Journal of Theoretical and Applied Information Technology
10th February 2013. Vol. 48 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

ASSOCIATION RULE MINING BASED VIDEO CLASSIFIER WITH LATE ACCEPTANCE HILL CLIMBING APPROACH

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ABSTRACT

Video classification is an essential step towards video perceptive. In recent years, the concept of utilizing association rules for classification emerged. This approach is more efficient and accurate than traditional techniques. Associative classifier integrates two data mining tasks such as association rule discovery and classification, to build a classifier for the purpose of prediction. The accuracy of classification will be influenced by the choice of appropriate values for whatever thresholds are used. In this paper, we present an effective video classification technique which employs the association rule mining and examine the effect of varying the support and confidence thresholds on the accuracy of the proposed algorithm. Instead of two stage associative classification method, Total from Partial Classification technique integrates the association rule discovery and classification in a single processing step to reduce the cost of pruning. TFPC uses two enumeration trees such as Partial support tree (P-Tree) and Total support tree (T-Tree). TFPC algorithm first loads the input data into the P-tree structure to reduce the storage requirements. In the second stage, T-tree is used to hold the information regarding to frequent items. We proposed Late Acceptance Hill-Climbing (LAHC) method is to find the effective support and confidence coupled with TFPC. The LAHC method accepts the candidates with cost function better than the cost solution which were the current several iterations before. Experimental results show that the performance of classification accuracy can be significantly improved.

Keywords: *Video Clustering, Video Classifier, Late Acceptance Hill-Climbing, Rule Based Classification*

1. INTRODUCTION

Digital video technology has recently taken a center stage in the communication world, which highlights the importance of digital media information management and indexing. It is of great interest for the video research community to find methods and solutions that could help bridge the gap that exists between the low-level features and the high-level semantics of the data. Video mining is one of the methods which will extract high-level concepts from the low level features. Associative classification is a relatively new method which integrates association rule discovery and classification tasks. Association rules are well suited for classification, because its handles large number of attributes and generate well studied, fast, scalable and transparent rules [3]. The association rules mining concept over market basket analysis was introduced in [13] for finding associations between items or itemsets in transactional data. Formally, the problem is stated as follows: Let I = $\{i_1, i_2 \ldots i_m\}$ be a set of literals, called items where 'm' is considered the dimensionality of the problem. Let D be a set of transactions, where each transaction T is a set of items such that $T \subseteq I$. A unique identifier, TID, is given to each transaction. A transaction T is said to contain X, a set of items in I, if $X \subseteq T$. An association rule is an implication of the form "$X \Rightarrow Y$", where $X \subseteq I$, $Y \subseteq I$, and $X \cap Y = \emptyset$. An itemset X is said to be frequent if its support s is greater or equal than a given minimum support σ. The rule $X \Rightarrow Y$ has a support s in the transaction set D if s% of the transactions in D contains $X \cup Y$. It is said that the rule $X \Rightarrow Y$ holds in the transaction set D with confidence c if c% of transactions in D that contain X also contain Y. The problem of discovering all association rules from a set of transactions D consists of generating the rules that have a support and confidence greater than given thresholds. These rules are called strong rules [15].

The aim of the associative classification is to construct a classifier that can forecast the classes of test data objects. To build a classifier using an

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

associative classification algorithm, the complete set of class association rules is first discovered from the training data set and a subset is selected to form the classifier [3][15]. Several studies [1][2][8][7] have provided evidence that Associative classification algorithms are able to extract classifiers competitive with those produced by decision trees rule induction and probabilistic approaches [15]. Some of the advantages of associative classifiers highlighted in [3], such as the training is very efficient regardless of the size of the training set; training sets with high dimensionality can be handled with ease and no assumptions are made on dependence or independence of attributes; the classification is very fast and presents higher accuracy than traditional classification methods; the output of an associative classification algorithm is represented in simple if–then rules, which makes it easy for the end-user to understand and interpret it and can be edited.

