Mining Best-N Frequent Patterns in a Video Sequence

Vijayakumar.V*
Research Scholar,
Bharathiar University, Coimbatore,
&
Department of Computer Applications,
Sri Ramakrishna Engineering College,
Coimbatore, Tamil Nadu,
India - 641 022
E-mail: veluvijay20@gmail.com
*Corresponding Author

Nedunchezhian.R,
Professor and Head,
Department of Information Technology,
Sri Ramakrishna Engineering College,
Coimbatore, Tamil Nadu,
India-641 022
E-mail: rajuchezhian@gmail.com

***ABSTRACT*— Video mining is used to discover and describe interesting patterns in video data, which has become one of the core problem areas of the data mining research community. Compared to the mining of other types of data (e.g., text), video mining is still in its infancy, and an under-explored field. There are many challenging research problems facing video mining. Video Association Mining is a relatively new and emerging research trend. It consists two key phases are (i) Video pre-processing and (ii) Frequent Temporal Pattern Mining. The first phase converts the original input video to a sequence format. The second phase concerns the generation of frequent patterns. Frequent pattern generation plays an essential role in mining of association rules. The usual framework is to use a minimal support threshold to obtain all frequent patterns. However, it is nontrivial for users to choose a suitable minimal support threshold. The paper addresses the issue of frequent temporal pattern mining and studies algorithms for the same. In this paper, we proposed a new mining task called mining Best-N frequent patterns, where N is the largest rank value of all frequent patterns to be mined. An efficient algorithm called Modified VidApriori is used to mining Best-N frequent patterns. During the mining process, the undesired patterns are filtered and useful patterns are selected to generate other longer potential frequent patterns. This strategy greatly reduces the search space. The existing Apriori based algorithm is compared with Modified VidApriori. We also presented results of applying these algorithms to a synthetic data set, which show the effectiveness of our algorithm.**

Keywords- Video mining; Video sequence database; Pattern mining; Frequent patterns

I. INTRODUCTION

Development in multimedia data acquisition and storage technology have led to tremendous growth in multimedia databases like surveillance video, movies, sport videos, news, medical videos and world wide web repositories. With the enormous amount of multimedia information stored in repositories, it is increasingly important to develop powerful means for analysis and perhaps interpretation of such data and for the extraction of interesting knowledge that could help in decision-making [13]. Data Mining encompasses tools and techniques for the “extraction or ‘mining’ [of] knowledge from large amounts of data”. It is about finding patterns and relationships within data that can possibly result in new knowledge.

The management of multimedia data is a one of the crucial task in the data mining due to the non-structured nature of multimedia data. Multimedia data mining systems can automatically extract the semantic knowledge from the multimedia database [1]. Video data is one of the perfect example of multimedia because of it contains several kinds of data such as text, image, metadata, video and audio [3, 13, 14]. The video presents temporal (motion) and spatial (colour, texture, shapes and text regions) properties. The audio consist of speech, music and various special sounds. The textual information is represented in linguistic form.

Nowadays people are accessing to a tremendous amount of video, both on television and the internet. Two types of videos are used in our daily life [3, 5]: videos with some content structure and videos without any content structure. The videos such as movies and news are used to convey video content. These are usually edited (or post-processed) by editors. The various shots are packed back and forth to convey scenarios or context information, such as “dialog” scene. However, for videos without content structure, e.g., sports videos, associations may still exist where the associations could be characterized as a series of sequentially related actions. For “raw” videos like surveillance videos, they have no scene change and therefore no content structure can be found among them.

Video data typically has a complex structure that cannot be processed as a whole by available data mining algorithms. Therefore, Video mining involves two basic steps:

• Extraction of appropriate features from the data; and

• Selection of data mining methods to identify the desired information.

The first step is to transform video from non-relational data into a relational data set. The video data modal is used to manage the video contents. The hierarchical structure of video database model is exploited by partitioning the video contents into a set of hierarchical manageable units such as clusters, sub-clusters, sub-regions, shots or objects, frames or video object planes, and regions[5].

