Mining Video Association Rules Based on Weighted Temporal Concepts

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Abstract

Discovery of video association rules has been found useful in many applications to explore the video knowledge such as video indexing, summarization, classification and semantic event detection. The traditional classical association rule mining algorithms can not apply directly to the video database. It differs in two ways such as spatial and temporal properties of the video database and significance of the items in the vide cluster sequence. The proposed paper discovers significant relationships in video sequence using weighted temporal concepts. The weights of the video items take the quality of transactions into considerations using modified link-based models. The proposed Modified HITS based weighted temporal concept did not require pre-assigned weights. The mined association rules have more practical significance. This strategy identifies the valuable rules comparing with Apriori based video sequence algorithm. We also present results of applying these algorithms to a synthetic data set, which show the effectiveness of our algorithm.

Keywords: *Video Temporal Sequence, Video Segmentation, Frequent Pattern, Modified HITS.*

1. Introduction

Association rules mining are one of the most popular and well researched methods and it is used to find out interesting and valuable knowledge which is implicit in large databases. It is expressed in the form of X=>Y, where X and Y are the itemsets. Support and confidence are the two statistical measures of significance for association mining [1][6]. It was first announced by Agrawal in 1994 and the most famous algorithm is Apriori [1] as a means of identifying frequently related items in a market basket database consisting of several transactions. Digital audio and video have recently taken a center stage in the communication world. There is an imminent need to discover useful knowledge from the unstructured video databases. The process of discovering association between the video items is referred to as Video Association Mining [7][8][9]. Video data contains several kinds of data such as video, audio and text which consists the special properties like temporal and spatial properties. Conventional data mining algorithms do not incorporate temporal properties. Hence they are not suited for video data. There are lot of challenges of mining semantic information in the video such as the gap between low-level features and high level video semantic concepts and identification of temporal boundaries.

The video associations can be established between various objects in a key frame or the key frames extracted from the shots. The generated associations could also be used to predict futuristic events based on the occurrence of a certain sequence of events frequently. Reference [8] discusses the different types of knowledge that can be mined from video and its applications. Generated associations can be employed in video classification to determine the overall nature of the video such as movie can be classified as romantic, comic, etc. Video associations are also employed in summarization by including the most frequent patterns in the summary [13].

The video association rule mining task leads to the following two problems that may hinder its popular use. First, Frequent set construction in video temporal data domain is an emerging research trend. Existing algorithms for mining association rules cannot be applied to temporal databases directly. This is because, in the existing algorithms, if an itemset is supported by a tuple, the tuple must contain all the items in the itemset. For temporal databases, an itemset, e.g. {A,B}, is supported as long as all the items in {A,B} are contained in a set of tuples which satisfy certain temporal constraint. The incorporation of temporal semantics into the traditional data mining techniques has caused the creation of a new area called Temporal Data Mining. Temporal association rule mining is first introduced by Wang, Yang and Muntz in years 1999-2001 together with the introduction of the Temporal Association Rule algorithm [14]. It helps to find the valuable relationship among the different item sets, in temporal database. A video can be treated as a temporal video sequence and there are two major challenges in

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temporal sequential association rules mining such as presentation period of the item set in the database that should be allowed to differ from one to another and the significance of the items in the sequence. Second, Existing frequent pattern mining algorithms in the video domain all are based on the low level features and not considered the importance of the items; hence suffer from the temporal properties and significance of the items.

This paper proposed an efficient association rule mining based weighted temporal concepts that identifies the efficient rules in video database. The rest of this paper is organized as follows. The background of video association mining is given in Section 2. The proposed weighted temporal rule mining in video discussed in the Section 3. The experimental results and analysis are presented in Section 4. Section 5 concluded the paper.