Generally, Associative classification task can be divided into four main steps [16]. In the first step, all frequent rule items are discovered. The second step produces all class association rules that have confidences above the minconf threshold from frequent rule items extracted. The third step selects one subset of class association rules to form the classifier. In the fourth step, the quality of the derived classifier measured on test data objects. The Associative classification is performed any kinds of data that can be modelled as transaction database. The database contains records of entities of particular domain. Each record consists of m attribute a_1, $a_2 \ldots a_m$ and one important attributes known as predictive attribute (Class Label). The class label has to be part of any frequent itemset {A, B, C, Class}.The class label is a consequent, and all other items are the antecedent of a rule A, B, C -> Class[3]. These rules are called Class Association Rules (CARs) and, after their generation, they are used to generate a classification model [15]. The main objective is to discover strong patterns that are associated with the class labels in the training set [3]. Algorithms for generating classification rules can be broadly categorised into two types according to when the required pruning is performed [22] namely; First, Two stage algorithms, which first produce a set of candidate Classification Rules, by a CARM process or otherwise. It adopts the association rule generation methods like Apriori candidate generation [5], or FP growth [6] algorithms to generate class association rules. In second stage the generated rules are ranked and the rules that satisfy certain threshold conditions are used to construct the classifier. After rule ranking, only the high-ranking rules are chosen to build a classifier and the rest are pruned. The associative classification method uses support and confidence measures to evaluate the rule quality. Examples of this approach include CMAR, CBA and REP. Second, Integrated algorithms where the classifier is produced in a single processing step, i.e. rule generation and pruning is closely coupled. Examples of this approach include such as CPAR [17] and TFPC[23].

2. REVIEW OF LITERATURE

One of the first associative classification algorithms was Classification Based on Associations (CBA) which focuses on integrating two data mining tasks, association rule discovery and classification [3]. It employs Apriori candidate generation and first generates all the CARs with minimum support and minimum confidence thresholds, provided by the user, as candidate rules. A small set of rules from them is selected using rule pruning in order to create the classifier. The Classification based on Multiple Association Rules (CMAR) [8] methods adopts FP growth algorithm for rule generation. A major difference is that the classification is performed based on a weighted chisquare analysis using multiple rules. ARC-AC and ARC-BC [3] take all rules that apply within a confidence range, but instead, calculate the average confidence for each set of rules grouped by class label in the consequent and select the class label of the group with the highest confidence average [12]. The difference between CBA, CMAR and ARC-AC and ARC-BC lies in the strategy for rule selection during the classification. They also have some differences in pruning rules. CBA ranks all discovered rules by precedence ordering (using confidence then support) and simply selects the first ranked rule that applies given an object to classify. CMAR takes all rules that apply within a confidence range and selects one with the highest χ^2 measure.

Classification based on Predictive Association Rules (CPAR) combines the advantages of both associative classification and traditional rule-based classification [7]. It integrates the rule discovery and classification tasks and generates a small set of predictive rules from the dataset based on rule prediction and the instances covered by a rule (i.e., instances that satisfy the conditions of a rule). The rule prediction is the accuracy of the rule, and is measured with the Laplace expected error estimate.

Zhonghua Tang and Qin Liao, proposed algorithm with synchronizing the rule generation

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

and classifier building phases, shrinking the rule mining space when building the classifier to help speed up the rule generation. The class label is taken good advantage of in the rule mining step so as to cut down the searching space [19]. A. Zemirline, L. Lecornu, B. Solaiman, and A. Ech-cherif proposed an Association Rule Mining algorithm for Classification (ARMC) based on the extraction of both common and exception rules, specific to each class. It uses a fuzzy method to automatically select the items that generate the rules and does not require the user to provide thresholds [14]. S.P.Syed Ibrahim K. R. Chandran M. S. Abinaya proposed weighted associative classification, which integrates weighted association rule mining and classification to construct the efficient weighted associative classifier[9]. Rafal Rak, Wojciech Stach, Osmar R. Zaıane, and Maria-Luiza Antonie presented Associative Classifier with Reoccurring Items for mining associations with reoccurring items on Apriori-based MaxOccur. It is considering a repetition of observed features is beneficial. It becomes more effective as the number of rules increases in particular with cosine measure for rule selection. It seems to be less sensitive, with respect to accuracy, to the support threshold [21].

