Discovery of Anomalous event against frequent sequence of video events

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***Abstract*—Events occurring in observed scenes are one of the most important semantic entities that can be extracted from videos [1]. Most of the work presented in the past is based upon finding frequent event patterns or deals with discovering already known abnormal events. In contrast in this paper we present a framework to discover unknown anomalous events associated with a frequent sequence of events (A_{EASP}); that is to discover events which are unlikely to follow a frequent sequence of events. This information can be very useful for discovering unknown abnormal events and can provide early actionable intelligence to redeploy resources to specific areas of view (such as PTZ camera or attention of a CCTV user). Discovery of anomalous events against a sequential pattern can also provide business intelligence for store management in the retail sector.**

Keywords: Video Event Mining, Multimedia Mining, Sequential Pattern, Abnormal Events Discovery

I. INTRODUCTION

The proliferation of TV channels and video-based surveillance systems has enabled us to store almost every activity which mirrors our world. This generates huge volumes of data; too much for human operators to process, therefore there is a great need for automated analysis. Motivated by the success of sequential pattern mining approaches in analysing transactional data, much research effort has been devoted to applying these techniques to multimedia data.

Most of the work presented in the past is based upon finding frequent event patterns to provide a hierarchical structure of events for video retrieval and indexing. Research into surveillance videos mainly deals with discovering already known abnormal events. In contrast, the work presented in this paper is focused on the problem of discovering unknown anomalous events against sequential patterns (A_{EASP}). That is to discover events which are unlikely to follow a frequent sequence of events. This information can be very useful for discovering unknown abnormal events and can provide early actionable intelligence to redeploy resources to specific areas of view (such as PTZ camera or the attention of a CCTV user). Discovery of anomalous events against a sequential pattern can also provide business intelligence for store management in the retail sector. The importance of anomalous events against a frequent sequence of events can be seen from the following examples.

Suppose we have the frequent sequence of events: 'a vehicle on the road' → 'a vehicle on the parking road'→ 'a vehicle in the parking place' <sequence duration 4 minutes>. This sequence becomes more interesting if it is followed by an unlikely event such as 'vehicle on the parking road again', this might be a hit and run accident; therefore, the attention of the CCTV user needs to diverted to the specific video stream. It is important to note that an anomalous event isolated from the specific sequence could be a normal event (see Fig 1).

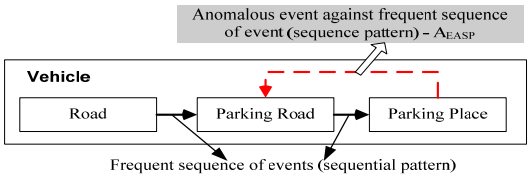

Figure 1 Anomalous event against frequent sequence of events

In a retail store environment, suppose we have the following frequent sequence of events: 'section D is crowded'→ 'high customer activity in section A'→ 'long queues on tills 7 and 8'. Although this information provides business intelligence to depute resources to tills 7 and 8; it does not provide information regarding what resources can be spared to supply tills 7 and 8. But, if we had additional information that the sequence of events is unlikely to follow 'high activity on tills 1 & 2' then information about the anomalous event can be used for effective store management (see Fig 2).

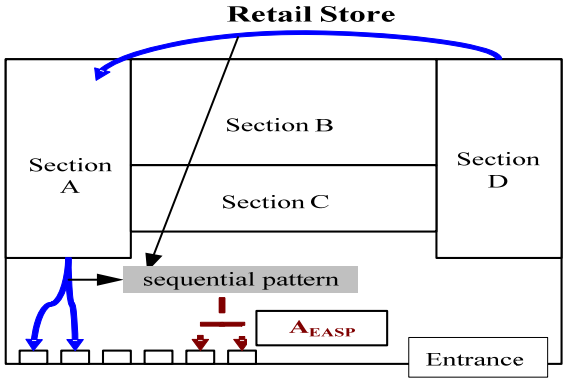

Figure 2 Anomalous event against a frequent sequence of event

The remainder of the paper is structured as follows: in section 2 we will review related work from both areas of video event mining and traditional data mining. Section 3 gives a formal definition of anomalous events following frequent sequential patterns. In section 4 we will present the main algorithm for discovering A_{EASP}. Section 5 presents a dynamic sequential pattern support counting procedure (DSCP). Lastly in section 6 we conclude the work and discuss further research work.

