ISSN 1750-9823 (print)
International Journal of Sports Science and Engineering
Vol. 04 (2010) No. 02, pp. 089-094

Data Mining in Movement Visual Information

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(*Received November 26, 2009, accepted December 22, 2009*)

Abstract. Using the association rule mining, the paper analyses the fixation area of football players and non-athletes in order to search fixation discipline of different subjects and to find their visual search strategy when they watch videos of games. So it can provide a new method and a new idea for visual search research.

Key words: data mining, association rules, fixation pause area

1. Introduction

Confrontational sports demand that athletes have quick and accurate ability to predict and respond. [1] Because high sports vision of athletes, so they respond faster and more accurate than non-athletes. [2] How athletes searcher visual information in changing process of game? More and more attentions have been pay on research about sport vision. [3-7] Previous findings of scholars shows that most existing research of visual search patters adopt direct observation or general statistical analysis methods such as frequency analysis, t test and ANOVA analysis to compare the difference between expert and novice in predictive ability and visual search capabilities and to analyze the effect of the different characteristics between athletes and other factors on sport vision ability, which used to study the difference between expert and novice in fixation counts, fixation length, watch track and fixation areas. But because these researches don't consider the feature of time series and Ignores the time continuity of visual information, these researches don't answer some problem such as what is the information processing of athlete and how players explore the visual cues and how transfer the visual attention and so on.

Data mining, which is also known as knowledge discovery in databases, is product of artificial intelligence such as database technology and machine learning. And it is a new intelligent data analysis technique. The so-called data mining is to extract data from a large number of mining knowledge and to explore and analysis large amounts of data by automatically or semi-automatic tools and to find meaningful patterns and rules from mining result further. [8] Now, data mining is widely used not only in traditional retail, telecommunications, banking, insurance and other fields, but also in the medical, tax, web and other field. With data mining making great achievements in traditional applications field in recent years, the emerging fields such as sports have begun to try to use data mining technology [9-12], and have made some progress.

Association rules mining is a important mining technology in data mining. The nature of association rules mining is extraction relationship from large amounts of data or objects. It can reveal the dependencies among the data, especially for time series data. So according to features of natural time series of visual cues，the use of association rule mining is to be able to answer some problem such as how players explore the visual cues and how transfer the visual attention, which can not be solved by traditional statistical methods in the past .

Using the association rule mining, the paper analyses the fixation area of football players and non-athletes in order to find their visual search strategy and to reach further exploitation and utilization of fixation area of players. So from mining results, visual search patters and disciplines can be found. So it is significant to improve the level of athlete training and competition. Meanwhile, the research can provide a new method and a new idea for visual search research.

2. Association rules mining of fixation area of player

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2.1. Association Rule Mining technology

An association rule is an implication of the following logical entailment: $A \Rightarrow B$, where A, B are itemsets. To the transaction set D, $A \in D$, $B \in D$, $A \cap B = \Phi$. Two parameters are generally used to describe the attribute of Association Rules.

Support: Support ($A \Rightarrow B$) is the sum of tuples containing A and B$(A \cup B)$. Support describes the appearance probability of A and B tuple in all the transactions, $P(A \cup B)$.

Confidence: Confidence ($A \Rightarrow B$) irefers to "reliability". The confidence of ($A \Rightarrow B$) can be defined as: Confidence ($A \Rightarrow B$) equals the sum of tuples contaning A and B/ containing the tuples of A; Confidence describes the probability of itemset B in D when itemset A is in D, $P(B|A)$.

The main issue of Association Rule mining is to find out in a mass database association rules between the given min_sup and min_cof.

The computation of the Association Rule mining is largely a two step process:

(1) Find out all the frequent item set in a large database. If support(X)≥min_sup, then X is a frequent itemset. By definition, each of these itemsets will occur at least as frequently as a predetermined minimum support count.

(2) Generate association rules from the frequent itemsets. For each frequent itemset X, if $Y \subset X$ and $Y \neq \Phi$ and confidence ($\{Y \Rightarrow (X-Y)\} \geq \min\_conf$), then there is a association rule $Y \Rightarrow (X-Y)$.

The second step is relatively easy. Currently, the majority of researches focus on the first step, of which the Apriori computation is the most classic one.

Apriori Algorithm

$Input$: DB, $\min\sup$.

$Output$: $\mathrm{Re}\,sult =$ all frequent itemsets and their supports

Method:

$\mathrm{Re}\,sult := \{\}$;

$k := 1$;

$C_1 :=$ all 1-itemsets

$while(C_K)do$

$begin$

Make a counter for each itemset of C_k

$for(i = 1;\ i \leq |DB|;\ i++)$

$begin$ /*to record T of all DB*/

To each itemset of C_k, the counter will plus one if record T(i) support it.

end

$L_K := C_K$ (L_K :=all itemsets which supports frequency >min_sup)

L_K saves the support frequency of L_K ;

$\mathrm{Re}\,sult := \mathrm{Re}\,sult \cup L_K$;

$C_{K+1} :=$ those(k+1)-itemsets whose all k-subsets are in L_K

$k = k + 1$;

$enddo$

2.2. Data collection and pretreatment

The paper discuss visual search capability of football player, taking video clips of two scenes of penalty shot and 3 vs. 2 in small space as the experimental stimuli. Subjects consist of football players and non-athletes. And fixation data are collected using eye tracker when subjects watch videos of games.

