Video Synopsis Generation Using Spatio-Temporal Groups

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Abstract—Millions of surveillance cameras operate at 24×7 generating huge amount of visual data for processing. However, retrieval of important activities from such a large data can be time consuming. Thus, researchers are working on finding solutions to present hours of visual data in a compressed, but meaningful way. Video synopsis is one of the ways to represent activities using relatively shorter duration clips. So far, two main approaches have been used by researchers to address this problem, namely synopsis by tracking moving objects and synopsis by clustering moving objects. Synopses outputs, mainly depend on tracking, segmenting, and shifting of moving objects temporally as well as spatially. In many situations, tracking fails, thus produces multiple trajectories of the same object. Due to this, the object may appear and disappear multiple times within the same synopsis output, which is misleading. This also leads to discontinuity and often can be confusing to the viewer of the synopsis. In this paper, we present a new approach for generating compressed video synopsis by grouping tracklets of moving objects. Grouping helps to generate a synopsis where chronologically related objects appear together with meaningful spatio-temporal relation. Our proposed method produces continuous, but a less confusing synopsis when tested on publicly available dataset videos.

I. INTRODUCTION

Surveillance videos recorded at 24×7 are normally not of much use unless summarized meaningfully. There exist a few approaches to produce video synopsis. For example, the fast-forward approach proposed in [1] is well-known to generate video synopsis. Unfortunately, the method misses events such as fast moving objects while skipping video frames. To mitigate this problem, a few alternatives have been proposed in [2], [3], where key frames are chosen conditionally to generate synopsis. However, frame-based approaches tend to produce longer duration synopsis by combining activity video clips sequentially [4], [5]. To reduce the length of the synopsis, a number of approaches have been proposed that extract activity area from the raw video and montage these activities together [6], [7]. In the synopsis video, several activities coming from different times are stitched in continuous frames. In this case, it often produces unpleasant synopsis due to blending seams coming from different image patches.

To address such problems, researchers have proposed object-based non-chronological video synopsis approach [4], [8], [9]. In object-based approaches, moving objects are tracked using multi-object tracker, segmented at real-time, and then shifted to different time in the synopsis according to user’s requirements. Although object-based methods can reduce duration of synopsis, it may cause collisions between objects that appear within same spatial domain and sometimes produces confusing synopsis by showing several activities simultaneously. To reduce such collisions, a few improvements have already been proposed. For example, Nie et al. [5] and Kang et al. [10] have proposed methods by shifting the moving objects in spatial and temporal domain. Although these methods reduce collisions, both temporal and location information of objects are violated. Pritch et al. [4] have proposed a method by energy minimization with only temporal shifting of objects. Results produced by their method produces confusing synopsis as several activities are shown simultaneously. Xuelong et al. [11] have proposed methodology to minimize object collision with minimum time shifting by scaling down the object size. Pritch et al. [9] have proposed method by clustering moving objects and showing similar activity together to deal with the confusing synopsis. Their method deals with trajectory clustering and displays similar activities together.

Video synopsis methods enable fast and efficient browsing of surveillance videos, however create a summary that are often confusing to humans for visual inspection. In this paper, we have proposed a new method that is primarily built upon the concept proposed in [4], [8], [9], [12] and [11]. However, our proposed method enables displaying a group of activities simultaneously which originate from different time periods. Also, it creates meaningful summaries by minimizing sudden appearance and disappearance of objects, and also reduces confusions by grouping different activities.

A. Motivation and Contributions

Short duration tube or activity based synopsis generation described in [4], [8], [9], [12] and [11] often produces poor synopsis. It can produce synopsis with shorter lengths by showing simultaneously multiple activity segment of same object, which is confusing. Therefore, the outputs are
not always meaningful to correlate with ground truths by human video analysts. The algorithm suffers from the below drawbacks:

- Sometimes objects may appear and disappear in the synopsis video as depicted in Fig. 1 and Fig. 2.
- Activity segments or tubes of the same object may appear non-chronologically resulting discontinuous synopsis as depicted in Fig. 2.
- Activity segments or tubes of the same object may appear at the same time resulting confusing synopsis as depicted in Fig. 3.