II. RELATED WORK

We can divide video data into two broad categories: video with and without some content structure. The former are videos such as movies and news where scenarios are used to convey video content. "Raw" videos like surveillance videos, have no scene change, therefore no content structure can be found in them. Work presented in, for example [2-17] provide excellent frameworks for indexing and mining video information by utilising semantic information; however, these approaches are based purely on structured data and video indexing is based on already known relationships in a specific domain. In [18] Alexander et. al. explore the effectiveness of discovering sequential patterns from unstructured videos. Simple events such as ("vehicle crossing entrance", "vehicle on the road", "vehicle move to left") were used as input to the model for the discovery of complex events such as car parking, driving off etc. The main aim of their work was to discover previously unknown frequent events; as compared to the discovery of anomalous events against a frequent sequence of events that is presented in this paper.

In traditional data mining most of the previous work presented in the area of sequential patterns is based upon finding sequential patterns having "Positive Behaviour", i.e. they predict what will be the next event/event-set in a sequence. However, an aspect of sequential patterns which can be very helpful in multimedia data mining systems has not been fully explored, and that is to find the events which have anomalous events associated with the given frequent sequential event, i.e. to discover the events/event-sets which are unlikely to follow a sequence of events. There has been some research efforts to mine both positive and negative association rules [19-21]; however they ignore the temporal aspects of events (temporal order of events in a pattern). Recently in [22], Kaziekno, concentrated his work on discovering the negative conclusion for a given sequential pattern in a post mining environment. The work presented in [22] is similar to our concept of discovery of anomalous event/action against the given sequential pattern; however, their proposed algorithm does not make a specific commitment to confront the most intensive process in the algorithm, that is to find the support of given sequential patterns. The complexity of the algorithm is due to the fact that the suggested algorithm has to find sequential pattern support within the given sequence duration (SD). Therefore, the process of finding the support of a sequential pattern in each data-sequence can span into different search spaces. We can call these search spaces moving windows (MW) (Fig 3).

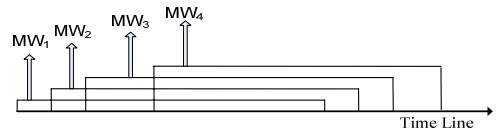

Figure 3 MW (Moving Windows)

III. ANOMALOUS EVENT AGAINST FREQUENT SEQUENCE OF VIDEO EVENTS (A_{EASP})

Formally we can define the A_{EASP} as an event or events that are unlikely to follow a specific frequent sequence of events (a sequential pattern).

$$A_{Event}=SP \sim Event$$

For a comprehensive definition, two user defined parameters are introduced. The Maximum Time Interval ($maxt_{ITVL}$) is a time interval during which we have to find support of A_{EASP}. This parameter is important since we are not interested in an event which is widely separated in time from the sequential pattern. Maximum Tolerance (max_{TOL}) is introduced to determine the maximum representation allowed for an event in order to be considered as A_{EASP}.

Formally we can define the problem to investigate as:

We have a database of video events "**D**" spanning a time domain "**T**", each record is a pentuplet of <$Event_{ID}$, Event start time, Event end time, $Camera_{ID}$, $Area_{ID}$>; a proven sequential pattern of events SP(e_1, e_2,$e_{3...}e_{i....}e_n$), where e_i is an event of a sequence ($e_{1\ ...} < e_{j\ ...} < e_n$) along with sequence duration, and temporal granularity parameter; a list of candidate events and the user defined parameters of max_{TOL} and $maxt_{ITVL}$. The problem to investigate is to find all the events or event-sets, which are unlikely to follow the given sequential pattern during the time interval $maxt_{ITVL}$.

IV. THE PROCESS OF DISCOVERING A_{EASP}

Firstly, we divide the events database into user defined temporal granularity. For example if the granularity is defined as hours then we will divide the events database into different data sequences; each will contain all the events occurring during that specific hour. To capture the sequential pattern support span over the boundaries of the user defined temporal granularity, we generate a flying data sequence by taking a portion of the current and previous data sequences (Fig 4). The discovered support will be assigned to the data sequence in which the majority of the events of the sequential pattern are found, if equal numbers of events found in both data sequences then support will be counted against the current data sequence.

