Sports Video Analysis for Player Strength and weakness psychiatry in the context of Object-Relational Data Bases

UmaMaheswari[1] ,M.Rajaram[2], S.N.Sivanandam[3]

[1] *Computer Science and Engineering , Sona College of Technology*
Anna University , Salem, Tamil Nadu, INDIA
[2] *Electrical and Electronics Engineering, Government College of Engineering,*
Tirunelveli, Tamil Nadu , INDIA
[3] *Prof and Head , Computer Science and Engineering , PSG College of Technology*
Coimbatore, Tamil Nadu, INDIA

Abstract: **The advent of video coverage of sports has provided an impetus to develop models for tactics analysis for providing training assistance by summarizing the play tactics from video streams. Though there are plenty of sports data and statistics available, there has been no real effort to scientifically extract value from such data. The rapid growth in size of the match database far exceeds the human abilities to analyze such data, thus creating an opportunity for using data mining on this database. The aim of this work is to mine sports video annotation data to extract knowledge about match play sequences and applying that knowledge for classification of players for developing player specific training taxonomy. The major objective of this paper is to analyze individual player's performances and to devise a classification technique so as to classify them into appropriate groups using the frequently played patterns and other performance indices like strike rate , six-runs and four-runs. This classification helps the coaches to know the current form of the player and to understand their strengths and weaknesses. With this information, a coach can assess the effectiveness of certain coaching decisions and formulate game strategy for subsequent games. To achieve the objective of this work, video stream of cricket matches were observed manually and ball shot descriptions were taken as annotation and stored into an object-relational data model. Frequently occurring patterns were identified, then further evaluation was carried out on those patterns to group them into different clusters based ontheir influence in producing success and failure. Classification mechanism is applied to analyze each and every individual player's strengths and weaknesses to fix them into a respective class of training taxonomy.**

Keywords : **Tactical analysis, Sports Video mining, Player classification, mining on object-relational databases, mining on cricket data, player strength weakness analysis, knowledge extraction for tactical training.**

I. INTRODUCTION

A. Motivations

Although Data Mining has been widely and successfully used in the domain of business operations, Data Mining in sport is just in its infancy (Fielitz and Scott, 2003; Lefton, 2003). In other words, the sports industry has generally been a poor and light user of Data Mining (Jutkins, 1998). An extensive performance study of all the test-playing cricket teams around the world since 1950's till the 2000s has been done by Barreta et al (2008) and the observations of this study have been pointed out: On taking the performance of Indian team, it was slowly inclined during the period 1950 to 1980 and there was a great fall down during 1980-1990 and then it was at the increasing edge at 2000's. Now as per the win/loss ratio, India is in 4th position and at highly competitive spectrum. But at the same time Australia is at top level and proven to have spectacular performance. It is evidential that Australia has a strong scout and does effective data analysis on individual player performance. Many other countries are spending massive fund on training and testing the abilities of players. All such activities are relying on human-based knowledge utilization which has very low prospective on continual analysis against fast growing data size.

B. Literature Review

Nowadays, extensive research efforts have been devoted to sport video data analysis in recent years due to their wide viewer ship and huge commercial potential. Many indexing and retrieval techniques were addressed such as structure based annotation, event based annotation and ontology based annotation. Yatabe et al(2000) proposed a method that has enriched video contents with the objective to provide a multi-layer video object database, based on users' interactive description of video objects. They have modeled a database that will have the ability to organize incomplete descriptions of video objects in each frame, mainly annotation, position and motion and have implemented the prototype system, which provides users functions such as semi-automatic enrichment of annotations, similarity retrieval of objects, and semantic indexing, based on the video object database. In this paper, the authors describe how to concentrate on the objects in video frames and propose a construction method for a video database which is not fully automatic, and needs the assistance of human interaction.

Wang and Parameswaran(2004) have presented a detailed survey on sports video analysis such as slow motion replay, pattern analysis, statistics collection, video archiving, tracking and tactic analysis etc. The authors reviewed the current research in sports video analysis and have discussed the research issues of the field and the potential applications. Assfalg et al(2002) have proposed a temporal logic model to marketable sports video archive and have addressed the problem of detection and recognition of sports highlights from sports videos. Blak et al(2001) have proposed sports video structure analysis both at frame level and shot level. Krishnamurthy(2000) in his research has modeled a framework for annotating game database in object-relational context.