There are two widely accepted approaches for accessing video in databases: shot-based and object-based [5]. The shot based retrieval approach is used in the scripted video database which consist some content structure. The object based retrieval approach is used in the unscripted content which does not consist any content structure.

The aim of the video data mining is finding correlations and patterns previously unknown from large video database [15]. Many video mining approaches have been proposed for extracting useful knowledge from video database. Generally, it can be classified in three categories, such as spatial pattern detection, video clustering and classification and video association mining [5]. One of the important problems in video data mining is video association rule mining. Mining association rule from video data is usually a straightforward extension of association rule mining in transaction databases.

In our paper, we presented a technique to convert the video data base to temporal sequence database. Then, we Modified AprioriVidSeq algorithm was proposed for extracting frequent item sets which is used to extract the association between the video items. The rest of this paper is organized as follows. The concepts of Video Association Mining are given in Section 2. Section 3 gives an overview of frequent temporal pattern mining in video database. The overall system framework proposed in this paper is presented in Section 4 and experimental results and analysis are discussed in Section 5.

II. VIDEO ASSOCIATION MINING

A video database contains lot of semantic information. The semantic information describes what is happening in the video and also what is perceived by human users. The semantic information of a video has two important aspects [4]. They are (a). A spatial aspect which means a semantic content presented by a video frame, such as the location, characters and objects displayed in the video frame. (b). A temporal aspect which means a semantic content presented by a sequence of video frames in time, such as character’s action and object’s movement presented in the sequence. To represent temporal aspects, the higher-level semantic information of video is extracted by examining the features audio, video, and superimposed text of the video. The semantic information includes the detecting trigger events (e.g. any vehicles entering a particular area, people exiting or entering a particular building), determining typical and anomalous patterns of activity, generating person-centric or object-centric views of an activity, classifying activities into named categories (e.g. walking, riding a bicycle), and clustering and determining the interactions between entities. Video mining differs from its other multimedia counterparts in the presence of temporal properties in the input data [10].

Association rule mining, one of the most important and well researched techniques of data mining, was first introduced in [1,2]. It aims to extract interesting correlations, frequent patterns, associations or casual structures among sets of items in the transaction databases or other data repositories. A lot of work was developed to find the association in the traditional transactional database. Video association mining is still in its infancy, and an under-explored field. Only limited work was developed in this area.

Generally, two measures (support and confidence) have been used to evaluate the quality of an association [2]. However, these measures do not consider temporal information of the items in the association. For video associations, the temporal distance between neighboring items implies some useful information: The smaller temporal distance between neighboring items, the larger is their correlation. For example, if two neighboring shots contain applause and scoreboard change, respectively, we naturally believe that they are correlated. However, the applause that happens several shots (e.g., three more shots) before the scoreboard change rarely indicates any correlation between them. That is, for associations with a large temporal distance between neighboring items, their items usually have a weaker correlation and, therefore, can imply only limited knowledge.

Accordingly, instead of using the traditional support measure, we adopt a temporal support (TS) to evaluate the video association. References [5, 8, 9, 10, 11, 12] incorporate the temporal aspect in the video association mining process via two parameters namely temporal support and distance thresholds. Temporal distance (TD) between two items or shots is the number of shots between them. The temporal distance of the pattern AB in the input sequence ACEB is 2. The support measure based on temporal distance is referred to as temporal support. It is the number of times the association is shown sequentially in the input video, subject to the temporal distance threshold value. For example in the input sequence ABABACABC, the temporal support of pattern ABC for TD=∞ is 2 and TD=0 is 1. A temporal distance threshold value of ∞ denotes infinite distance between the various possible patterns or shot clusters.

Zhu, X., Wu, X., Elmagarmid, A., Feng, Z. and Wu, L. transformed the video data into hybrid stream from four separate streams (Video, Audio, Text, and Motion). With such a mechanism, the temporal order information in each separate stream is well maintained in the transferred hybrid stream and combining multiple streams into a single stream will not lose information for effective association mining from data streams. Multilevel Association rule mining algorithm was used to extract the association between the video sequence item sets. The associations were used to construct a knowledge based video indexing structure to support efficient video database management and access [5].