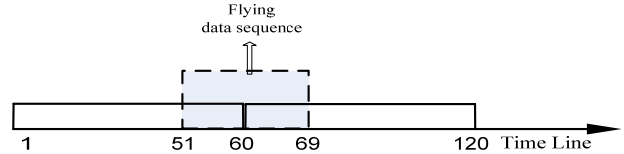

Figure 4 Flying data sequence (suppose SD is 10 minutes)

A. *Interested Time (I_{TIME})*

We define I_{TIME} (Interested Time) as the time interval between SP_{et} (a discovered sequential pattern's support end

time) and $maxt_{ITVL}$_et (the end time of the user defined parameter of $maxt_{ITVL}$). For each sequential pattern support found there will be a specific I_{TIME}. I_{TIME} is always greater than or equal to the end time of the sequential pattern found in the data-sequence and less than or equal to the user defined $maxt_{ITVL}$_et (maximum interval end time) (Fig 5)

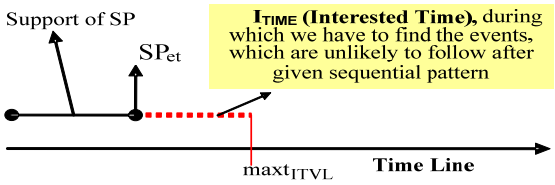

Figure 5 Interested Time Interval

The algorithm has two main phases, which work alternately. First, we find the support of a given sequential pattern in the data-sequence. Once the support of a sequential pattern is found, the algorithm moves to the second phase in which we attempt to discover the support of all candidate events CEL during the specific I_{TIME}. Since a sequential pattern can occur multiple times in any data-sequence, we may have to find all the supports of the pattern in each data sequence and then find the support of CE (candidate events) in the interested time (Fig 6)

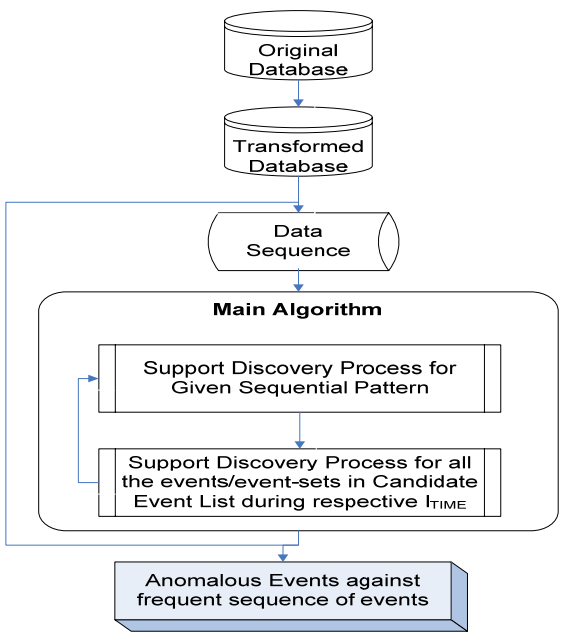

Figure 6 Discovery process for A_{EASP}

V. Sequential Pattern Support Discovery Process

It is observed that the most intensive process in the algorithm is finding the support of sequential patterns in different moving windows (MW). The complexity of the algorithm is due to the fact that it has to find sequential pattern support within the given SD (sequence duration) as discussed in Section II. For MW we mean the limited search space in which we have to find the support for a sequential pattern. For example if SD is given as 28 minutes and the data-sequence length is 30 minutes then we will have the three MW {(1-28) (2-29) (3-30)}.

A sequential pattern can exist multiple times during each data-sequence, so it is very likely that the algorithm will have to find multiple instances in each data sequence. This is because support of all candidate events (CE) needs to be discovered during each data-sequence in order to find all A_{EASP}

A. *Dynamic Support Counting Process (DSCP)*

With reference to these considerations, it is important to devise a mechanism which can minimise the expensive data processing during the discovery of sequential pattern support. A Dynamic Support Counting Process (DSCP) is introduced here to minimise this expensive data processing. DSCP scans only the minimum number of required data-sets from the database in order to find the support of a given sequential pattern and thus improves the process considerably. To discuss the concept of DSCP in more detail, we first need to introduce how we will perceive the status of sequential pattern events during the DSCP. We divide the given sequential pattern into three main statuses.