Most of the research on sports video focuses on event detection and summarization. In this scenario, Li and Sezan(2002) have dealt with time segments of football play for event detection. In this approach, play is defined as basic segments of time, then deterministic as well as probabilistic models were developed to detect play and then detected plays are concatenated to generate compact, time compressed summary of original video which contains meaningful action. Ekin and Teklap(2003) have proposed a fully automatic and computationally efficient framework for analysis and summarization of soccer videos using kinematics and object-based features.

Another important research focus on sports video is highlight extraction. Kaufmann et al (2000) have dealt with automatic extracting of highlights for TV baseball programs by detecting audio track features. This approach uses generic sports features and baseball specific feature. Xu et al(2008) have dealt at length this principle for soccer ball in which multimodal framework approach has been adopted for semantic annotation and effective personalized retrieval.

Tracking on sports video is another research topic in sports video analysis. Pingali et al(1998) have proposed a real time tracking model for enhanced broadcast of Tennis game in which spatio-temporal trajectories of motion of players and ball, provide a number of statistics about the game. Such statistics as distance travelled by player, speed, acceleration as well as court coverage patterns can be used for enhancement in broadcast. Sudhir et al(n.d) have dealt with a different approach for tracking players which involves content based retrieval for baseline rallies, passing shots, server and volleying etc. An improved approach has been adopted in literature (Nepal et al 2001) where content based retrieval is based on high-level semantic descriptions rather than the traditional low-level features such as motion, color, texture, beat and loudness. YuX et al(2003) have described trajectory-based ball detection and tracking through semantic analysis on broad cast video of soccer games.

One of the major aims of sports video analysis is to provide assistance for training. There is a need to summarize the play tactics from video streams. Much research has been done on classifying a play sequence into an existing tactic pattern and recognizing unknown patterns. Han et al(2002) proposed a multimodal integration with semi-automatic annotation for tactic analysis in baseball. The same attempt has been done by Assfalg et al(2002) for soccer game. Babaguchi et al(2002) proposed intermodal collaboration approach for American football. Sudhir et al (1998), Wang

and Parameswaran (2003) have proposed feature classification for tactics analysis in tennis game.

Choudhury et al (2007) proposed a neural network based outcome prediction on cricket tournaments. To train the neural networks, they used results of various matches played by the teams in the past 10 years. Once trained, the current tournament's match information will be run through the neural networks. Possible input variables include, for each team, number of matches played, number of matches won, number of matches lost, recent standings of teams, conditions of match locations, number of times a team reached the quarterfinal stages and the semifinal stages of a tournament, as well as number of tournaments a team won. The domains used for training and testing include overall performance in the tournament. To predict a tournament's outcome, the data through all the networks are run and the scores for each team are added up. The team with the highest score is the winner.Duckworth and Lewis(2008) stated a new principle to give an effective solution to calculate revised target to tackle real time problem of inclement weather (such as rain or bad light). Adopting this philosophy in a one-day match, could easily prevent the match from completing in a single day due to time constraints. New Zealand Cricket(NZC) Team identified the need to help coaches and the captain in determining their match play strategy in real time to make decisions at any point during the innings most likely to produce a win. New Zealand Cricket now has a single data mart with models that are easy for coaches and others to use for real-time match data analysis and decision making. This work was done using SAS software tool which provides New Zealand with a competitive edge in matches. It is also helping to develop players' skills. This information has been published in the website: www.sas.com/newzealand

C. Existing Vs Proposed System

This research area centers on the Indian cricket team and evaluating their performance using the concepts of data mining. This research work is specifically tailored for cricket coaches and statisticians. The process of match data gathering and analyzing them for identifying any fascinating patterns is quite obligatory nowadays. Data Mining can be viewed as the process of extracting previously unknown information from large databases and utilizing this information to advance the development and to take key decisions. Very few efforts has been taken to extract knowledge from cricket data base, but they all are concentrating at statistical information like runs scored, matches played, batting average, strike rate and the like. Through this statistical analysis, the performance can be analyzed and each player and team can be rated accordingly. But this analysis cannot help to rectify anomalies and to formulate tactical coaching strategies to further improve the performance. To improve the performance and rating of players, it is necessary to know the strengths and weaknesses of them priorly and train them in such a way to pick up their strengths and resolve their weaknesses. On developing individual spirit, automatically the team spirit raises up.