This paper proposes a method to generate synopsis of a time bounded video by overcoming aforementioned drawbacks. In contrast to these methods proposed in [4], [8], [9], [11], [12], our proposed method groups the moving objects to generate the synopsis. Grouping is done with respect to relative spatio-temporal distance and chronological appearance of the objects. Results reveal the superiority of our method over existing approaches. Also, our method produces synopsis that originally reflect continuous activities of moving objects. For example, An object appeared in a scene at 10:00:00 AM and exit the scene at 10:01:15 AM. Proposed method preserve the chronological appearance of the same object in different location, and produce continuous synopsis of the same object.

**Fig. 1**: Examples of two moving objects appear at different times in the in-house KIST dataset video and how they appear in the synopsis video. It has been observed that a small tube (activity segment) appears in a very short period, For example, a sample small tube appeared and disappeared in between Frame 72 to Frame 73 (red border). It creates sudden appearance and disappearance of moving objects in the synopsis video.

Rest of the paper is organized as follows. In the next section, we present the proposed methodology in detail. Section III, we present the results obtained using publicly available datasets as well as using the videos of in-house KIST dataset. Conclusion and future directions of the present work are discussed in Section IV.

**II. PROPOSED SYNOPSIS GENERATION METHOD**

In this section, we will present the proposed method in detail. The main approach is presented in Fig. 4. The method can be divided into two phases similar with the method proposed in [4]. First, moving objects are segmented using improved Mixture of Gaussian [13] and then tracked using Kalman filter based multi-object tracker [14].

**Fig. 2**: Example of a synopsis segment (Frame 92 to Frame 99) of a moving object that appears at different times in the KIST video. It has been observed that, two small tubes or activities (green and orange) appear non-chronologically. Tube represented by the top row actually appears after the tube represented by the bottom row in the original video. It also creates sudden appearance and disappearance of objects, therefore does not reflect the ground truth.

**Fig. 3**: Example of a set of synopsis frames taken from the KIST video and the results synopsis reported in- [4]. It has been observed that, same object may appear multiple times at the same time frame. Therefore, it creates confusing synopsis.

A tube/activity is defined by the continuous position of the object, and activity segment is the part of the scene between entry and exit in a scene of an object. Tracking and extracting activity is done in real-time which is denoted by the online-phase. Next, moving objects are grouped in unsupervised manner and then each group is stitched into the background using the Poisson image blending [15]. Stitching is done by blending multiple activity in a known background. Synopsis length ($L$) is also minimized before generating the synopsis during this response phase. A response phase is responsible to generate the synopsis of a time bounded video according to user requirements.

Video synopsis can be considered as an index of the original video. In addition, video synopsis can save storage for storing surveillance videos by discarding frames when there is no activity. The quality of the synopsis highly depends on the content of the original video and the length of the synopsis. Also, there are lagging of standard quantitative measurement that method can be used to compare the quality of synopsis. However, there are some baseline standards in video synopsis [4], [9]. They are as follows:

- The video synopsis should be substantially shorter than the original video and should preserve the maximum activities presented in the original video.
Fig. 4: Our proposed method of generating synopsis of a time-bound video. In real-time, moving objects are tracked and segmented, known as tubes. Tube database is actually populated during video recording. Synopsis is generated in response phase by grouping and optimizing the length.

- Collision among objects, i.e. overlapping should be minimized and if possible, be avoided to produce smooth synopsis.
- Temporal relation among objects, i.e. interaction among objects must be preserved in the final synopsis.

To maintain quality of the synopsis as mentioned earlier, we present a method for grouping object activities or tubes before generating the final synopsis. We calculate the energy difference between original and synopsis videos. Energy is defined by calculating pairwise spatio-temporal relation and chronological order of appearance among the objects.

A. Energy Differences

We first define the energy difference between original and synopses video. If the difference is lower, the synopsis quality will be higher. The energy summarizes interaction and chronological appearance among segment of objects. Let \( O \) be the original video and \( S \) be its synopsis. Each tube \( t \) is defined over a time-bound segment in the original video stream \( t_b = [t_b^s, t_b^e] \), where \( t_b^s \) and \( t_b^e \) are the start and end frames.