2. Background

Association Rule Mining is viewed as a two step process namely, frequent item-set construction and rule generation [1]. The second step is relatively less complex and straight forward in comparison to the first step. Frequent itemset construction aims at generating all possible itemsets that satisfy the minimum support condition. Video is one of unstructured data base. Before applying the association rule mining techniques on the video database, the video database must be transformed as structured data set using video processing techniques. The video association mining technique employs two phases such as Transformation and Mining. The transformation phase converts the original video data into an alternate transactional data format. References [13,15,16] discussed various techniques of generating video associations by transforming the original video input data into an equivalent transactional data format. This is done by grouping the various shots of the original video into different clusters, each of which consists of visually similar shots. A shot cluster sequence consisting of cluster information of each shot arranged by its temporal order is constructed. Two types of associations identified in [9, 12] are Intra and Inter associations. Intra associations are those in which all items involved in the association are the same. This could be a result of scenes composed of visually similar shots of the same object taken from different viewpoints. Inter associations are those which consists of items of different types, which are scenes that consist of visually distinct shots of different objects. By the end of the transformation phase, the problem of video association mining gets reduced to mining frequent patterns from the transformed sequence. Temporal information in a video sequence plays an important role in conveying video content. This process of frequent pattern mining subject to the temporal factors is referred as Frequent Temporal Pattern mining.

Temporal concept analysis and association in the video databases are great importance to bridge the semantic gap with the low-level features and high-level semantic concept. The higher level concepts are recognized based on the events. The events are identified using low level features. The interesting event affects two consecutive shots. Video databases are treated as collection of a temporally ordered set of events [4]. For example, in movie data base there are some interesting events like crying, clapping, bomb blasts and gun shots. These events indicate emotions, mood, serenity and violence level. It also provides a useful knowledge. Crying may indicate sadness or happiness, clapping or laughter may indicate happiness and bomb blasts or gunshots may indicate street violence. The sequence of event patterns also gives useful knowledge such as violence is followed by sad scenes with some probability [8]. Temporal pattern mining differs from the traditional ARM in two aspects. The first aspect is an item-set in traditional ARM contains only distinct items without considering the temporal concepts and significance of each item in the item-set. In event detection, an event is characterized by not only the attribute type but also its occurrence frequency in the video sequence. For instance, in surveillance video, a car passes by a bank once is considered normal, whereas special attention might be required if the same car appears frequently within a temporal window around the building. In soccer video, several close views appear in a temporal window might signal an interesting event, whereas one single close view is generally not a clear indicator. The second aspect, in traditional ARM, the order of the items appeared in a transaction is considered as irrelevant. Therefore, transaction {a, b} is treated the same as {b, a}. A sequence is defined as an ordered list of elements. In other words, the sequence {a, b, c} is considered to be different from {c, a, b}. The problem differs from its non-temporal counterpart in two key factors namely; temporal support and temporal threshold. The temporal properties bounded with the video were discussed in the [12] [13].

Video association can be defined as a sequential pattern [13] with $\{X_1..X_i\ldots X_L;\ X_i^t<X_j^t$ for any $|i<j|\}$ where X is a video item, L denotes the length of the association, X^t denotes the temporal order of X and $X_i^t<X_j^t$ indicates that X_i happens before X_j.
To convey the video content, traditional association measures such as support and confidence integrated with video temporal information to evaluate video associations.

The basic definitions are given as follows [13]:

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- An item is a basic unit, which denotes a keyframe from each shot.
- Given a shot cluster sequence, the temporal distance (TD) between two items is the number of shots between them. For example, given sequence "ABDEC", the temporal distance of "AB" is TD (AB) =0, and for "AC" is TD (AC) =3.
- Given a temporal distance threshold (TDT) =T, the temporal support {TS} of an association $\{X_1...X_L\}$ is defined as the number of times that this association appears sequentially in the sequence database.
- Given TDT=T, the confidence of an association $X_1..X_i\ldots X_L$ is defined as the ratio between the temporal support of {X} when TDT=T and the number of maximal possible occurrences of the association {X}.

References [13,15,16] incorporate the temporal aspect in the video association mining process via two parameters namely temporal support and temporal distance thresholds.

Min Chen et al. presented an association based framework for video event detection plays an essential role in high-level video indexing and retrieval [17].

Mahesh Kumar et al. proposed hierarchical framework to extract the silent events from the video soccer (football) event sequence and classified each event sequence into a concept by sequential association mining. A top-down video scene classification technique used to avoid shot clustering and maintained the temporal order of shots. They computed the association for the events of each excitement clip using apriori mining algorithm [18].

Jia et al. developed a method based on frequent pattern tree for mining association rules in video retrieval. They proposed the TFP-Growth algorithm to mine temporal frequent patterns from TFPTree for finding the rules of the motion events [10].