Finally, the highly interesting patterns are analyzed for their interrelationship using association mining techniques. On extracting a particular player's frequent patterns summary, if most of them are under six, four or run yielding, then that player is fitted to the form 'excellent', and so on. Based on that intelligence, the team coaches will determine the best short-term strategy. It might be, for example, to change the batting order and advise the new batsman what he and his partner should do during their next course of action and to change the fielding positions according to the type of ball drive and strike. The proposed research work predicts an outcome based on the point-in-time situation, and the coaches use this prediction to determine the best course of action.

II. METHODOLOGY

The raw data from Cricket matches were initially collected using a specialized system designed for logging cricket annotation data. Annotation is the markup definition of ball shots which includes different actions such as bowling, bating, and fielding and the description of the entities involved in those actions, their role, relationships and the type of action they performed and finally the result turn out of that ball shot. This can be done manually by the people who boast expressive familiarity in cricket match.

To carry out this trial, a wide collection of annotations to the extent of 20,000 ball shots were taken in the cricket master table which is constructed in oracle 10g application development wizard.The proposed methodology is depicted in Figure 1. Cricket match has granularities at different level which can be modeled into a concept hierarchy as shown in Figure 2.

A. Data Modeling

Since cricket match concept hierarchy shown in Figure 3 has been structured as a collection of objects and its relevant actions, the model developed to depict this data is
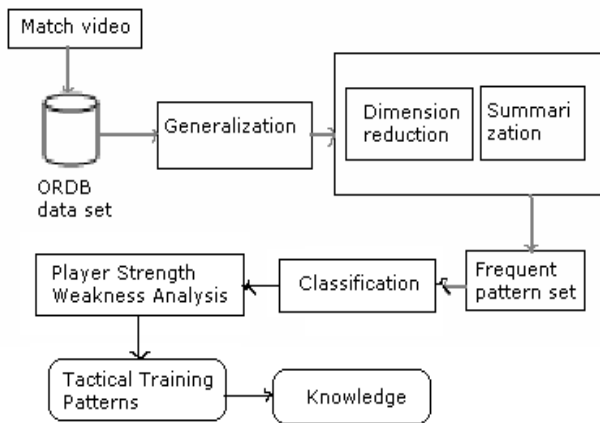

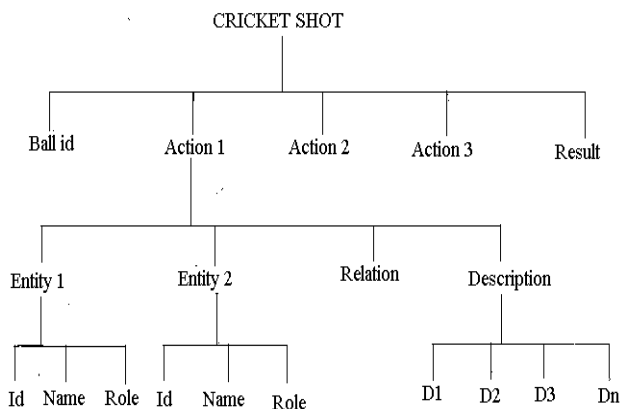Figure 1: Proposed System Model

Figure 2 Concept hierarchy of cricket data model

termed as Object-Action Model. This model describes the entire ball by ball scenario of each event that occurs in the match. Here, object- relational data model is established which encapsulates and relates the objects that are involved in a particular action.

Cricket database model is structured at multilevel hierarchy as shown in Figure 2, where a ball sequence is considered being an event. Each event consists of a unique identifier 'ballid' which can be used as the primary key of the cricket database, three actions such as: Action-1, Action 2 and Action 3, and result of that ball shot. An action intern consists of many objects like entities of an action and its description and also a singular attribute relationship between events. An entity object refers to the name of the player involved in that particular action along with his role and identification. Each action may have two entities. The description object comprises a set valued attribute where each element in the set defines different styles of action attempt. The data model encompasses different granularity levels that are incorporated in the form of alphanumeric representation of the ball identifier which is used as the key attribute of the match master table.

Object-Relational Data Structure for Cricket data

With reference to the concept hierarchy given in Figure 3, the cricket database schema definition is formed in Object-Relational data model, and further the ball shot annotations are stored in this database. The cricket database structure is as follows:

> *{ballid, Action1, Action 2 , Action 3, Result}*
> *Action {{<Entity 1>, <Entity 2> , ...}, Relation,*
> *   Dlist}*
> *Entity { EName,   Role, Attributeid }*
> *Description {D1- D2-,…….., Dn}*

The data model as described in previous section will be modeled using Object-Relational Database Structure. Once after the Object-Relational table structure for the cricket dataset is created, then the annotations of ball shots can be input through an interface.