Before data mining, data are collected according to requirements of football game analysis firstly. According to study of savelsbergh[13], fixation areas are divided into head and shoulder and arm and trunk and hip supporting leg and kicking leg and area between the man and the ball and ball when subjects watch penalty shot video. And according to study of vaeyens[14], fixation areas are divided into middle player and left offensive player and right offensive player and left defender and right defender and left marked area and right marked area and ball .Different areas are encoded in the paper in order to facilitate analysis of data.

All areas are divided into significant areas and meaningless area (10) in penalty shot scenes. Significant areas consist of head(1), shoulder(2), arm(3), trunk(4), hip(5), supporting leg(6), kicking leg(7), area between the man and the ball(8)and ball(9).

All areas are divided into significant areas and meaningless area (9) in 3 vs. 2 scenes. Significant areas consist of middle player(1), left offensive player(2), right offensive player(3), left defender(4), right defender(5), left marked area(6), right marked area(7)and ball(8).

According to division rule of the fixation, the script-describing tech is adopted and a symbol system about the division of fixation is set up, as shown in table 1.

Table 1: Data of fixation

ID	Group	Type	Procure	Watch_Pos
1	Player	Penalty	1	10
1	Player	Penalty	2	6
1	Player	Penalty	3	7
1	Player	Penalty	4	8
1	Player	Penalty	5	9
2	Player	Penalty	1	10
2	Player	Penalty	2	8
2	Player	Penalty	3	9
2	Player	Penalty	4	8

The table includes the following names: ID(Subject number), Group, Type（Video Type）, Procure(Watch step), Watch_Pos(Fixation), as shown in table 1.

2.3. Data Analysis

The research mine fixation areas of players and no-athlete using association rule mining. Using support frequency, visual searching features of both groups can be analyzed after finding out the first few combinations of fixation areas with high support frequency. The results show that non-athletes haven't visual search pattern and that players have the visual search pattern. Table 2 and table 3 show detailed results of mining fixation area.

Table 2: results of association rule mining in penalty shot scenes

Serial number	Frequency	Support	Step1	Step2	Step3	Step4
1	6	0.22	10	7	8	9
2	5	0.19	10	4	8	9
3	3	0.11	10	9	8	9
4	14	0.52	10	8	9	
5	8	0.30	10	7	9	
6	8	0.30	10	4	9	
7	6	0.22	7	8	9	
8	6	0.22	10	7	8	
9	6	0.22	10	4	8	
10	5	0.19	4	8	9	
11	4	0.15	10	6	9	
12	4	0.15	10	9	8	
13	3	0.11	9	8	9	
14	3	0.11	10	10	9	
15	3	0.11	10	9	9	
16	23	0.85	10	9		

17	15	0.56	10	8
18	14	0.52	8	9
19	10	0.37	10	4
20	9	0.33	4	9
21	9	0.33	10	7
22	8	0.3	7	9
23	6	0.22	7	8
24	6	0.22	4	8
25	6	0.22	10	6
26	5	0.19	10	10
27	4	0.15	6	9
28	4	0.15	9	8
29	4	0.15	10	3
30	3	0.11	9	9

Head(1), Shoulder(2), Arm(3), Trunk(4), Hip(5), Supporting leg(6), Kicking leg(7), Area between the man and the ball(8), Ball(9)and Meaningless area(10)

From mining results of fixation areas in penalty shot scene, The most frequent combination is area 10→area 9, support is 85%, which shows that most players watch meaningless area firstly before watching ball in the visual search process. In combinations of 3 fixation areas, the most frequent combination is area 10→area8→area 9, support is 52%, which also shows that area between the man and the ball is the most critical area. Ball is the key to predict the direction of ball for players when in penalty shot scene. And players analyze the direction of the ball through ball and effective information around ball.

Table 3: results of association rule mining in 3 vs. 2 scenes

Serial number	Frequency	Support	Step1	Step2	Step3	Step4	Step5	Step6
1	9	0.33	9	1	7	3	7	1
2	7	0.26	9	1	7	3	8	1
3	16	0.59	9	1	7	3	1	
4	11	0.41	9	1	7	7	1	
5	11	0.41	9	1	3	7	1	
6	10	0.37	9	7	3	7	1	
7	9	0.33	1	7	3	7	1	
8	9	0.33	9	1	7	8	1	
9	9	0.33	9	1	7	3	7	
10	8	0.3	9	1	3	8	1	
11	8	0.3	9	7	3	8	1	
12	7	0.26	1	7	3	8	1	
13	7	0.26	9	1	7	3	8	
14	6	0.22	9	1	7	1	1	
15	21	0.78	9	1	7	1		
16	19	0.7	9	1	3	1		
17	17	0.63	9	7	3	1		
18	16	0.59	1	7	3	1		
19	16	0.59	9	1	7	3		
20	12	0.44	9	1	8	1		
21	12	0.44	9	7	7	1		
22	12	0.44	9	3	7	1		
23	11	0.41	1	7	7	1		
24	11	0.41	1	3	7	1		
25	11	0.41	9	7	3	7		
26	11	0.41	9	1	3	7		
27	11	0.41	9	1	7	7		
28	10	0.37	9	7	8	1		
29	10	0.37	7	3	7	1		
30	9	0.33	9	3	8	1		

