feature can help discern volley pass state and ground pass state.

In [16], Lemire proposed an adaptive segmentation algorithm (hereafter referred to as Lemire algorithm). Here we'll use it to model coordinate data of football's trajectory. Lemire algorithm can fit polygonal lines formed by some straight lines which are connected end to end and are temporally segmented. It splits adaptively those lines to numerous segments. Each segment can be adaptively fitted by an appropriate model. Those models include flat model and linear model. To analyze states of the ball, we perform fitness analysis of trajectory data of the ball in pass state by Lemire algorithm. If the ball rolls on the ground by some players, its real trail is one broken line. Therefore, Lemire algorithm can adapt well to the ball's trajectory data, *i.e.* to acquire a small fitting

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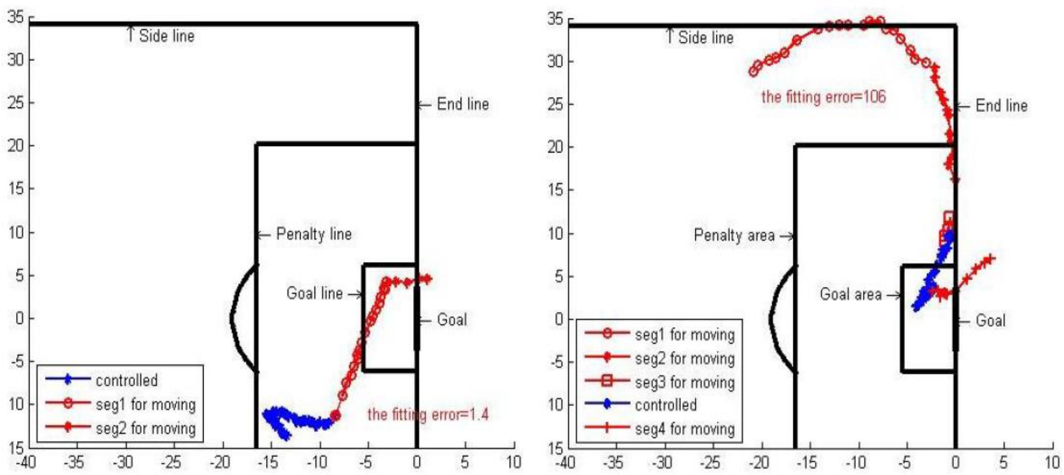
error. If the ball is delivered above the ground, its real trail is a curved line. We'll get a big error after fitness by the algorithm. Apparently, Lemire algorithm distinguishes effectively volley pass and ground pass. To be more specific, set ball's real coordinate series $(x_0, y_0), \ldots, (x_{n-1}, y_{n-1})$, which can be interpreted as to be composed of $lx: \{(0, x_0), \ldots, (n-1, x_{n-1})\}$ and $ly: \{(0, y_0), \ldots, (n-1, y_{n-1})\}$ with time as independent variable and locations in x and y axis as dependent variables. For the series lx in x axis, we cut it into Kx segments with Lemire algorithm $S_{jx} = \{(i, x_i) \mid z_{jx-1} \le i \le \mid z_{jx}\}, jx = 1, 2, .., Kx$, where $z_{jx}, jx = 0, 2, \ldots, Kx$ is sequence number of segment point. For each segment $S_{jx}, jx = 1, 2, \ldots, Kx$, the fitness error $Q(S_{jx})$ is calculated by (1). For the series ly in y axis, make similar calculation. Finally for $(x_0, y_0), \ldots, (x_{n-1}, y_{n-1})$, the serial number set of segment points is $\{z_{jx}\, jx = 1, 2, \ldots, Kx\} \cup \{z_{jy}\, jy = 1, 2, \ldots, Ky\}$ and the summation of errors is $Q = \sum_{jx=1}^{Kx} Q(S_{jx}) + \sum_{jy=1}^{Ky} Q(S_{jy})$. The selection of both serial number of segment points and model (flat model and linear model), the calculation of fitness parameter a, b, c as well as fitness error are all automatically finished by Lemire algorithm.

$$Q(S_{jx}) = \min_{p} \sum_{r=z_{jx-1}}^{z_{jx}} (p(r) - x_r)^2$$
$$where\ p(r) = \begin{cases} c & \text{flat model} \\ ar + b & \text{linear model} \end{cases} \quad (1)$$



(a) The Ground Offensive (b) The Air Offensive

Figure 1. Analysis of the Soccer State and Track

In a ground offensive and an air offensive as an example, on a football state recognition and football real trajectory segmentation description.