Mahesh Goyani et al. proposed an algorithm to detect semantic concepts from cricket video by applying A-Priori algorithm. Hierarchical tree was constructed for event detection and classification [4].

The classical model of video association rule mining employs the support measure, which treats every transaction equally. In contrast, different transactions (video shot cluster sequence) have different weights in real-life video data sets. Video items have importance in every scene cluster. For example, in the movie if villain appears multiple frame sequence, there may be interesting event will occur. In sports video, the grouping of the players and high audio frequency has an interesting event such as wicket fall or appeal. There should be some notion of importance in those data. For instance, video shot cluster sequence with a large amount of items should be considered more important than sequence with only one item.

C. H. Cai et al. proposed weighted association rule mining for discovering the significant items in the market basket transactions [2]. Weight is used to show the importance of the item. There are not weights to items and transactions directly in the most of the algorithms. Sun et al. calculated the weights of items and weights of transactions on the basis of internal structure. The relationship of transactions and items is represented as like the relationship between hubs and authorities in the HITS model[3].

Balasubramamian et al. applied a temporal mining algorithm with priority items involved the mining. The weights assigned to the items according to their importance and the time at which the transaction took place to assist the Bayesian classification [11].

Current video association mining algorithms not considered the significance of the items in the temporal video sequence. If the itemset appears in a large quantity for every video cluster sequence in which it is present, and may lead to very high profit. For example, In a surveillance video, if a vehicle appears in multiple frame sequence there may be abnormal event may occur. The proposed method considered the significance of items in the video sequence without pre-assigned weight.

3. Proposed Method

The proposed weighted temporal association rule mining consist two steps. First, the video pre-processing step transformed the input video into video sequence database applying video processing techniques. The generated sequence is governed by temporal support and distance factors. Second, weights is assigned to items depend on the importance of the items using Modified HITS concepts and finally weighted temporal association rules are generated. The proposed system architecture of is shown in Figure.1.

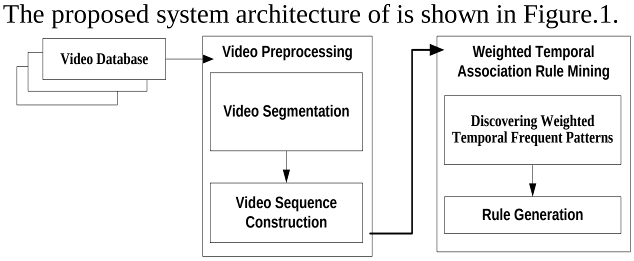

Fig. 1 Proposed System Architecture

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3.1. Video Pre-processing

This stage can be divided into two major steps based on their functionalities, namely video segmentation and video temporal sequence label construction. These steps are beyond the scope of this paper.

3.1.1. Video Segmentation

Video can be viewed as hierarchy structures such as video, scene, shot, and key-frame. The keyframes are adopted as the basic unit for processing. The visual features are captured with the assistance of edge analysis and object segmentation techniques. These features are considered to temporally segment the raw video sequences into a set of consecutive video [5].

3.1.2. Temporal Sequence Construction

Each keyframe in the video scene cluster is treated as a time unit and the extracted features are transformed into symbolic streams. For example, in a movie video the temporal sequence is constructed according to the Look-up Table mapping as shown Table 1. The transformed structured video sequence is used to mine the association in video. The Sample Video Sequence Database as shown in the Table. 2.

Table 1. Look-up Table

Key Item	Hero	Heroine	Hero+ Heroine	Anti Hero	Hero+ Anti-Hero	joker
Symbol	A	B	C	D	E	F

Table 2. Sample Video Sequence Database

Scene Id	Key Items
Sid1	A B C B
Sid2	C D C A C
Sid3	B C A B D A
Sid4	B C D B E

3.2. Weighted Temporal Association Rule Mining

It is a new extension to ARM by allowing a weight to be associated with each item in the item-set for a temporal video database. The motivation behind is to capture the various importance degrees of the items in the video database so that the applicability of ARM could be improved. Several efficient methods were developed for mining the weighted association rules. The calculation of item weight and transaction weight is too difficult. The application of the HITS algorithm is to the ranking of the transactions and weights are completely derived from the internal structure of the database based on the assumption that good transactions consist of good items. The Apriori algorithm is one of the most commonly used algorithms. It first finds the frequent itemsets satisfying the minimum support threshold and then generates the strong rules from the frequent itemsets which satisfy the minimum confidence threshold. The existing Apriori based association rule mining algorithm is modified to incorporate the temporal property and significance of the item.