Middle player(1), Left offensive player(2), Right offensive player(3), Left defender(4), Right defender(5), Left marked area(6), Right marked area(7), Ball(8), Meaningless area(9)

From mining results of fixation areas in 3 vs. 2 scene, In combinations of 4 fixation areas, the most frequent combination is area 9→area 1→area 7→area 1, support is 78%, which shows that most players watch meaningless area firstly n the visual search process, and watch middle player finally. In middle step, area 3 and area 7 have a high probability to emerge. This shows that it is more possible to extracted information from the two areas. That is, players predict the direction of ball through the action of middle player. Later watch the action middle player again to verify their own forecasts after searching effective information areas.

3. Conclusions

(1) The association rule mining is suitable for further using and analysis of fixation area of players and is able to reveal more discipline of fixation area of players, providing higher application value to find their visual search strategy.

(2) We find from results of association rule mining that players have the visual search pattern. We have found that players use some fixed pattern to analyze video in a penalty shot scene. First they fix their vision on meaningless area. After judging picture, they predict with ball to find available information around, and verify their own forecasts finally. In 3 vs. 2 scene we have found that players first fix their vision on meaningless area, and observe area with ball, and fix their vision on middle dribbler and verify their own forecasts finally. The result of two scene shows that player have the visual search pattern and have different visual search pattern for different scenes and have similar visual search pattern for a same scene.

4. References

[1] Jingcheng Li, Shousen Xu, Sen Zhang. A Review of Eye Moving Researches in Sports Psychology. *Journal of Capital Institute of Physical Education*. 2006, **18**(3):3.

[2] Williams AM, Davids K,Williams JG. Visual perception and action in sport. *London: E & FN Spon*. 1999, pp. 110-116.

[3] Claude Goulet, Chantal Bard, Michelle Fleury. Expertise Differences in Preparing to Return a Tennis Serve: A Visual Information Processing Approach. *Journal of Sport & Exercise Psychology*. 1989, **11**: 382-398.

[4] Petrakis E. Analysis of Visual Search Patterns of Tennis Teachers. In:Gd' Ydewalle, J van Rensbergen(Eds). Perception and Cognition: Advances in Eye Movement Research. North-Holland: Elsevier Science Publishers, *B.V.* 1993, pp.159-168.

[5] Helsen WF, Pauwels JM. A cognitive approach to visual search in sport. In Visual Search II. London: *Taylor & Francis.* 1992, pp. 177-184.

[6] Helsen WF, Pauwels JM. The relationship between expertise and visual information processing in sport. In Cognitive Issues in Motor Expertise. *Amsterdam: Elsevier*. 1993, pp.109-134.

[7] Ripoll H, Kerlirzin Y, Stern et al. Decision Makin and Visual Stra ies of Boxers in a Simulated Problem Solvin Situation. In: G. d' Ydewalle, J van Rensber en(Eds), Perception and Cognition Advances in Eye Movement Research. North-Holland: Elsevier Science Publishers, *B.V.* 1993, pp.114-147.

[8] Michael.J.A.Berry. *The Science and Art of Customer Relationship Management.* Beijing: Financial & Economic Publishing House. 2004..

[9] Hongge Gao, Huiqun Zhao. Application of Association Rule Mining in Analyzing Techniques and Tactics of Table Tennis Match. *Journal of North China University of Technology*. 2006, **18** (1): 15-19.

[10] Gregory. Advanced Scout: Data Mining and Knowledge Discovery in NBA Data. *Data Mining and Knowledge Discovery*. 1997, **1**(1): 121-125.

[11] Flip Korn. Quantifiable Data Mining Using Principal Component Analysis. *Data Mining and Knowledge Discovery*. 2001, **4**(7): 13.

[12] Chen M S, Han J, Yu PS. Data Mining: An Overview from a Database Perspective. *IEEF Trans.on Knowledge and Data Eng*. 1996, **8**(6):866-883.

[13] Geert JP Savelsbergh, Williams AM, John Vandrr Kamp, et al. Visual Search, Anticipation, Expertise in Soccer Goalkeepers. *Journal of Sports Sciences*. 2002, **20**:279-287.

[14] Roel Vaeyens, Matthieu Lenoir, Williams AM, et al. Mechanisms Underpinning Successful Decision Making in Skilled Youth Soccer Players: An Analysis of Visual Search Behaviors. *Journal of Motor Behavior*. 2007, **39**(5): 395-406.