Zhu, X., Wu, X. proposed an association mining rules for generating summary. The detected shots of video clustered into visually distinct groups, and then constructed a sequential sequence by integrating the temporal order and cluster type of each shot. An association mining scheme (Apriori) was designed to mine sequentially associated clusters from the sequence, and these clusters were selected as summary candidates [8].

SivaSelvan.B., and Gopalan.N.P., presented the frequent temporal pattern mining scheme that generation of patterns subject to the temporal distance and support thresholds [6].

Min Chen, Shu-Ching Chen, and Mei-Ling Shyu presented a novel framework for video event detection, which plays an essential role in high-level video indexing and retrieval. A hierarchical temporal association mining approach was developed to systematically capture the characteristic temporal patterns with respect to the events of interest [7].

Generally, Association Rule mining first identifies frequent item sets and then forming conditional implication rules among them. The second step is easier, but the overall performance of a mining algorithm is determined by the efficient generation of frequent item sets.

III. FREQUENT TEMPORAL PATTERN MINING

Frequent pattern mining discovers patterns in transaction databases based only on the relative frequency of occurrence of items without considering their temporal distance. Traditional ARM does not use temporal information; however, the real video application data always changes with time. An interesting extension to ARM is including the temporal dimension. Finding frequent patterns in a long temporal sequence is a major task of temporal data mining with many applications. Temporal association rule mining discovers valuable relationships among items in the temporal database.

Methods for finding frequent patterns are important because they can be used for discovering useful rules, which in turn can be used to infer some interesting regularities in the data. Frequent item set construction in temporal domain; an emerging research trend is the focus of the study. Video data can be represented as symbolic temporal sequences. So, FTP mining, can also be treated as Temporal Sequence Pattern Mining [10]. The search of frequent itemset subsequence is commonly called sequential pattern mining.

Sequence pattern mining was first introduced by Agarwal and Srikanth (1995), it is one of the active research areas in the temporal sequence mining. Earlier algorithms for sequential pattern mining are Apriori-like algorithms, based on the Apriori property proposed for mining frequent pattens.

Zhu, X., Wu, X. [8] created a summary from the video data using association based video summarization scheme. An Apriori video association mining scheme was designed to mine sequentially associated clusters from the sequence and these clusters were selected as a summary candidates. The sequence was constructed from movie dialog scene using appropriate symbols. They denoted the actor by ‘A’, the actress by ‘B’ and shot contains both of them by ‘C’. Then, they implemented the AprioriVS algorithm for generation sequence summary.

Zhu, X., Wu, X [10] presented a Video association mining scheme to mine sequentially associated clusters from the sequence. The video sequence parsed into discrete shots using video shot segmentation. Then the shots clustered into visually distinct groups. Finally, they constructed a shot cluster sequence by using the class label of each shot.

In this paper, we will introduce a novel frequent pattern mining method for extracting sequential patterns from the temporal data sequence.

IV. PROPOSED METHOD

Video Association Mining process consists of key phases of VAM are (i) Video Pre-processing and (ii) Video Association Mining. The Video Pre-processing phase converts the original input video to an alternate transactional format, namely a temporal video sequence. Video association mining phase concerns about the generation of frequent patterns subject to the temporal distance and support thresholds.

The overall system architecture is shown in the figure 1.

A. Video Pre-Processing

To access the semantic information from the video, first the video data transformed from the non-structured data into a structured form. Then it is converted into a temporal sequence data base. Finally, this temporal sequence database is subjected to extract the frequent sub-sequences by applying mining algorithm. The above steps are elaborated in the sub-sequent section.

1) Video Feature Extraction:

A video can be viewed as sequence of images bounded with spatial and temporal properties. These are typically segmented into shots, where each shot represents a contiguous scene with a certain context. Automatically identifying the boundary between shots (shot boundary detection) is an active area of research that has made great strides. Once a shot has been identified, it is often represented by a key frame (i.e., a frame that is the most representative of all frames in the shot). The key frame is then used for extracting features such as colour, motion, audio, text and objects. The object feature is one of the features which involves in the video semantic concept and event. So, in our work we studied the objected based featured extraction. Annotation work was carried out manually for generating the video sequence.