A database of transactions (scene clusters) can be depicted as a bipartite graph without loss of information. Let D = {S(1),S(2),…….,S(m) }be a list of Video Scene Clusters and I = { i(1), i(2),…i(n) } be the corresponding set of video items. Then, D is equivalent to graph G = (D,I,E),where E = {(T , I) : i belongs to T , T belongs to D, i belongs I }. It is crucial to have different weights for different transactions in order to reflect their different importance. The evaluation of item sets should be derived from these weights. A good transaction, which is highly weighted, should contain many good items; at the same time, a good item should be contained by many good transactions. The reinforcing relationship of transactions and items is just like the relationship between hubs and authorities in the HITS model.

3.2.1. Modified HITS Algorithm:

The HITS algorithm cannot be applied in the video scene cluster directly because the video items may appear more quantities in a sequence like ABCBCB. The number of the items in the sequence is maintained using weighted bipartite graph. The edge weight is used to denote as the number of time occurrence of video items. The modified hits algorithm calculates the Hub score and Authority score for a node is calculated with the following algorithm.

1. Calculate initial authority score in the following:
   Initial authority score = Total Number of time the item appears in the scene Cluster Database / Total number of scene cluster
2. Run the Authority Update Rule
   $$auth(i) = \sum_{T:i\in T} hub(T)$$
3. Run the Hub Update Rule
   $$hub(T) = \sum_{i:i\in T} auth(i)$$

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4. Normalize the values by dividing each Hub score by the sum of the squares of all Hub scores, and dividing each Authority score by the sum of the squares of all Authority scores.
5. Repeat from the second step as necessary

When the HITS model eventually converges, the hub weights of all transactions are obtained. These weights represent the potential of transactions to contain high-value items. A transaction with few items may still be a good hub if all component items are top ranked. Conversely, a transaction with many ordinary items may have a low hub weight.

3.2.2. Enhanced Fast Mining Algorithm

The weighted association rule mining can be decomposed into two sub-problems, First, Finding all significant item sets with w-support above the given threshold. The w-support of an item set X is defined as

$$wsupp(X) = \frac{\sum_{T:X\subset T \wedge T\in D} hub(T)}{\sum_{T:T\in D} hub(T)}$$

where hub(T) is the hub weight of Transaction T. An item set is said to be significant if its w -support is larger than a user specified value. These weights are not determined by assigning values to items. The global link structure of the database is used to determine the weight of items and transactions. Second, Deriving rules from the item sets found in Step 1. The w-support of an association rule X => Y is defined as wsupp(X=>Y)=wsupp(XUY) and the w-confidence is wconf(X=>Y)= wsupp (XUY) / wsupp(X). If wconf(X→Y) is large, it shows that many good hubs that choose X also choose Y, although the fraction of these hubs may be small.

The first step is more important and expensive. The key to achieving this step is that if an item set satisfies some minimum w-support, then all its subsets satisfy the minimum w-support as well. It is called the downward closure property of w-support. Significant item sets extracted in a levelwise manner, as the Extended Fast Apriori-like algorithm demonstrated in Fig. 2.

```
// Initialize the authorities
for (l=0; l<num_it; l++)
    {
    for each i set auth (i) = Total Number of time
    the item appears in the scene Cluster Database /
    Total number of scene clusters in a video
    sequence
}
//Hub Weight and Authority Weight Calculation
for (l=0; l<num_it; l++)
    {
    for each i set auth' (i) =0
    for all transaction t belongs to video sequence
    database
        {
        hub (t) = sum of all auth (i) where i
    belongs to t
        auth' (i) +=hub (t) for each item i
    belongs to t
        }
    auth (i) =auth' (i) for each i
    Normalize auth
    }
// Rule Generation
L1= {{i} | wsupp(i)>minsupp}
k=2
While (L_{k-1} ≠ϕ)
{
    C_k = Apriori-gen (L_{k-1})  //  C_k contains K-
    itemsets using Apriori-gen function
    for all transactions t εD
        {
        C_t = subset (C_k, t) //check weather C_k
    belongs to Transaction t
        for all candidates c εC_t
            {
            if (T_d>1)        // T_d temporal
    distance between the items
            {
            hub(t)=sum of hub weights of
    the transactions / sum of the temporal distance
    between the items
            }
            c.wsupp+=hub(t)
            }
        h+=hub(t)
        }
    Add L_k to result list
    L_k = {cε C_k | c.wsupp/h >= minsup}
    Increment k by 1
    }
```