Lukasz Kobyli´nski and Krzysztof Walczak extended existing Class Association Rules (CARs) associative classifier building algorithms and apply them to the problem of image classification [17]. They used class association rules with recurrent items and considered the spatial proximity of the features of a particular image to accurately classify a set of photographs. Themis P. Exarchos, Alexandros T. Tzallas, Dimitrios I. Fotiadis, Spiros Konitsiotis, and Sotirios Giannopoulos, presented a four-stage methodology based on data mining techniques for the detection and classification of transient events in EEG recordings. In the first stage, the EEG signal was preprocessed and transient event detection took place. In the second stage, the transient events were clustered in order to obtain the prototypes, and feature extraction was realized. In the third stage, the extracted features were discretized and a subset of them was selected. Finally, in the last stage, classification algorithms based on association rules were applied in order to extract rules for classifying the new transient events [18]. Osmar R. Zaıane, Maria-Luiza Antonie, Alexandru Coman, described the use of association rule mining in an automatic medical image classification process [10]. It consists of three phases such as a preprocessing, mining the resulted transactional database, and organize the resulted association rules in a classification model.

Lin Lin, Guy Ravitz, Mei-Ling Shyu, Shu-Ching Chen proposed framework uses the apriori algorithm and association rule mining to find frequent itemsets in the feature data set and generate classification rules to classify video shots to different concepts [4]. They extracted audio and visual features from the broadcast and use association classification to classify the different shots so as to bridge the gap between the low-level features and the high-level concepts. Ling Chen, Sourav S. Bhowmick and LiangTien Chia presented a video classifier which employs the association rule mining technique to discover the actual dependence relationship between video states. The discriminatory state transition patterns mined from different video categories are then used to perform classification. The proposed an association rule based classification model captures the temporal information of videos as the HMM-based approaches do, but avoids making any Markov assumption. The association between low-level features are utilized together to improve the accuracy of the classifier. Furthermore, wild card operators are introduced into the set of symbols to tolerate some un- certain video states, which improve the robustness of the classifier [11].

3. MOTIVATION

The cost of the pruning in two-stage algorithms is a product of the size of the data set and the number of candidate rules, both of which may in some cases be large. It is clear that the choice of support and confidence thresholds will strongly influence the operation of CBA. The coverage analysis is performed either as a separate phase or integrated into the rule-generation process, to verify the applicability of rules generated to the cases in the training data. The accuracy of the classifiers obtained using any methods may be improved by a careful selection of the thresholds. In this paper, we proposed an efficient method called Late Acceptance Hill Climbing approach to select the threshold of support and confidence.

4. TOTAL FROM PARTIAL CLASSIFICATION APPROACH

It is an extension of the Apriori-T (Apriori Total) association rule mining algorithm [22]. Apriori-T is an "apriori" style algorithm designed to process a binary valued input data set so as to identify frequent itemsets and store the resulting frequent itemset information in a "reverse" set enumeration

Journal of Theoretical and Applied Information Technology
10th February 2013. Vol. 48 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

tree called a T-tree(Total support tree). This T-tree can then be processed to identify association rules [23]. The top level of the tree records the support for 1-itemsets, the second level for 2-itemsets, and so on.

TFP is first pre-processed and placed in a P-tree (Partial support tree). The P-tree offers two advantages: 1) It merges duplicated records and records with common leading substrings, thus reducing the storage and processing requirements for these and 2) it allows partial counts of the support for individual nodes within the tree to be accumulated effectively as the tree is constructed. The overall structure of the P-tree is represented as a compressed set enumeration tree. To construct a P-tree, the input data is passed record by record. When complete, the P-tree will contain all the itemsets present as distinct records in the input data. The support stored at each node is an incomplete support total, comprised of the sum of the supports stored in the subtree of the node [23].

Total From Partial Classification (TFPC) is an extension of TFP designed to produce Classification Association Rules whereas Apriori-T and TFP are designed to generate association rules. The method makes use of two set-enumeration tree structures.

The TFPC algorithm first loads the input data in to the P-tree structure, which contains all the required information contained in the input data while at the same time performing a partial support count. The P-tree orders sets of items according to some defined ordering of the single items, so that each subtree contains only following supersets of its root node [23]. As each record in the data is examined, the set of items it contains is inserted into the P-tree. If a node representing the set already exists, its support count is incremented; otherwise a new node is created. When two nodes added to the tree share a common prefix, this prefix is used to create a new parent node for them if this does not already exist. These additional nodes are required to prevent the tree degenerating into a list structure. The final P-tree, however, is of the same order of size as the original database, and may be smaller if there are duplicate records. As each database record (a set of items) is considered, the current tree is traversed to find the position of the node at which this itemset is placed and counted. During this traversal, the algorithm examines each preceding subset of the node that is found in the tree, and adds to the count of this. The effect is that in the final P-tree, the count recorded at each node is a summation of the counts of all nodes in the subtree of which it is the root, i.e. of all the supersets that follow it in the set ordering. The significance of this structure is that, without any loss of information, it carries out a significant part of the summation of support counts by a procedure that is efficient in time and conservative in space requirements.