Figure 1 (a) expressed the true trajectory a ground offensive football: football control by No. 1 athletes (blue line identification), and then transfer to the No. 2 player along the ground (red segment of 1 logo), and ultimately by the No. 2 player to complete shooting (red line segment 2 identity).

To track data transfer in ground state football (red line 1 and 2), the Lemire algorithm will be divided into two segments, the fitting error is 1.4 units.

Figure 1 (b) expressed an air offensive real trajectory: football is transferred from No. 1 to No. 2 athletes (red segment of 1 to 3 identity), and then controlled by No. 2 athletes (blue line marking) and complete (red line 4 identity) shot.

Trajectory data of in the air passing state football (red line 1 to 3 identity), Lemire algorithm divides into three sections (with red line identifies different), the fitting error is 106 units. Obviously, in football ground state trajectory can fitting error is very small by Lemire algorithm

2.2. Offensive Modes

According to the football professionals, such as professional coach and commentator, summary of the analysis of the soccer offensives, most of the offensives have certain rules to follow, which has certain offensive mode.

According to the statistical analysis of FIFA World Cup goal event, offensive mode can be divided into two categories: one category is organization formed by air transmission, namely air offensive; another said offensive is the organization formed by ground transmission, namely the ground offensive.

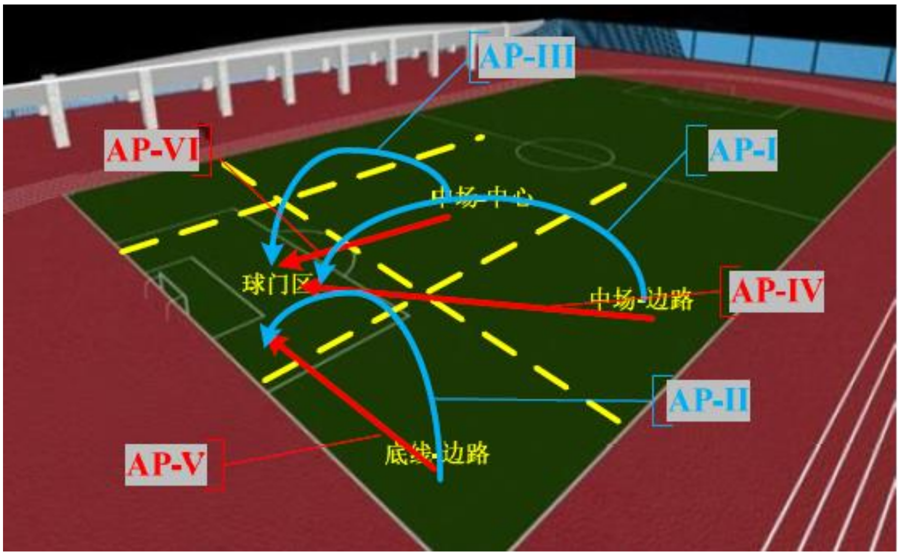


Figure 2. Division of Regional Football Stadium, different Paths and the Corresponding Six Kinds of Offensive Mode

As shown in Figure 2. According to the regional football from which the ways by which the transfer to the goal area, offensive patterns can be further divided into six kinds of modes.

AP-I (wide area from midfield to the goal zone according to the air mode); AP-II (from the bottom line wide area to a goal area according to the air mode); AP-III (from midfield the central area to the goal area according to the air mode);AP-IV (wide area from midfield to the goal zone according to the ground mode; (AP-V) from the bottom line wing area to a goal area according to the ground mode; (AP-VI) from midfield - the central area to the goal area according to the ground mode)

2.2. Recognition of Offensive Modes

Offensive mode, as its definition, can be represented by the segmentation of ball’s real trajectory, *i.e*. ball’s states and pitch area the ball passes over. For that reason we choose a rule-based approach to recognize offensive modes, considering it’s simpler and more efficient than a learning-based method.