B. Data Preprocessing

High dimensional data can pose problems for predictive models or machine learning because many attributes may redundant or highly correlated which can lead to degradation of prediction accuracy. Since the foremost efficient mining algorithms are all pertinent for simple relational data base structures, preprocessing is a good solution to deal with complex data. After the data input, a series of consistency checks are performed to ensure that the data are accurate as possible before any analysis occurs. The original object-relational storage of cricket data is seem to be very complex and has very high storage requirement and slow down the search process drastically. To effectively extract information from a huge amount of data on complex databases, Data Mining algorithms must be efficient and scalable. Since it is difficult to abstract the relevant information from the complex database, reducing the size complexity of the database will improve the efficiency. Reduction of complexity is achieved through Attribute-Oriented Induction based Data generalization. After generalization, the space complexity is reduced to some extent but still it seems to be required to do compression and dimension reduction. Compression yields a good rate of space complexity reduction and dimension reduction simplifies the database by identifying more relevant attributes for mining.

C. Player Strength and Weakness Analysis

To formulate player specific coaching strategies, the coaches must analyze and realize the individual player performance by means of their strengths and weaknesses. In this scenario, strength means the player's ability to drive successful patterns most frequently and weaknesses represents their frequent attempts to unsuccessful patterns. This analysis has been done for different roles(bowler and batsman) of players.

Before initiating this analysis, the patterns must be thoroughly analyzed and categorized according to their outcomes. For example, while looking for batsman strength, the patterns that are driving the ball to maximum strike rate in the sense of hitting most likely sixes and fours are considered. But at the same time while dealing with bowler

the strength means lower strike rates most likely no runs and wicket falls are considered.

D. Pattern Analysis and Clustering

Each and every pattern must be evaluated against its yield and should be grouped accordingly. For this grouping, the evaluation constraint is strike rate which is computed as given in equation (1) :

$$\text{Strike Rate}(P_i) = \text{Total Run Scored} / \text{Count}(P_i) \qquad (1)$$

To do so, for a batsman, the pattern having more strike rate will be considered as good pattern and can be used for tactical training. But for a bowler and fielder, the pattern with low strike rate is treated as good pattern and can be used for tactical training most likely to win. There are two sets of clusters maintained: one for bating and another for bowling and fielding. The Knowledge for clustering patterns is given as below:

For batsman view:

   if strike rate > 1.0 then pattern => 'Goodbat' Cluster

   else if strike rate > 0.7 and 1.0 then

     pattern => 'Averagebat' Cluster

else if strike rate < 0.7 then

    pattern => 'Deprived bat' Cluster

 For bowler and field view:

   if strike rate < 0.7 then pattern => 'Goodbowl' Cluster

    else if strike rate > 0.7 and 1.0 then

      pattern => 'AverageBowl' Cluster

     else if strike rate > 1.0 then

      pattern => 'Deprived Bowl' Cluster

     To compute probability of a player P belongs to a class C, frequently played patterns of that player is taken and the parameters X,Y and Z are measured for each pattern according to its existence in pattern clusters.

$$Probability\ P_1(X) = \frac{X}{Total\ Number\ of\ patterns\ in\ Good\ cluster}$$

$$Probability\ P_2(X) = \frac{Y}{Total\ Number\ of\ patterns\ in\ Average\ cluster}$$

$$Probability\ P_3(z) = \frac{Z}{Total\ Number\ of\ patterns\ in\ Bad\ cluster}$$

The probability values are helping to determine the current form of the players. Batsman's form is classified as good, average and bad based on the following criteria:

If P_1 > 0.5 and P_3 < 0.2 then

  Batsman form is "Good"

If P_1 , P_2 , P_3 ≥ 0.4 and < 0.5 then

  Batsman form is "Average"

If P_3 > 0.5 then

  Batsman form is "Bad"

Similarly

If P_1 > 0.5 and P_3 < 0.2 then

  Bowler form is "Good"

If P_1 , P_2 , P_3 ≥ 0.4 and < 0.5 then

  Bowler form is "Average"

If P_3 > 0.5 then

  Bowler form is "Bad"

That is the batsman form is classified as good if he most likely plays more run yielding patterns and least likely plays low run yielding patterns. Similarly there are predefined set of conditions for average and bad patterns. Further, Bowlers are classified as good if he most likely plays low run yielding as well as wicket hitting patterns and least likely plays more run yielding patterns.