The T-tree is designed to hold information regarding the frequent sets contained in a binary valued input data sets. A T-tree can be constructed in an apriori manner direct from an input file. To avoid number of file accesses. To complete the generation of frequent sets, we apply a second stage of the algorithm that builds a second set-enumeration tree structure called the T-tree. Like the P-tree, the T-tree stores itemsets at nodes such that each subtree contains only supersets of its parent node, but in this case the nodes in the subtree are those that precede their parent according to the ordering of itemsets. The T-tree is constructed by a breadth-first iterative process that ends with a tree that contains only the frequent sets. The TFPC algorithm adapts these structures and procedures to the task of generating classification association rules. For this purpose, class labels are defined as items, and placed at the end of the ordering of items.

TFPC provides a efficient algorithm for generating a relatively compact set of classification rules. Because no coverage analysis is carried out, however, the choice of appropriate support and confidence thresholds is critical in determining the size of the final rule set. In its simplest form TFPC determines a classifier according to given support and confidence thresholds. The natures of the selected thresholds are therefore the most significant influencing factors on classification accuracy. TFPC uses a hill climbing technique to find a best accuracy given start support and confidence thresholds.

5. VIDEO ASSOCIATIVE CLASSIFICATION

In this paper, we proposed an association rule based video classifier based on Total from Partial Classification with Late Acceptance Hill Climbing approach. It is built as follows. A preliminary step of creating a symbolic representation of the source video is required before applying any data mining methods to the video database. Next, the video associative classifier based on Total from Partial Classification with Late Acceptance Hill Climbing approach is applied on the video sequence database. Finally, we test the accuracy of the constructed classifier by predicting the class labels for unknown videos. The overall system architecture as shown in Figure.1.

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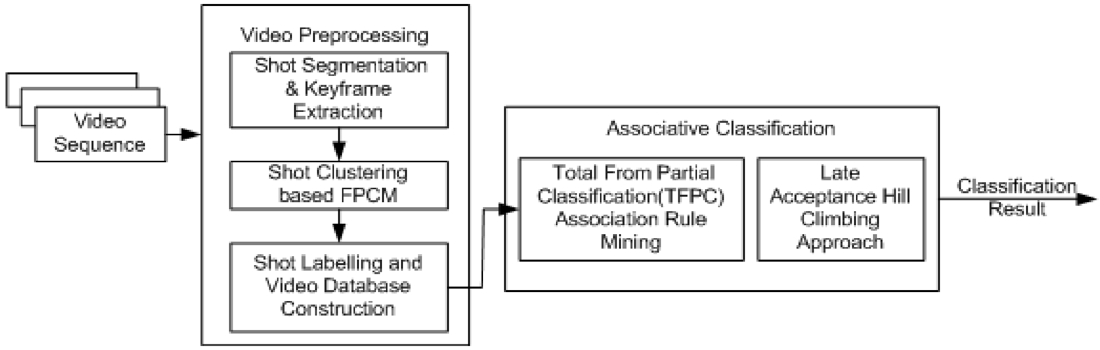

Fig.1. Overall System Architecture

5.1. Video Pre-Processing

This section summarizes the techniques used to construct the video transaction database for mining from vide sequences. We model the videos with a set of transactions, each transaction representing one shot cluster with the visual features extracted as well as other given characteristics along with the class label. The pre-processing consists three steps namely, key frame extraction, video shot clustering and video data transformation. The entire video is first segmented and set of key-frames are extracted from each shot by applying the histogram technique. Next, the Fuzzy Possiblitic C-Means algorithm is applied to cluster the key-frames which are "similar" to one another to different extents. Then, the label is assigned to each shot according to the group that it belongs to. Video database is constructed by using scene change detection algorithm.

5.2. Video Associative Classifier Based On Tfpc With Lahc

This section describes how the video associative classification system is built using this system. Given a Video database, table B containing N cases (training examples) belonging to C classes, each one is described by an itemset and let I be the set of all items of B. Classical classification methods seek a rule or a hypothesis that predicts the label of an unseen example. The class association rule is an implementation of the form $X \rightarrow c$, where $X \subseteq I$, and $c \in C$. The objectives are to generate the complete set of class association rules that satisfy the minimum support as well as the minimum confidence (minConf) constraints and to build a classifier from the class association rule set.