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Step 1: Extract ball's real trajectory

Step 2: Separate ball's trajectory to control state and pass state segments. The moving speed of the ball in control state is slower than in pass state. Based on formula (2), we mark ball's states frame by frame, $(\ln d_n = 1)$ for control state and $(\ln d_n = 0)$ for pass state; where $D_{n,n-1,}(n = 2, \ldots, N)$ is Euclidean distance between two adjacent frames of rubber ball in real coordinate system. Since such states may be falsely classified, we smooth tag sequence with the median filtering algorithm, attempting to eliminate some wrong marks. Next, we join up points with the same tag. We'll see the entire track of ball divided in many sections;

$$\ln d_n = \begin{cases} 1 & D_{n,n-1} < D_{th} \\ 0 & \text{else} \end{cases} \tag{2}$$

Step 3: Re-classify the acquired track segments of the ball in pass state in Step 2 into:

(1) Ground pass state;

(2) Volley pass state. As discussed previously, the trail data of ball delivered on the ground can be well fitted by Lemire algorithm. We create the model of coordinate data $S^t = \{(x_i, y_i), (i = 1, 2, \ldots, N)\}, t = 1, 2, \ldots, T$ of trajectory segmentations in every pass state and compute fitness error $e^t, t = 1, 2, \ldots, T$. Finally, by equation (3), we categorize track segments, where $S^t = 1$ means the ball is in ground pass state; $S^t = 0$ means the ball is passed in the air;

$$S^t = \begin{cases} 1 & e^t < E_{th} \\ 0 & \text{else} \end{cases} \tag{3}$$

Step 4: Perform rough classification of offensive modes according to ball's states and trajectory segmentations. Generally, for air offensive, the ball is mostly in volley pass state; for ground offensive, the ball is mostly in ground pass state. Make the P_{th} of each trail segment. Then the total length of all trail segments P_{th} for the ball in ground pass state. By comparing it with a threshold value, we can classify offensive modes as follows:

$$CAP = \begin{cases} \text{air-attack} & \sum_{t=1}^{T} S^t Len^t < P_{th} \\ \text{ground-attack} & \text{else} \end{cases} \tag{4}$$

Step 5: Subdivide offensive modes to three kinds by depending on the coordinates of real trail's start point belonging to which pitch area; based on (5), we can discern the modes of offence.

$$FAP = \begin{cases} \text{AP-I} & \text{if CAP=air-attack and } C_{begin} = \text{middle-side} \\ \text{AP-II} & \text{if CAP=air-attack and } C_{begin} = \text{bottom-side} \\ \text{AP-III} & \text{if CAP=air-attack and } C_{begin} = \text{middle-center} \\ \text{AP-IV} & \text{if CAP=ground-attack and } C_{begin} = \text{middle-side} \\ \text{AP-V} & \text{if CAP=ground-attack and } C_{begin} = \text{bottom-side} \\ \text{AP-VI} & \text{if CAP=ground-attack and } C_{begin} = \text{middle-center} \end{cases}$$

$$\text{where } C_{begin} = \arg\max_{pos} \sum_{t=1}^{T_{begin}} Rg(t, pos), \tag{5}$$

Where, $Rg(t, pos)$ represent the real coordinate football article in t frames, it shown in formula (6).

$$\begin{cases} Rg(t, pos) = \begin{cases} 1 & \text{if ball is in the } pos \text{ of playfield} \\ 0 & else \end{cases} \\ pos \in \{\text{middle-side,bottom-side,middle-center}\} \end{cases} \tag{6}$$

3. Experimental Analysis and Results

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%

From the table1, we learnt that:

(1) Six offensive modes mentioned here can basically describe most offensive events; the other offensives are generally accomplished by a single player, like penalty kick and long drive, which are easily recognized; our defined offensive modes are helpful to excavate strategies conducive to win the game and also for coaches to promote training efficiency;

(2) Ground offensives are often initiated in midfield-central area, taking 26.8% of all goal events;

(3) Air offences are generally launched in sideways area, of which the offensive in bottom lines-sideways area reaches 14.2% and 13.7% in midfield-sideways area, totaling 27.9% of all goal events.