2) Video Sequence Construction:

Mining video sequence is much easier then mining the video low-level features as it involves large amount of raw data. However, we need to guarantee that there is no information loss when generating video sequence database, which means that, after the data base construction, we should maintain the original temporal order information of video stream.

Generally, most videos from our daily life are edited by editors, where various kinds of shots are packed as scenes to convey video scenarios [10], as shown in Fig.2. There are two typical video scenes: (1) scenes that consist of visually similar shots, as demonstrated in Fig.2 (a); and (2) scenes that consist of visually distinct shots, as shown in Fig.2 (b). In the first type of scenes, most video shots are visually similar. Take Fig.2 (a) as an example, if we denote each of the shots by "A", all shots form a sequence "AAAAAAA", and the self-coherence of "A" indicates an association of itself. This type of association is called as an intra-association, i.e., all items in the association are the same. In the second type of scenes, sequential associations exist too. In Fig.2 (b), if we denote the actor by "A", the actress by "B" and the shot containing both of them by "C", all shots form a sequence "ABABACAB". The co-occurrence of "A" and "B" implies an association. This type of association is called as an inter-association, i.e., items in the association are different.

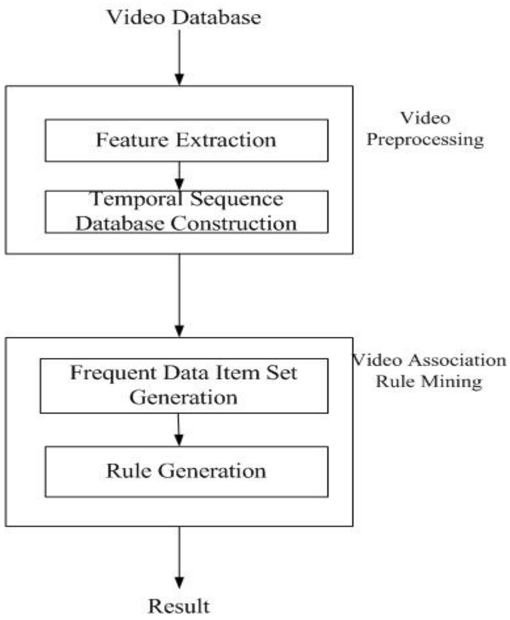

Figure 1. Video Association Mining System Architecture

A A A A A A

(a). Surgery scene in a medical video

B A C A B

(b). A Dialog scene

A B A B A C A B

(c). Shot cluster sequences

Figure 2.Sample Video scenes and video data transformations

In our work, the video sequence was constructed using the class labels assigned in the table. The video object features were extracted and transformed into the symbolic streams according to the mapping table. The video stream is transformed into a video sequence database according to the mapping given in Table 1.

The Video sequence database was constructed after the transformation. The transformation phase converts given video (continuous frames) into a video sequence database VSDB. The Sample Video Sequence Database is shown in the Table. 2.

After constructing these video sequence databases, we conducted video sequence mining as explained in the following sections.

B. Video Sequence Association Mininig

Sequential pattern mining is to find all frequent sub-sequences, ie the sub sequences whose occurrence frequency in the set of sequences is no less than min-support. Many research efforts have been conducted to find patterns in a sequence database.

1) Basic Concepts:

Let S= { i_1, i_2, i_3, . . . i_m} be the universal item sets (Key objects). Video Database (VDB) = { S_1,S_2,S_3…..S_n} be a video sequence database. Where S_i ($i \in [1…n]$) is a set of scenes which is a unique identifier and contains a set of items (Key frames) in S. A is called a pattern if A is a set items (or a subset of S). The support of A is number of the times occurs in the video sequence database.

Video association as sequential pattern with {X_1,….X_i….X_l; X^t_i<X^t_j for any i<j} where X_i is a video item L denotes the length of the association, $X_1 \cap \ldots \cap X_i, \ldots \cap X_l = \phi$, X^t_i denotes the temporal order of X^i and $X^t_i < X^t_j$ indicated that X^t_i happens before X^t_j. The sequence patterns obtained from the video association mining differs with patterns derived by the conventional frequent pattern mining. Since changing the position of frequent items in a pattern leads to another pattern which is different. For instance, in video association mining the pattern ABCD differs from ABDC because in the second pattern D occurs before C.

