



## Video Data Mining Framework for Surveillance Video

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### ABSTRACT

This paper presents a framework for surveillance videos of stationery places. To start with, we implement an algorithm to group incoming video stream into meaningful pieces called segments. Further we extract a feature of segment (i.e. motion) which is used to characterize the segments. Motion of a segment is extracted using two dimensional matrix which is constructed using accumulated pixel differences among all frames in a segment. Video segments are then clustered using K-means algorithm. Then we find the abnormality in the segments of the video.

**Keywords:** Motion Extraction, Video Data Mining, Video Segmentation, Video Data Clustering, Video Surveillance.

### 1. INTRODUCTION

Video surveillance systems are now used at various places like banks, hotels, schools and so on. These systems are used for real-time monitoring or post checking. Current video surveillance systems have lower intelligence and it need people to monitor them. So it is required to have some intelligence within systems so that systems can take decision on their own without need of people to monitor them [5, 6].

Data mining is very active research topic nowadays and is the process of extracting previous knowledge and detecting interesting patterns from large set of data. There are various tools and product available in market for video surveillance. Among them traffic surveillance systems [3, 4] are getting more popular because of the use and decision making of the system and there is availability of cheap sensors and processors at reasonable cost. Most of the video surveillance systems provides motion detection and there is facility for recording video when motion is detected so as to reduce the storage and processing time and It can also record a video in different formats and allows multiple cameras to be operated and provides view of multiple cameras at a single place and produces reasonable good results.

The speed and amount of motion in surveillance video can reflect the amount of moving targets and can also model the motion due to stationery surveillance camera and motion which comes from objects in surveillance video. The video is divided into frames and we group incoming video frames into meaningful pieces called segments. For each of the segment, feature (motion) is extracted. Segments are further

clustered using k-means algorithm to determine abnormality in segments.

### 2. VIDEO SEGMENTATION

The incoming video stream is divided into frames. These frames are grouped into homogeneous pieces called as segments. To find a segment boundary we compare each frame with a background frame. A background frame is a frame with only non-moving components and since we assume that camera remains stationery in our purpose we can manually select a background frame which consist of only non-moving components.

The algorithm to group the video into meaningful segments is elaborated as follows [1, 7]. The step 1 is extraction of background frame. Step 2 through 5 is performed by real time-processing. Since segmentation algorithm is generic frame comparison can be done by using pixel-matching or colour histogram. We use a pixel-matching technique in our purpose.

Step.1: A background frame ( $F_B$ ) is extracted from a given sequence and it is applied to low pass filters to reduce noises (false detection of motion which is not actually motion but detected as motion).

Step.2: Each frame ( $F_k$ ) arriving the system is also applied to low pass filters to reduce noise.

Step.3: Compare all the corresponding (same position of) pixels of two frames (background and each frame). Compute the difference ( $D_k$ ) between the background ( $F_B$ ) and each frame ( $F_k$ ) as follows. Assume that the size of frame is  $m \times n$  pixels. Note that the value of  $D_k$  is always between zero and one.

$$D_k = \frac{\text{Total number of different value pixels}}{m \times n} \quad (1)$$

Step.4: Classify  $D_k$  into 10 different categories based on its value. Assign a corresponding category number ( $C_k$ ) to the frame k. We use 10 categories for illustration. The classification is given below.

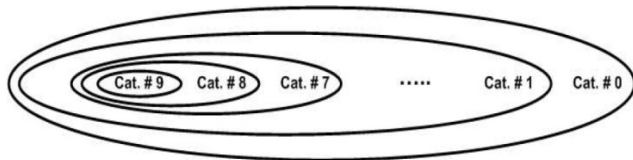
- Category 0:  $D_k < 0:1$
- Category 1:  $0:1 \leq D_k < 0:2$
- Category 2:  $0:2 \leq D_k < 0:3$
- Category 3:  $0:3 \leq D_k < 0:4$
- Category 4:  $0:4 \leq D_k < 0:5$
- Category 5:  $0:5 \leq D_k < 0:6$
- Category 6:  $0:6 \leq D_k < 0:7$
- Category 7:  $0:7 \leq D_k < 0:8$
- Category 8:  $0:8 \leq D_k < 0:9$
- Category 9:  $D_k > 0:9$

Step.5. For real time processing a table is maintained such as Table 1 is maintained. To do this and to build a hierarchical structure from sequences we compare category of current frame ( $C_k$ ) with category of previous frame ( $C_{k-1}$ ). We can build a hierarchical structure from a sequence based on these categories. We consider that lower categories can contain higher categories as shown in figure 1. In our segmentation technique, we look for category boundaries in which we find a starting frame ( $S_i$ ) and an ending frame ( $E_i$ ) for each category  $i$ . The following algorithm shows how to find these boundaries.