The associative classification algorithm is integrated into two fundamental parts: association rule mining and classification. The mining of association rules is a typical data mining task that works in an unsupervised manner. A major advantage of association rules is that they are theoretically capable of revealing all interesting relationships in a database.

The Late Acceptance Hill-Climbing algorithm

The LAHC [26] represents a typical one-point iterative stochastic search procedure, i.e. it starts from a single (usually random) initial solution and at each iteration randomly modifies the current solution in order to produce a candidate one. Then an acceptance condition is applied to decide: whether or not the candidate will take a role of the current solution at the next iteration; and so on. The search is usually terminated when it converges (no improvement is detected during a given number of iterations).

The basic idea of LAHC approach is to accept the candidates with cost function better (or equal) than the cost of the solution, which was the current several iterations before. Thus, the LAHC maintains the list (fitness array) of a particular length, which contains previous current costs. At each iteration the candidate cost is compared (to be accepted or not) with the last element of the list. After the acceptance decision the current cost is inserted into the list and the last element is removed from the list.

The LAHC has two major advantages over its competitors. Firstly, it requires to set up just one parameter length of the fitness array (Lfa) rather than a cooling schedule such as Simulated Annealing, Threshold Accepting, Great Deluge. Hence, it is much easier for tuning and maintenance and correspondingly, more efficient in practical applications with minimum user intervention as well, as in fully-automated systems. Secondly, the absence of a cooling schedule makes the algorithm more reliable. There are known situations (e.g. problems with non-linearly rescaled cost function) where the above competitor algorithms fail to produce a good solution, but the LAHC works well. The elements of the list are unmovable and the list

Journal of Theoretical and Applied Information Technology
10th February 2013. Vol. 48 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

appears as a fitness array Fa of length Lfa (Fa = $\{f_0, f_1, f_2, \ldots f_{Lfa-1}\}$). Its virtual beginning v, at the ith iteration, is calculated as:

v = i mod Lfa

where "mod" represents the remainder of integer division. At each iteration, the value of fv is compared with the candidate cost and after accepting or rejecting, the new value of the current cost is assigned to fv.

At the beginning of the search, the initial list can contain any arbitrary values. If these are much higher than the initial cost, the algorithm will produce a corresponding number (equal to the Lfa) of random perturbations while filling the list with current costs. If all elements of the initial fitness array are too low, then the algorithm will produce the same number of non-accepted moves and again, will fill the fitness array with the value of the initial cost. Either variant can cause just a small delay in the search procedure. If we do not wish to wait until the algorithm does it automatically, then we could set up all elements of the fitness array to be equal to the initial cost before starting the search. Thus, its final acceptance condition at the ith iteration can be expressed by Formula.

$Ci^* \leq Ci\text{-}Lfa$ or $Ci^* \leq Ci\text{-}1$

In this formula, Ci* is the candidate cost, Ci-1 is the current cost and Ci-Lfa denotes the cost of the current solution Lfa iterations before, which is equal to f(i mod Lfa). Obviously, when Lfa is equal to 1 or 0, LAHC is simply greedy HC. Hence, LAHC obtains its unique properties with Lfa equal to 2 and higher. The pseudocode of the complete search procedure is shown in Figure 2.

```
Produce an initial solution s
Calculate initial cost function C(s)
Specify Lfa
For all kε{0...Lfa-1} fk:=C(s)
First iteration I=0;
Do until a chosen stopping condition
        Construct a candidate solution s*
        Calculate its cost function C(s*)
        v: = I mod Lfa
        If C(s*)≤fv or C(s*)≤C(s)
        Then accept the candidate (s:=s*)
        Else reject the candidate (s:=s)
        Insert the current cost into the fitness array
                    fv:=C(s)
        Increment the iteration number I:=I+1
```

Fig. 2. Late Acceptance Hill Climbing Procedure

6. EXPERIMENTAL RESULTS

In this section, we have evaluated the accuracy of our video associative classifier algorithm. We report on our experimental results by comparing on TFPC Late Acceptance Hill Climbing approach with TFPC Hill Climbing approach. All the implementations were written in Java 1.7. Experiments were conducted 2.10 GHz Intel Dual core system with 4GB RAM running on Microsoft Vista. We investigated the classification accuracy that can be achieved using five video databases. Table 1 shows the classification accuracy of the classifiers extracted by HC and LAHC. We have assumed a support threshold of 1% and a confidence threshold of 50%.