Temporal distance and temporal support are the important properties for video associations. In addition, each time video association appears, the temporal distance between any two neighboring items of the association should satisfy the given TDT (i.e., no more than T shots). The smaller the TDT, the stronger the semantic correlations among the mined associations are. Sometimes the semantic correlations may be missed. If TDT as ∞ (i.e., ignoring the temporal distance); It will increase the number of frequent patterns and identifies additional semantic concepts.

2) Discovering Best-N Frequent Patterns:

The common framework of mining frequent patterns is to use a minimal support threshold to ensure the generation of the correct and complete set of frequent patterns.

TABLE I. SYMBOL TABLE

Key Item	Hero	Heroine	Both (Hero + Heroine)	Anti-Hero	Hero + Anti-Hero	Comedian
Symbol	A	B	C	D	E	F

TABLE II. SAMPLE VIDEO 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

However, this framework leads to the following two problems that may hold back its popular use.

1) Setting minimal temporal support threshold is quiet tricky. User cannot know the exact threshold in advance. A too small threshold may lead to generation of thousands of patterns, while a too big one may or may not generate few patterns. Both cases are undesired to users.
2) Frequent pattern mining often lead to the generation of large number of patterns, which may be much larger than the number of interesting rules.

In this paper, we present a Modified VidApriori algorithm that uses top-down approach for mining long sequences. The algorithm extracts the Best-N frequent patterns, where N is the largest rank value of all frequent patterns to be mined.

During the mining process of Modified VidApriori, the undesired patterns are filtered and useful patterns are selected to generate other longer potential frequent patterns. This strategy greatly reduces the search space. Our algorithm defines dominant of the sequences and uses it for minimizing the scanning of the data set.

a) Algorithm for Finding Frequent Item sets

Modified VidApriori Algorithm employs an iterative approach that is the same as Apriori. The iterative approach, which is known as a level-wise search, uses *l*-patterns to explore (*l* +1)–patterns. Below are the processing procedures.

// Best-N Table maintains the Best N candidates//

1) Scan the video sequence database VSDB. Collect the set of Best-N frequent 1-length patterns. Insert these Best-N frequent patterns into the Best-N table. The Best-N table consists of two fields, (1) Count and (2) list of patterns. For any tuple of the Best-N table, all patterns in the list of the tuple have the same support, which is the value of count of the tuple. The number of tuples of the Best-N table is no more than constant N. In addition, tuples in the Best-N table are sorted in Count descending order.
2) Use the 1-patterns in the Best-N table to generate candidate 2-length patterns. Scan DB again to gain the supports of candidate 2-patterns. If the support of a candidate 2-patterns is no less than the values of Count of the Best-N table, the candidate 2-patterns is inserted into the Best-N table. After each insertion, the Best-N table is checked to ensure the number of tuples is no more than N. If the number is great than N, the tuples behind the Nth tuple are deleted from the Best-N table.
3) Repeat procedure 2 by using l–patterns in the Best-N table to generate Best-N (*l* +1)-patterns.

b) Example

Let the video sequence database, VSDB, be table 1 and threshold *N*= 3. The algorithm first find all patterns in VSDB and gain the supports of these patterns, and then filter the Best-N frequent patterns in term of their supports. The sample frequent pattern generation was shown in the figure 3.

Obviously, the brute-force method is inefficient because it enumerate all patterns. For finding Best-N frequent patterns, the brute-force method may generate about $n*(2^{m}-1)$ patterns (Let a VSDB have *n* Sequence and the average length of Sequence is *m*). Therefore, the brute-force method is inefficient in both time and space. On the contrary, Algorithm Modified VidApriori can greatly reduce space and candidate pattern.