The synopsis video \( S \) is generated based on a temporal mapping \( M \) over \( O \). The mapping defines the shifting of objects \( \hat{b} \) into the time segment \( t_b = [t_b^s, t_b^e] \) in the synopsis video. \( M(\hat{b}) = \hat{b} \) indicates the time shift of tubes \( b \) into the synopsis. Optimized synopsis of the video is generated by minimizing the following energy function defined by modifying the energy function originally presented in [4]. The energy is defined (1), where \( b \) and \( b' \) represent the tubes present in the video

\[
E(M) = \sum_{b,b' \in S} (E_a(b \cup \hat{b}) + E_t(b,b') + E_o(b,b') + E_c(b,b'))
\]

Activity cost of objects is defined by the continuous position of the object during a bounded time. \( E_a \) is the activity cost of the tube segment \( (\hat{b} \cup b') \) that is not included in the synopsis, \( E_t \) is the spatio-temporal consistency cost, \( E_o \) is the chronological appearance cost and \( E_c \) is the collision cost. Higher collision cost \( (E_c) \), for example, will result in a denser video, where objects may overlap.

When collision cost and activity cost in the final synopsis are zero, i.e. \( \sum E_c = 0 \) and \( \sum E_o(b \cup b') = 0 \), all activity tubes are mapped in the synopsis video. Therefore, the energy of the synopsis can be defined using (2), where the spatio-temporal consistency cost \( (E_t(b,b')) \) is the spatio-temporal distance between \( b \) and \( b' \) in original and synopsis videos.

\[
E(M) = \sum_{b,b' \in S} (E_t(b,b') + E_o(b,b'))
\]
B. Effect of Energy Difference $E(M)$

The length of the synopsis ($L$) depends on the energy difference $E(M)$. If $E(M) = 0$, there is no difference between original video and synopsis. Hence $L$ is equal to the length of the original video. If $E(M)$ is maximum, we allow a maximum shifting of tubes. It may produce a synopsis of different length based on the original content of the video. However, sometimes tracking of objects fails losing identity [16] or force fragmenting tubes as described in [4]. It creates multiple tubes for the same moving object or group of objects. During optimization, these tubes are considered as different objects. Generated synopsis using these short-duration tubes often suffers from the below drawbacks:

- Shifting tubes randomly may produce confusing synopsis by showing multiple appearances of an object in the same frame.
- Sometimes, tubes belonging to the similar activity group violate the order of chronological appearance in synopsis. It may cause sudden appearance and disappearance of the objects and loss in chronological activity may be observed in the synopsis. This is explained as follows. Let, $t_a$ and $t_b$ be two tubes such that $t_a^s < t_b^s$. In the synopsis, if $t_a$ and $t_b$ are part of the same moving object, i.e. $t_a, t_b \in T$, when $t_b$ appears before $t_a$, it loses the chronological ordering.
- Sometimes, objects are shifted to different temporal segment to minimize the synopsis length despite having strong interaction. For example, they may share similar spatio-temporal segment in the original video. It loses the interaction information.

C. Grouping of Tubes and Synopsis Length Minimization

To overcome the aforementioned problems, we have proposed a method of grouping object trajectories or tubes. Shifting of objects in the synopsis is then restricted by grouping them together. Relative spatio-temporal distance and chronological appearance of objects in the same group is unchanged in the final synopsis. Hence $E_i(a,b) = 0$ and $E_o(a,b) = 0$ such that $a,b \in G$. Grouping helps to bind related tubes together. Groups are generated based on the spatio-temporal distance ($d_s(a,b)$) and chronological distance. Let the original video ($O$) be represented using (9), where $t_i$ represents the tubes present in the scene. Tubes are grouped together, and the scene is represented using (10), where $G$ is a set of tubes grouped together.

$$O = \{t_1, t_2, ..., t_n\} \quad (9)$$

$$S = \{G_1, G_2, ..., G_m\} \quad (10)$$

$t_a$ and $t_b$ are assumed to be in the same group, if they chronologically appear or interact within a fixed threshold. It can be expressed as $t_a, t_b \in G$, when $d_s(a,b) < \alpha$ or $t_a^s - t_b^s < \beta$, where $\alpha$ is the maximum distance to measure the interaction and $\beta$ represents the maximum chronological distance for grouping. The algorithm for grouping the tubes are presented in Algorithm 1.

The original video is represented by a set of groups. The synopsis length is minimized by shifting and stitching the groups in the synopsis. The groups are initially selected in chronological order. Then, a group is fitted into a desired location. The process is depicted in Fig. 5.