E. Tactical Training Patterns

After classifying players into appropriate classes, tactical training module will be started. For every player, all his good patterns may be considered as his strength and are taken as tactical patterns to initiate tactical pattern based training to uphold his strength. And all his bad patterns may be considered as his weakness for which sufficient training must be given to tackle those ball shots in a successful way. For all bad and average patterns found, it is necessary to identify corresponding alternative style from good pattern cluster and this alternative suggestion will be assumed in diverting the unsuccessful leadings into successful one to most likely to score more. This process is presented in Figure 3.
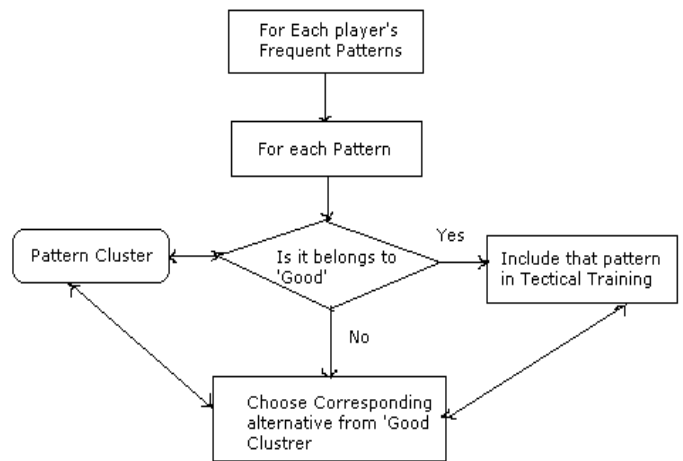

Figure 3   Tactical Training Pattern generation process

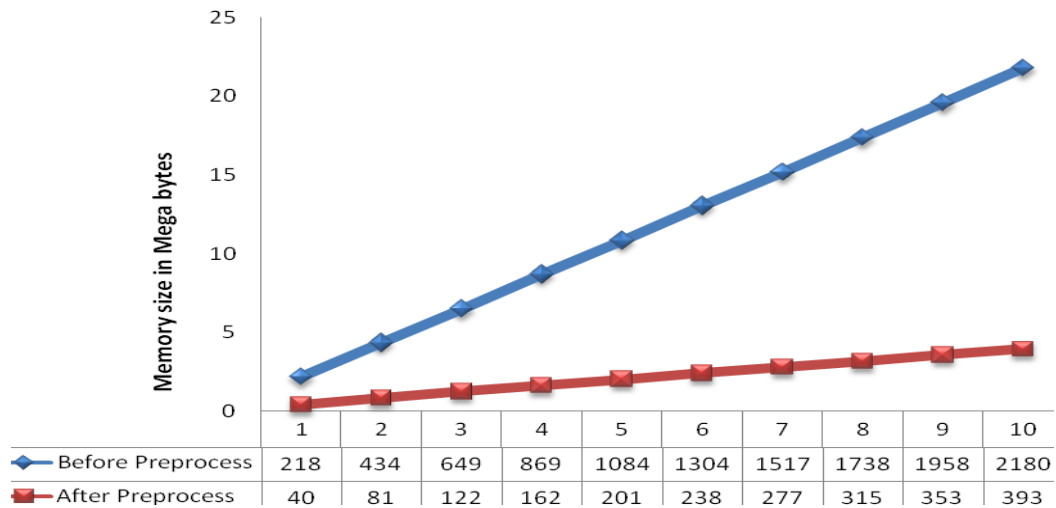|	1	2	3	4	5	6	7	8	9	10
Before Preprocess	218	434	649	869	1084	1304	1517	1738	1958	2180
After Preprocess	40	81	122	162	201	238	277	315	353	393

Figure 4   Database Size Complexity Before Preprocess Vs. After Preprocess

F. Classification of New Players

This is developed for existing players based on their frequently played patterns since they have enough track records of prior play styles. Despite of the new players who have joined the team very recently may not have sufficient track record to extract frequently played patterns, tactical training must be given to them. But at the same time on admitting a new player into the tactical training requires additional care on generating their frequent pattern summary. To collect this information, the new player can be subjected for few tactical tests as well as their play track in state level or regional level can be considered. For a sample, the new player Munef Patel is taken into account here and his ball shot track has been extracted from the few test matched he took part in. through this system, his current form is acknowledged as 'Average batsman'.