The classification accuracy produced using TFPC may vary significantly depending on the choice of support and confidence thresholds. To obtain a best classification the TFPC algorithm was applied in an iterative manner in conjunction with a "Late Acceptance hill-climbing" procedure. The "Late acceptance hill-climbing" strategy, seeking to maximise accuracy while varying the thresholds concerned.

It is note worthy, also, that both overall and in many particular cases, TFPC-LAHC achieves a higher classification accuracy than TFPC-HC. The LAHC procedure was used to find the support and confidence thresholds that led to the most accurate classification of this test set. These thresholds were then used to apply the TFPC.

The accuracy of the classification is improved with the FPCMeans video shot clustering when comparing with K-Means clustering as shown Figure.3. For each plot the X axis represent video database from 1 to 5, and the y axis the corresponding percentage classification accuracy obtained.

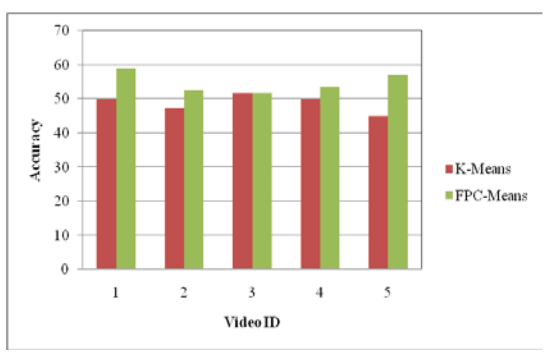

Fig.3. Classification Accuracy comparing with FPCM and K-Means clustering

Journal of Theoretical and Applied Information Technology
10th February 2013. Vol. 48 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

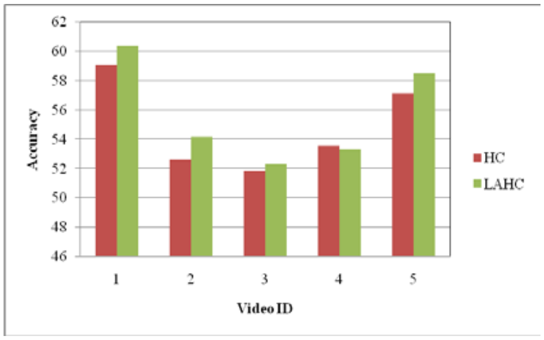

Fig. 4. Classification Accuracy comparing with HC and LAHC

Figure 4 shows the accuracy of the video classification is improved with the Late Acceptance Hill Climbing when comparing with Hill Climbing with TFPC.

7. CONCLUSION

In this paper we proposed a classification method applied to video data. The T-tree and the P-tree offers significant advantages in terms of hash tree structures, generation time and storage requirements. One major advantage of the association rule-based classifier is its relatively fast training time. The maintenance of this classifier is straightforward. The experimental result shows that the LAHC based association-based classifier performs well and its effectiveness is comparable to Hill climbing classifiers. LAHC can improve the accuracy of the classifier. In the near future, we will investigate new methods for the rule generation for video database. Associative classification of video is a promising area of research, as many different approaches to association rule mining and pruning may be proposed to improve accuracy of the process. The hill-climbing procedure is, of course, more time-consuming than TFPC without hill climbing. In future, the cost of the algorithm reduced.

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Table 1. Video Associative Classification Results

Video dataset	Video Shot Clustering Method	Hill Climbing			Late Acceptance Hill Climbing		
		Accuracy	AUC	No. of Rules	Accuracy	AUC	No. of Rules
VWC102T_input.avi	K-Means	50.0	0.4231	12	50.8	0.4635	6
	FPC-Means	59.09	0.5909	7	60.4	0.60	7
BR130T_input.avi	K-Means	47.37	0.5	6	47.41	0.53	6
	FPC-Means	52.63	0.45	9	54.2	0.54	7
Fight_Chase.mpeg	K-Means	51.89	0.5189	10	52.2	0.532	10
	FPC-Means	51.89	0.5189	12	52.31	0.53	12
620-72_l.mov	K-Means	50.0	0.5	8	50.6	0.54	8
	FPC-Means	53.57	0.5357	11	53.3	0.542	11
DO01_013_input.avi	K-Means	45.0	0.45	5	46.1.0	0.48	5
	FPC-Means	57.14	0.5909	8	58.47	0.62	8