![Fig. 5: Process of minimization of synopsis length.](image)

Algorithm 1: Grouping of Tubes

```
1: procedure GROUP TUBES(O)  \triangleright Group tubes
2:   R = \{Φ\}
3:   for (a=t_1...t_n) do
4:     if a ∉ R then
5:       G = \{a\}
6:       R = R ∪ G
7:     end if
8:   for (b=t_1...t_n) do
9:     if b ∉ R then
10:    if d_s(a,b) < α OR (t_a^s - t_b^s) < β then
11:      G = G ∪ b, where a ∈ G
12:      break
13:    end if
14:  end if
15: end for
16: end for
17: return R
18: end procedure
```

D. Effect of $\alpha$ and $\beta$

The energy difference ($E(M)$) and length of synopsis ($L$) are related to each other. Spatio-temporal threshold ($\alpha$) can be defined in the boundary as $\alpha = \min(d_s(a,b))$, max($d_s(a,b)$) and chronological ordering threshold ($\beta$) defined in the boundary as $\beta = \min(t_a^s - t_b^s), \max(t_a^s - t_b^s)$, $\forall a,b \in O$. If $\alpha = \min(d_s(a,b))$ and $\beta = \min(t_a^s - t_b^s)$, then the number of groups is equal to the number of tubes present in $O$. It may produce a synopsis.
with higher $E(M)$ when objects are shifted to reduce the synopsis length. Similarly, when $\alpha = \max(d_s(a, b))$ and $\beta = \max(t_a^s - t_b^s)$, all tubes belong to a single group, hence $E(M) = 0$ resulting the original video and the synopsis as of same length. It has also been observed that, grouping spatio-temporal or chronological tubes together, sometimes produces smaller synopsis.

Similarly, Fig. 7 shows the synopsis length by varying $\beta$, considering $\alpha = 0$. It has also been observed that, synopsis length gradually increases after a certain value of $\beta$. It happens because moving objects which appear chronologically with large $\beta$ interval, are considered in the same group. When $\beta$ reaches its peak value, all moving objects create a single group. The length of the synopsis then becomes same as the original video.

\section{Experiments and Results}

In this section, we present qualitative and quantitative analysis of our proposed method. We have experimented with two datasets, namely VIRAT [17] and in-house KIST. VIRAT dataset contains 16 minutes long video that are publicly available and KIST is our in-house dataset of approximately 30 minutes duration.

We first present the relation among spatio-temporal threshold ($\alpha$), chronological ordering threshold ($\beta$), synopsis length ($L$), and energy difference ($E(M)$). Fig. 6 shows the synopsis length by varying $\alpha$, considering $\beta = 0$. It has been found that the synopsis length becomes almost constant beyond a certain value of $\alpha$. It happens because all moving objects create a minimum number of groups based on the $\alpha$.

Fig. 8 shows how synopsis length vary when ($E(M)$) is varied. It has been observed that the energy difference decreases when the length of the synopsis increases after a threshold. The energy difference ($E(M)$) becomes zero when the length of the synopsis is same as the length of the original video.

Fig. 9 depicts a set of frames related to two different synopsis outputs obtained by the algorithm proposed in [4], [8], [9], [11], [12] and using our proposed method. Frames that are marked red show sudden appearance and disappearance of objects in the synopsis generated using the method proposed in [4]. If the synopsis length is minimized to show maximum activity, existing method produces synopsis with high $E(M)$ as depicted in the first row. It has been observed that, when $E(M)$ is low by grouping objects (second row), it produces better synopsis outputs. It has been observed that when the synopsis is generated using [4], [8], [9], [11], [12], due to high $E(M)$, the outputs are often discrete and confusing as compared to our method. We have restricted shifting of objects by grouping, therefore, our method produces longer synopsis with a lower energy difference.

\section{Conclusion}

We have proposed a method of video synopsis generation. Our proposed method produces more meaningful synopsis as compared to the existing methods. It has been observed that, by grouping object trajectories, spatio-temporal relations among the objects can be preserved with higher accuracy. We have tested our methodology on publicly available video dataset and in-house dataset. Initial results are encouraging and the method can be applied on larger scale. There are many possible extensions of the present work. We can
group the trajectories based on various other criteria such as interest area based [18]–[20], movement graph based [21], by supervised or unsupervised machine learning [22], [23], or by using deep learning to understand the activities based on region(s) of interest [18].

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