III. RESULTS AND DISCUSSION

At final, the preprocessed cricket dataset is in the form analogous to relational data where any existing mining algorithms can be applied to extract useful information. Space complexity is analyzed by comparing the initial ORDBM dataset versus reduced dataset. The result plotted in Figure 4 proves that the compressed dataset size is only **16.354%** of the initial object relational dataset size and

also the size of both database (ORDBMS and compressed) growing linearly.

On implementing this clustering and classification for player strength and weakness analysis, the players of Indian Cricket team has been classified and this is given in Table 6. The above result was compared with current rating which has been published by ICC and it seems to be matched. For clarification player rating is given here for courtesy.

Correctness Measure

In classification problems, it is commonly assumed that all objects are uniquely classifiable which means that each training sample can belong to only one class. Accuracy of classification is measured using a test set of objects for which the class labels are known.

GOOD	AVERAGE	BAD
Sachin Tendulkar	R.G.Sharma	Harbhajan singh
M.S.Dhoni	Suresh Faina	Zaheer Khan
Virendar Singh	G.Gambir	Munaf Patel
Shewag		I Sharma
Yuvaraj Singh		

TABLE 6 BATSMAN CLASSIFICATION

Accuracy is estimated as the ratio between the number of correct class predictions and the total number of test samples.

$$Accuracy = No.\ of\ Correct\ Predictions/Total\ No.\ of\ Samples \quad (2)$$

In order to evaluate the correctness and accuracy of the clustering algorithm, test data set is fed into the pattern cluster system. Around 10,000 ball shots were given for testing. Those patterns which are having null strike rate possess problem on classification. This can be treated by null value theorem. In this test, out of 10,000 test samples, only for 9446 samples, class prediction was correct and the remaining samples are wrongly classified due to null value and underflow. Hence, the classifier accuracy is found to be 94%.

IV. CONCLUSION

Cricket match video source of various matches held were collected, annotated and stored in a well structured Object-Relational model. The volume and space occupancy of initial data set was massive and it was multifarious. Hence effectual preprocessing was done to reduce the space and time complexities. The observed results prove that the compressed dataset size is only **16.354%** of the initial object relational dataset size and also the size of both database (ORDBMS and compressed) growing linearly. Therefore, improve the efficiency of further mining process. All possible frequent patterns are extracted without repeated scanning and also without swapping overhead. Frequent pattern set has been generated by applying summarization procedure over PCA results, and this novel approach is proven to be a time effective one. In depth analysis on the resultant frequent patterns gives more knowledge clues for the tactical training. Classification simplifies the process of player strength and weakness identification and the players are classified according to their strengths and weaknesses in order to develop player specific tactical training strategies. Clustering patterns according to their most likely outcome helps in formulating generic tactical training strategies. This system also classifies new players in appropriate class for training. Tactical analysis helps to find the abilities of the players and assists in coaching. This will help in identifying the efforts taken by players for measuring their performance. This work can be extended for the video sequences of other games like basket ball, football and the like with necessary modifications and advanced data base concepts.

REFERENCES

[1]. Agarwal and Srikant (1994) 'Fast algorithms for mining association rules', Proceedings of the 20th International Conference on Very Large Databases, pp. 487-499.

[2]. Assfalg J., Bertini M., Colombo C. and Del Bimbo A. (2002) 'Semantic Annotation of Sports Videos', IEEE International Journal of MultiMedia, Vol. 9, No. 2, pp. 52-60.

[3]. Bart Goethals (2007) 'Survey on Frequent Pattern Mining', Ph.D. thesis, HIIT Basic Research Unit Department of Computer Science, University of Helsinki, Finland.

[4]. Barreda L., Deepika Nim, Jagadish Ramamurthy and James Sanford (2008) 'Knowledge Management in Cricket', MIS 480/580 - Project Report University of Arizona.

[5]. Bhandari I. (1995) 'Attribute Focusing: Data Mining for the layman' (Research Report RC 20136), IBM T.J. Watson Research Center.

[6]. Bhandari I. and Group (1997) 'Advanced Scout: Data Mining and Knowledge Discovery in NBA Data', Data Mining and Knowledge Discovery, Springer Netherlands Publishers, Vol. 1, pp. 121-125.