Figure 2. Enhanced Fast Mining Algorithm

4. Experimental Results and Discussion

To evaluate the efficiency of the algorithm, an extensive performance study of was performed on Enhanced Fast Mining algorithm, on synthetic data set with various kinds of sizes and data distributions. The experiments were conducted on a 2.10 GHz Intel Dual core system with 4GB RAM running on Microsoft Vista. The Algorithm was implemented using Java. The synthetic data set, which we used for our experiments, is generated using the Dataset Generator. The synthetic data set "VidoSeqDB" was

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generated with five predicting attributes and five domain attributes. In this data set, the average sequence size and average maximal potentially frequent itemset size are set to five, respectively. The Enhanced FastMining algorithm was compared with and AprioriVS algorithm.

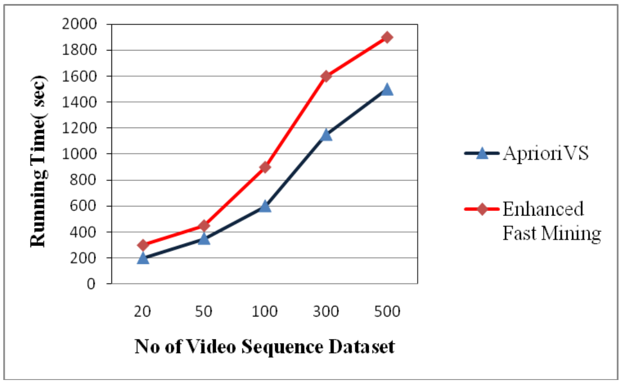

Figure 3. Running Time

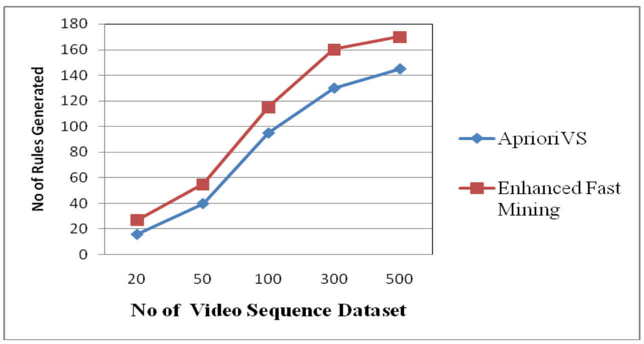

Figure 4. Space Complexity

Fig.3 shows that Enhanced Fast Mining algorithm is time-consuming because it needs to enumerate all subset of sequences. The space complexity of AprioriVS and Enhanced Fast Mining as the number of video sequence database increases from 20 to 500 is shown in Fig.4. It also produced that the antecedent and consequent of the rules generated by the proposed method have higher correlation and the generated rules also highlight the important itemsets as well as the influences brought by the new data and identifies the new missing rules. The proposed methods make the mined association rules have more practical significance. Experimental results show that w-support can worked out without much overhead, interesting patterns may be discovered through this new measure and missing knowledge may be identified. Hyperlink-induced Topic search (HITS) maybe first successful approach applied to link-based models to video association rule mining. To achieve best accuracy is highly improbable because of the inherent inconsistencies in video in itself.

5. Conclusions

Weighted Temporal Association rule mining has been developed to automatically detect knowledge from a video database taking the advantages of its good performance and ability to handle large databases. It is also adopted to bridge the semantic gap between low-level features and the concepts of interest. The proposed model integrates association rule mining and sequential pattern discovery to systematically determine the temporal patterns with the significance of the items. It is a relatively new and emerging research area with the potential for further efficient and application specific approaches such as semantic concept detection, event summary and classification. In future work one of existing associative classifiers is to be chosen or new algorithm needs to be developed that can be integrated with weighted association rule miner for classifying the video database.

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