The generated associations could be used to predict futuristic events based on the occurrence of a certain sequence of events frequently. Event (It means it is the scene in the video having some semantic meaning attached to it) has an associated time of occurrences. A, B, C, D, E, F are the event types. One of the basic problems is to find frequent event types in the sequence. Video is particularly an ordered set of events. In a sequence A and B occur, in either order C occurs soon. It can also be employed in the video classification to determine the overall nature of the video. Also, it employed in the video summarization by indexing the most frequent patterns in the summary.

V. EXPERIMENTS AND RESULTS

To evaluate the efficiency of the algorithm, we performed an extensive performance study of Modified VidApriori algorithms, on synthetic data set with various kinds of sizes and data distributions. The experiments were conducted on a 2.10GHz Intel Dual core PC with 4GB RAM running Microsoft Vista. The Algorithm Modified VidApiriori was implemented by using Java.

We have implemented two algorithms, which are AprioriVS algorithm (brute-force method), and Modified VidApriori Algorithm for mining Best-N patterns. The synthetic data set, which we used for our experiments, is generated using the Dataset Generator [16].

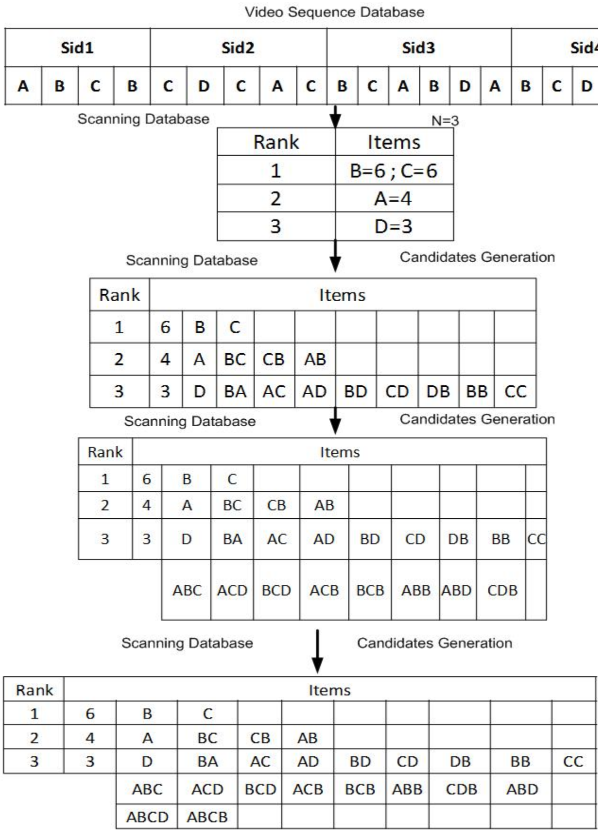

Figure 3. Frequent Pattern Generation

The synthetic data set that we generated was VidoSeqDB with five predicting attributes, five domain attributes and 300 tuples, which is denoted as VSDB. In this data set, the average sequence size and average maximal potentially frequent itemset size are set to five, respectively. For comparing AprioriVS algorithm with Modified VidApriori, we select a few video sequences from Sequence dataset randomly to construct small datasets.

Fig.4 shows that AprioriVS algorithm is much time-consuming even on dataset with the number of sequences less than 100. The bad performance of AprioriVS algorithm lies in that it needs to enumerate all subset of sequences. For example, let T be transaction of size 20, Ariori VS algorithm will generate $2^{20} \approx 10^{6}$ subset.

The space complexity of AprioriVS and Modified VidApriori as the number of video sequence database increases from 20 to 300 is shown in Fig.5. Modified VidApriori is better than Ariori VS because of the Modified VidApriori discovers large number of frequents. Modified VidApriori reduces the number of candidates with using the Best-N table. It also improves the speed of execution and reduces the space while increasing the number of records. It is obvious that the advantage of Modified VidApriori becomes more and more distinct as number of sequence increases.