[7]. Blak J. and Kuba P. (2003) 'Mining frequent patterns in complex structured data', In Proceedings of DATAKON, pp. 193-203.

[8]. Chen-Yueh Chen and Yi-Hsiu Lin (n.d) 'A New Market Research Approach in Sport-Data Mining', ISSN: 1543-9518.

[9]. Collins M., Dasgupta S. and Robert E. Schapire (n.d) 'A Generalization of Principal Component Analysis to the Exponential Family', AT and T Labs_ Research Lab.

[10]. Fielitz L. and Scott D. (2003), 'Prediction of physical performance using data mining', Research Quarterly for Exercise and Sport, Vol. 74, No. 1, pp. 25-31.

[11]. Fodor I.K. (2002) 'A Survey of Dimension Reduction Techniques', Centre for applied Scientific Computing, Lowrence livemore National Lab, Canada.

[12]. Han J. and Kamber M. (2006) 'Data Mining: Concepts and Techniques', Published by Tata MacGraw Hill, 2nd edition.

[13]. Han J., Cai Y. and Cercone N. (1992) 'Knowledge Discovery in Data base: An attribute_oriented Approach', VLDB, Vancouver, Canada, pp. 547-559.

[14]. Han J., Cai Y. and Cercone N. (2003) 'Knowledge Discovery in Databases: An Attribute-Oriented Approach', School of Computing Science Simon Fraser University Burnaby, British Columbia, Canada V5A 1S6, The work was supported in part by the Natural Sciences and Engineering Research Council of Canada under Research grants OPG0037230/OPG0043090 and a research grant from Centre for Systems Science of Simon Fraser University.

[15]. Han J., Lao W., Peter H.N. and de With (2007) 'Scene-level analysis for tennis sports video using weighted linear combination of visual cues', Proceedings of the 24th IASTED International Conference on

[16]. Internet and Multimedia Systems and Applications, Innsbruck, Austria, pp. 193-197.

[17]. Han J., Nishio S., Kawano H. and Wang W. (2003) Generalization-based Data Mining in object-oriented databases using an object-cube model', Part of research work supported by Natural Science and Engineering Research Council of Canada.

[18]. Han J., Pei J., Yin Y. and Mao R. (2004) 'Mining Frequent Patterns without Candidate Generation: A Frequent-Pattern Tree Approach', Data Mining and Knowledge Discovery, Kluwer Academic Publishers, Vol. 8, pp. 53-87.

[19]. Hsu and Ching-Tze (2004) 'Basketball Skill and Tactics Report', A Case Study of Tsai-Hsing High School, Technical Report of National College of Physical Education.

[20]. Jery Banks, Carson J.S., Nelson B.L. and Nicol D.M. (2005) 'Discrete-Event System Simulation', Prentice Hall – India, 4th edition.

[21]. Jianbing Huo, Xizhao Wang, Mingzhu Lu and Junfen Chen (2006) 'Induction of Multi-stage decision tree', IEEE International Conference on Systems, Man, and Cybernetics, October 8-11, 2006, Taipei, Taiwan-1-4244-0100-3/06/$20.00 C2006 IEEE 835-839.

[22]. Krishnamurthy I. (2000) 'A text Oriented validation technique for content Based Information Retrieval', A thesis submitted for the award of the Degree of Doctor of Philosophy to IIT, Madras.

[23]. Kuba P. and Poplinsky L. (2005) 'Mining Frequent patterns in Object-Oriented data', Partially supported by Czech Ministry of Education.

[24]. Kun-Tzu Yu, Zhong-Xin Su and Rui-Chen Zhuang (2008) 'An Exploratory Study of Long-Term Performance Evaluation for Elite Basketball Players', International Journal of Sports Science and Engineering, Vol. 02, No. 04, pp. 195-203.

[25]. Li B. and Sezan M.I. (2002) 'Event detection and summarization in American football broadcast video', Proceedings of SPIE Conference on Storage and Retrieval for Media Databases, Vol. 4676, pp. 202-213.

[26]. Li Juan Yu, Hui Zhang and Jin Ju Hu (2008) 'Computer diagnostics for the analysis of table tennis matches', International Journal of Sports Science and Engineering, Vol. 02, No. 03, pp. 144-153.

[27]. Nahar A., Daasch R. and Subramaniam K. (2005) 'Burn-in reduction using principal component analysis', Proceedings of ITC 2005, IEEE International Vol. 8.