- If  $C_{k-1} = C_k$ , then no segment boundary occurs, continue with next frame.
- Else if  $C_{k-1} < C_k$  then  $S_{C_k} = k$ ,  $S_{C_{k-1}} = k, \dots, S_{C_{k-1}+1} = k$ . The starting frames of category  $C_k$  through  $C_{k-1} + 1$  are  $k$ .
- Else if  $C_{k-1} > C_k$ , then  $E_{C_{k-1}} = k - 1$ ,  $E_{C_{k-1}-1} = k - 1, \dots, E_{C_k+1} = k - 1$ . The ending frames of category  $C_{k-1}$  through  $C_k + 1$  are  $k - 1$ .
- If the length of segment is less than a particular threshold value, then we ignore that segment as it is very small and does not contain enough semantic content.

**Table1:** Segmentation Table

Segment No.	Starting Frame No.	Ending Frame No.	Segment Length	Cat. ( $C_k$ )	Total Motion (TM)	Avg. Motion (AM)



**Figure1:** Relationship among categories

### 3. MOTION EXTRACTION

For each and every segment generated from incoming frames. We extract a feature of segment called motion of segment. We compute total motion of segment using Total motion Matrix ( $TMM$ ) which is represented using two dimensional matrix. For purpose of comparison among segments of different lengths (number of frames), we also compute Average motion ( $AM$ ), using Average Motion Matrix ( $AMM$ ).

The  $TMM, AMM, TM, AM$  for a segment with length  $n$  are computed using following algorithm. We assume the frame size is  $c \times r$  pixels.

Step.1: Each frame is applied to low pass filters to reduce noises in frames.

Step.2: An empty two dimensional matrix  $TMM$  whose size ( $c \times r$ ) is same as of incoming frame for a segment  $S$  is created as follows. All the values are initialized with zeroes.

$$TMM_S = \begin{bmatrix} a_{11} & a_{11} & \dots & a_{11} \\ a_{21} & a_{21} & \dots & a_{21} \\ \dots & \dots & \dots & \dots \\ a_{r1} & a_{r1} & \dots & a_{rc} \end{bmatrix} \quad (2)$$

$AMM_S$  is a matrix whose values are average values and are calculated as follows.

$$AMM_S = \begin{bmatrix} \frac{a_{11}}{n} & \frac{a_{12}}{n} & \dots & \frac{a_{c1}}{n} \\ \frac{a_{21}}{n} & \frac{a_{22}}{n} & \dots & \frac{a_{c1}}{n} \\ \dots & \dots & \dots & \dots \\ \frac{a_{r1}}{n} & \frac{a_{r1}}{n} & \dots & \frac{a_{rc}}{n} \end{bmatrix} \quad (3)$$

Step.3: Compare all the corresponding pixel values at the same position of each and background frame. If they have different pixel values increase the value in matrix by one. Otherwise it remains the same.

Step.4: Step.3. is repeated until all  $n$  frames in a segment are compared with a background frame.

Step.5: With the help of above  $TMM_S$  and  $AMM_S$ , we compute a motion (feature) of a segment  $TM_S, AM_S$  as follows.

$$TM_S = \sum_{i=1}^r \sum_{j=1}^c a_{ij} \quad (4)$$

$$AM_S = \sum_{i=1}^r \sum_{j=1}^c \frac{a_{ij}}{n} \quad (5)$$

$TM$  is the sum of all the values in total motion matrix ( $TMM_S$ ) and we consider this as a total motion of a segment. Total motion of a segment ( $TM$ ) depends not only on amount of motion but also on length of segment. A  $TM$  of long segment with little motion can be equal to  $TM$  of short segment with more amount of motion. To differentiate these, we simply use average motion ( $AM$ ) which is an average motion of a segment.