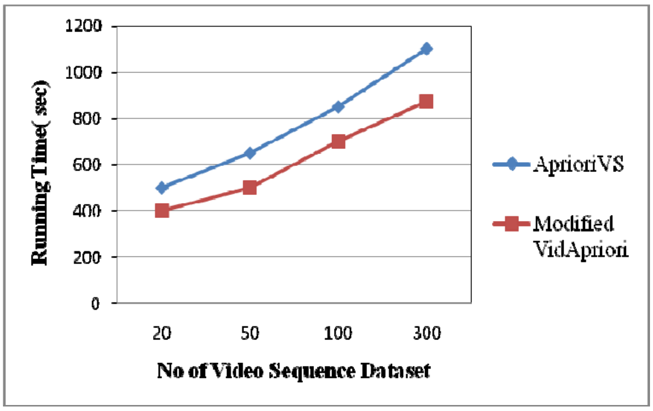

Figure 4. Running Time

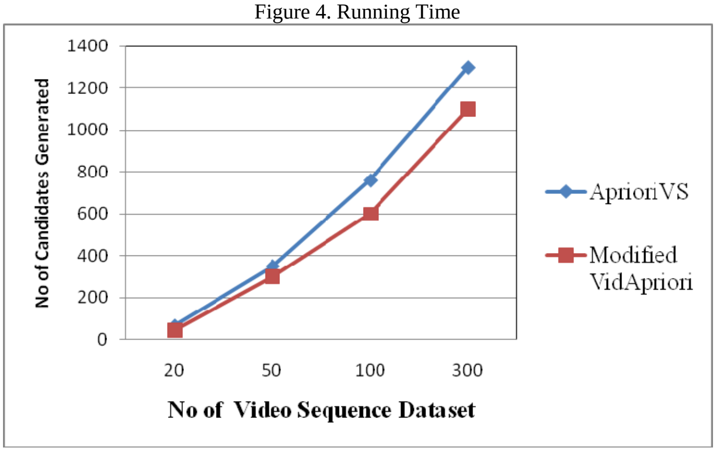

Figure 5. Space Complexity

VI. CONCLUSION

In this paper, we have studied an interesting problem, mining frequent patterns in a video database. Given video, we first transformed it from video frames to a video sequence dataset by using video pre-processing. Then we proposed a new Modified VidApriori Algorithm to generate frequent patterns. The main difference between this patterns mining problem and problems in [5,8] is that the threshold of minimal support of each patterns do not need to be set in mining Best-N frequent patterns. Modified VidApriori algorithm can greatly reduce the search space. The mining algorithm discussed in this paper are mainly derived from the existing data mining schemes (with some extensions for video mining scenarios); extensive studies are needed to explore efficient mining algorithms which are unique for mining knowledge from video data. Some specific applications of generated frequent patterns such as classification, summarization and event detection are a candidate for further research.

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AUTHORS PROFILE

Vijayakumar.V, Assistant Professor in the Department of Computer Applications, Sri Ramakrishna Engineering College, Coimbatore, Tamil Nadu, India. He is currently pursuing his doctoral degree at Bharathiar University, Coimbatore, Tamil Nadu, India in the area of Video Data Mining. He obtained his M.C.A degree and M.Phil degree in Computer-Science from Bharathiar University, Coimbatore. His research interests are Data Mining, Multimedia Information Retrieval, Image and Video Processing. He has presented various papers in National, International Conferences and International Journals. He has guided several undergraduate, post-graduate projects and seven M.Phil research scholars. He is a student member of IEEE and life member of ISTE.

Dr.Nedunchezhian.R., is currently working as the Professor and Head of Information and Technology, Sri Ramakrishna Engineering College, Coimbatore, Tamil, India. Previously, he served as Research Coordinator of the Institute and Head of Computer Science and Engineering Department (PG) at Sri Ramakrishna Engineering College, Coimbatore and worked as the Vice Principal of Kalaignar Karunanidhi Institute of Technology, Coimbatore. He has more than 19 years of experience in research and teaching. Currently, he is guiding many Ph.D scholars of the Anna University, Coimbatore, and the Bharathiar University. His research interests are knowledge discovery and data mining, distributed computing, and database security. He has published many research papers in national/international conferences and journals. He has edited a book entitled "Handbook of Research on Soft Computing Applications for Database Technologies: Techniques and Issues" which was published by IGI publications, USA in April, 2010. He is a Life member of Advanced Computing and Communication Society and ISTE.