[28]. Nepal S., Srinivasan U. and Reynolds G. (2001) 'Automatic detection of 'Goal' segments in basketball videos', Proceedings of ACM MM'01, Ottawa, pp. 261-269.

[29]. Niyomthum K. and Chittayasothorn S. (2003) 'A Transformation from an Object Database to an Object Relational Database', Proceedings IEEE southeastcon 2003, ISBN 0-7803-7856-3/03/$17.00 @ 2003 IEEE, pp. 7-11.

[30]. UmaMaheswari P, Rajaram M (2009) 'Principal Component Analysis based frequent pattern evaluation on Object-Relational Data model of Cricket match database' International Journal of Data Analysis Techniques and Strategies , Inderscience Publications, July 2009 issue.

[31]. Oracle8i SQLJ Developer's Guide and Reference Release 8.1.5, February, 1999 Part No. A64684-01.

[32]. UmaMaheswari P, Rajaram M (2009) "A Novel Approach for Mining Association Rules on Sports Data using Principal Component Analysis :Cricket Match Perspective" accepted for publication in the proceedings of **IEEE explorer.**

[33]. Pingali G.S., Jean Y. and Carlbom I. (1998) 'Real time tracking for enhanced tennis broadcasts', Proceedings of IEEE Computer Vision and Pattern Recording (CVPR), pp. 260-265.

[34]. UmaMaheswari P, Rajaram M (2009) , 'Diminution of Space And Size Complexity On Object-Relational Database Using Principal Component Analysis', accepted for Publication in International Journal of Computer Sciences and Engineering Systems Volume :3 , No:1 , January 2009.

[35]. Rene E.D., Ferdinands Uwe Kersting and Marshall R.N. (2008) 'A Preliminary Forward Solution Model of Cricket Bowling', International Journal of Sports Science and Engineering, Vol. 02, No. 04, pp. 211-215.

[36]. Roy Choudhury D., Preeti Bhargava, Reena and Samta Kain (2007) 'Use of Artificial Neural Networks for Predicting the Outcome of Cricket Tournaments', International Journal of Sports Science and Engineering, Vol. 1, No. 2, pp. 87-96.

[37]. Schoeman Johan H., Matthee Machdel C. and Van der Merwe Paul (2006) 'The viability of business Data Mining in the sports environment : cricket match analysis as application', Vol. 28, No. 1, pp. 109-125.

[38]. Smith L., Lipscomb B. and Simkins A. (2007) 'Data Mining in Sports: Predicting Cy Young Award Winners', The Consortium for Computing Sciences in Colleges, JCSC, Vol. 22, No. 4, pp. 115-121.

[39]. Solieman O.K. (2006) 'Data Mining in Sports: A Research Overview', Thesis report MIS Masters Project.

[40]. Sudhir G., Lee J.C.M. and Jain A.K. (1998) 'Automatic classification of tennis video for high-level content based retrieval', Proceedings of IEEE International Workshop on Content-based Access of Image and Video Database, pp. 81-90.

[41]. Wang J.R. and Parameswaran N. (2003) 'A scheme for archiving and browsing tennis video clips', Proceedings of IEEE Pacific-Rim Conference on Multimedia (PCM'03), Singapore.

[42]. Wang J.R. and Parameswaran N. (2004) 'Survey of Sports Video Analysis: Research Issues and Applications', Australian Computer Society, Inc. Conferences in Research and Practice in Information Technology, Vol. 36.

[43]. Xu C., Wang J., Lu H. and Zhang Y. (2008) 'A Novel framework for Semantic Annotation and Personalized Retrieval of Sports Video', IEEE Transactions on Multimedia, Vol. 10, No. 3, pp. 421-436.

[44]. Yatabe T., Kawasaki H., Hiroshi M. and Sakuuchi M. (2000) 'Multi Layer Video Object Database Based on Interactive Annotation and its Application', 0-7803-6536-4/00/$10.00 (c) 2000 IEEE, pp. 911-914.

[45]. Yu X., Xu C.S., Leong H.W., Tian Q., Tang Q. and Wan K.W. (2003) 'Trajectory-based ball detection and tracking with applications to semantic analysis of broadcast soccer video', Proceedings of ACM MM'03, Berkeley, pp. 11-20.

[1]. SAS Institute, Inc., Robin Way, 'Using SAS/Insight Software as an Exploratory Data Mining Platform', Paper 160, Available at : http:// www.USAtoday.com.