Next we utilized video data of 116 goal events in all six offensive modes to validate the performance of the offensive mode recognition algorithm.

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3.1. Result of Recognizing Ball's States

From the video data, we chose six typical video segments to verify the effectiveness of the algorithm. As indicated in Table3, for each trail, the recall ratio and precision rate of ball's states are computed by equation (6).

Table 3. Recognition Results of Football State

Trajectory	Frames number	Control			Transfer					
					Ground transmission			Air transmission		
		Manual calibration number	Precision	Recall	Manual calibration number	Precision	Recall	Manual calibration number	Precision	Recall
T1 (AP –I)	64	15	73%	80%	/	/	/	49	86%	96 %
T2 (AP – II)	50	10	72%	80%	/	/	/	40	86%	97 %
T3 (AP – III)	70	21	70%	75%	/	/	/	49	84%	92 %
T4 (AP – IV)	60	21	89%	97%	39	88%	95%	/	/	/
T5 (AP – V)	65	12	84%	90%	53	78%	83%	/	/	/
T6 (AP – VI)	50	10.	85%	92%	40	78%	88%	/	/	/

Again from the table3, we concluded that:

(1)For air offensive mode, ball is mostly in volley pass state; it's controlled shortly before it's delivered by one player to another; so the precision of recognizing this control state is a little lower than for ground offensive;

(2)For the offensive mode III, ball's real trajectory shows a smaller radian; so at the moment, the rate of identifying ball's pass state is relatively low.

3.2. Result of Recognizing Offensive Modes

We used the selected 116 goal events as data to evaluate the performance of the proposed recognition algorithm here. We still employed recall rate and precision ratio to measure the recognition result, which are listed in Table 4. Obviously the algorithm proved reliable. The recognition result can be affected by some key factors. Even for football experts, they can't divide unanimously areas of the pitch, *e.g*. the boundary between midfield-sideways area and midfield-central area is hardly determined uniformly. Therefore, it's inevitable that the recognition result of some offensive modes is not in line with manually calibrated result.

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Table 4. Recognition Results of the Offensive Pattern

Offensive mode	Nc	nm	nf	Recall (%)	Precision (%)
AP-I	21	2	1	91%	95%
AP-II	22	3	2	88%	91%
AP-III	10	3	4	77%	72%
AP-IV	2	0	0	100%	100%
AP-V	7	1	1	88%	87%
AP-VI	40.	5	6	87%	87%

3.3. User Survey about Strategy Analysis

The purpose of analyzing offensive modes is to discover important strategies for the football competition, as for footballers to improve skills and abilities and to help coaches conclude factors leading to gain the match. So it's necessary to examine whether the defined offensive modes here are effective.

We invited five experts to conduct user analysis experiment. One expert is a coach with four years' experience in training. Two are players with six-year experience in participating the match. The other two are commentators having related experience for three years. They all have rich strategy analysis knowledge. We took the same three indicators as in [1] to measure features of the proposed method: simplicity: we offer no redundant information; clearness: we present clear and understandable information; practicability: the information is useful for training and competition.

We used scores in five levels to quantify those indicators: best (5 points), good (4 points), general (3 points), bad (2 points) and terrible (1 point). The average scores of them are put in Table 5. Apparently our method was accepted by football experts.

Table 5. User Survey Results of Strategy Analysis

Experts	Simplicity	Clarity	Practicability
Experts1	4.5	4.7	4.2
Experts2	4.3	4.8	4.0
Experts3	4.7	4.9	4.3
Experts4	4.1	4.7	4.2
Experts5	3.8	4.2	3.8

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. Further, for football state are described, defines six types of typical offensive pattern. And gives an offensive pattern recognition algorithm. The experimental results show that the offensive modes are better than the existing methods from simplicity, clarity and practical aspects.

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