### 4. CLUSTERING OF SEGMENTS

To Find the abnormal events we use K-means algorithm to cluster the video segments [2]. We cluster the segments based on average motion ( $AM$ ). The k-means algorithm makes clusters which minimizes intra-cluster distance while maximizes inter-cluster distance. Clusters represent the relationship of the segments.

*A. Determination of number of clusters and initial centroids.*  
We can set the number of clusters and initial centroids to random values, but it has great connection with the results.. So to achieve effective results initial centroids are computed using following algorithm.

1. Use average motion ( $AM$ ) to quantify all segments and define them as objects.

2. Compute average of all  $AM$  values and define as initial centroid  $k_0$  and assume constant distance  $d$  and let  $k=1$ .
3. Compute the maximum distance  $d_i$  from  $k_0$  for each object. If  $d_i > d$ , then choose object  $o_i$  corresponding  $d_i$  as a new centroid, add it to set  $S$  and let  $k=k+1$ .
4. Repeat (3) until  $d_i < d$ . Then  $S$  has initial centroids and  $k$  number of clusters.

#### B. K-means Clustering Algorithm.

The algorithm is implemented as follows.

1. The initial centroids are chosen according to above section.
2. Compute the distance of each object with centroids and classify them to a cluster with the smallest distance.
3. Based on the classification, update cluster centroids by computing average of all objects again.
4. If any cluster centroid changes by its value in step (3) then go to step (4). Else stop.

### 5. EXPERIMENTAL RESULTS

Our test video data were digitised in WMV format at 30 frames/second. Their resolution is  $320 \times 240$  pixels. We used the frame rates of 30 and 4 frames/second as the incoming frame rate. Our test set has 21 seconds of raw video of Bank Locker Surveillance video which consist of total 630 frames divided into 87 segments.

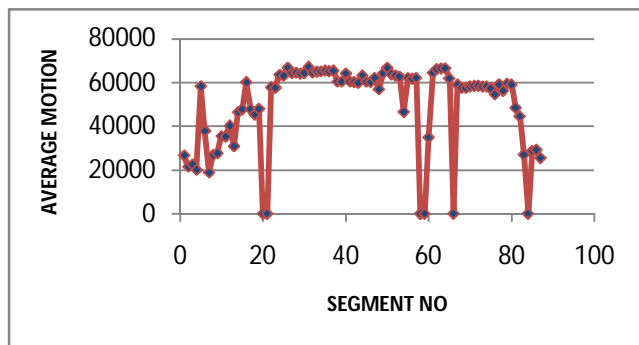


Figure 2: Average motion of segments.

As seen in the above figure, Average motion ( $AM$ ) is lower for initial segments (0-21) which indicate that fewer people move during those initial segments. But during segments starting from 22 average motion is higher until segment no 77. That indicate that more people move during those segments, and may be they are abnormal.

We use K-means algorithm to cluster segments into 3 clusters. Figure 3 shows the clustering result.

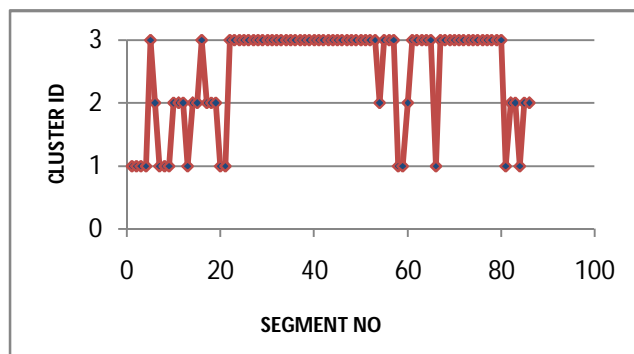


Figure 3: Clustering of Segments

As seen in the above figure most of the segments belong to the cluster id-3. Bigger cluster number contains segments which contain more amount of motion. Cluster id-3 contains segments which contain more amount of motion. All the Segments during (22-51) are consecutive segments and they belong to same cluster id-3. They contain more amount of motion so maybe there is an abnormality during those segments. Cluster id-1 contains all segments which contain less amount of motion and they are normal. If two consecutive segments do not belong to same cluster then it indicates that there is more change in amount of motion. So we can analyse the reason and can take some action.

### 6. CONCLUSION

In this paper we have implemented a data mining algorithm which is used in surveillance video of stationery places. The steps included video segmentation, feature extraction, clustering of segments. Experimental results show some positive results and can help to find out abnormality in the video.

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