- **C_{Event} (Current Event)** C_{Event} is a sequential pattern event for which DSCP is searching the support.
- **E_{LHS} (Lift Hand Side Events)** All the events of the given sequential pattern which are on the left side of C_{Event} are known as E_{LHS}.
- **E_{RHS} (Right Hand Side Events)** All the events of the given sequential pattern which are on the right side of C_{Event} are known as E_{RHS}.

If the C_{Event} is also the first event of given sequential pattern then there will be no E_{LHS} and if the C_{Event} is the last event of a sequential pattern then there will be no E_{RHS}. Figure 7 explains the different status of events during DSCP.

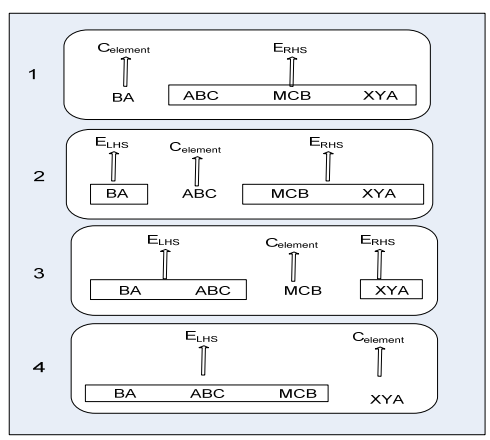

Figure 7 Sequential Pattern Events status in DSCP

The main idea behind DSCP is in the fact that MWs overlap each other. Therefore, the scanned result of the overlapped MW portion can be utilised during the sequential pattern support discovery process in the next MW; moreover, DSCP expands dynamically, that is it will only access the next

MW if it is required. DSCP is based on the following notions in order to minimise the database scanning during the process of finding the support of a sequential pattern.

Firstly, if the discovery process does not find the support of C_{Event} of a given sequential pattern then support of all the E_{RHS} (Right Hand Side Events) has no significance in the Current Moving Window (C_{MW}). This is due to fact that for a valid support of a given SP, every event has to be discovered within the $C_{MW.}$ Hence, the process of searching E_{RHS} in C_{MW} will be terminated and DSCP moves to Next Moving Window (N_{MW}), (Fig 8).

Suppose we have a sequential pattern:

SP= (BA→ABC→MCB→XYA→MBAC→GBA)

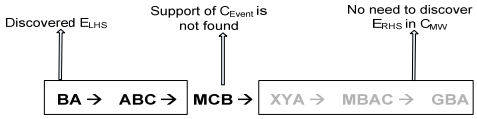

Figure 8 DSCP (First Notion)

Secondly, if a discovered Left Hand Side Event (E_{LHS}) of a Previous Moving Window (P_{MW}) is valid in C_{MW}, then all previously discovered E_{RHS} of P_{MW} are valid in C_{MW} as well. For the event to be considered as a valid discovered event, it has to satisfy the following conditions:

- The event time should be within the boundaries of C_{MW}.
- The event time should be greater than the last discovered E_{LHS}.

B. *Search Techniques*

By implementing these notions, the suggested algorithm can utilise the discovered events of sequential patterns in P_{MW} during the process of finding support of SP in C_{MW}. DSCP is based on three dynamic tables. By utilising these tables, DSCP needs only one database scan to discover all required supports of a given sequential pattern.

- **DWT (Dynamic Windows Table):** This table is used to hold information about MWs (boundaries of different MWs). The table is extended according to the need of new MWs during the process of finding the support of a given sequential pattern.
- **DET (Dynamic Event Table):** DET is basically a vertical transformation of the original database for the events of a given sequential pattern. This table expands as the process shifts to the next moving window.
- **DSPT (Dynamic Sequential Pattern Table):** This table holds the information about the current valid events of a given sequential pattern.

For better understanding of DSCP concept we will run through the algorithm with an example.

Suppose we have a sequence database "**D**" over a time domain "**T**" and a given sequential pattern (A→E→M→A→Q) with user defined parameters of SD. The problem to investigate here is to find a given sequential pattern's support in a data-sequence.

In the first step, DSCP populates DWT in accordance with the user-defined parameter SD. For simplicity we assign ordered numeric values to events according to date/time and call this the position of the event during these examples. The number of events within a MW can vary, however the length of all the MWs will be equal (Fig 9)

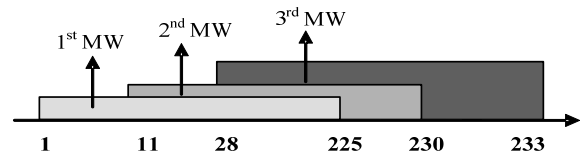

Figure 9 Moving Windows

First DSCP populates DWT with MW_1 which contains positions 1-225, (first row of Table 1).

WID	Start Position	End Position
1	1	225
2	11	230

Table 1 DWT (Dynamic Windows Table)

In the second step, DSCP populates DET by accessing the event position of the given sequential pattern events within the $C_{MW.}$ Different shadings in table 2 show how the table will be populated. In the first MW, DET will be populated up to event position 225 (table 2 first set of shading), for example, item A appears at 12, 28, 119… and Item E in 28, 39, 125…. etc.

A	E	M	Q
12	28	119	230
28	39	222	
119	125	225	
220	229	230	
226			
228			

Table 2 DET (Dynamic Event Table)

In the third step, DSCP populates the DSPT with valid events by checking that they satisfy the valid event conditions mentioned in the second notion of DSCP.

A	E	M	A	Q
12	**28**	**119**	**220**	**?**

Table 3 DSPT (Dynamic Sequential Pattern Table)

DSCP discovered the first four events in the C_{MW}. Since event Q is not discovered in the C_{MW}, the search process is terminated and DSCP moves to the next moving window (First Notion of DSCP). Next DSCP populates DWT and DET by only accessing the expanded portion of the new MW, which has the following five events (Fig 10, table 1, 2 and 4).

A(226) A(228) E(229) Q(230) M(230)

(Second set of shadings in table 1 and 2)

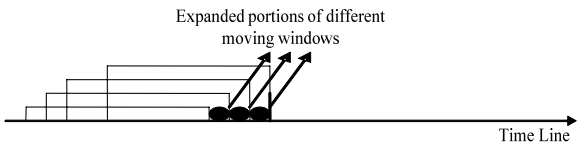

Figure 10 Expanded portions of different moving windows

DSCP populates DWT with information of the second MW (second row of table 1). DSCP also populates DET with events of the expanded portion, that is events from 226 to 230 (second set of shadings in table 2)

The process of finding the valid events proceeds again, since A is on (12) position in DSPT table and C_{MW} boundary is 11—230 positions, therefore, it is a valid event. According to the second notion, if a discovered E_{LHS} is valid, we do not have to check the discovered event's validity because it will be valid automatically. Therefore, we say if E_{LHS} is valid all the discovered E_{RHS} are valid as well.

Now support of the undiscovered event (Q) must be checked during the expanded portion of the DET only. DSCP finds Q support at position 230 (Table 2) which is higher than the last E_{LHS}. Since it satisfies all the given conditions of valid discovered events and it is the last event for the given sequential pattern, the DSCP process will terminate here with successful discovery of sequential pattern support in the second MW and the process of counting the support of all candidate events will start.

A	E	M	A	Q
12	28	119	220	230

Table 4 Updated Dynamic Sequential Pattern Table

VI. CONCLUSION AND FUTURE WORK

In this paper, we proposed the concept of anomalous event against a sequential pattern which can be very useful for discovering unknown abnormal events and can also provide business intelligence in a retail store environment. An algorithm to discover all the anomalous events against specific sequential patterns is also presented. It is observed that sequential pattern support counting is an expensive process. To minimise the expensive processing required for counting the support of given sequential patterns, a Dynamic Support Counting Process (DSCP) is presented, which discovers all the supports of a sequential pattern by scanning only minimum required data-sets of database. In future we will focus on discovering anomalous events for multiple given sequential patterns with single database scan.

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