Anomalous Event Detection in Traffic Video Surveillance Based on Temporal Pattern Analysis

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Abstract: Traffic video surveillance has received significant attention in recent years. Anomalous Event Detection is gaining popularity among vision community. Existing methods on Intelligent Traffic Surveillance (ITS) systems are inefficient in detecting abnormal events, as they employ high level object features. This paper proposes an alternate solution named Optical Flow based Frequent Pattern Mining (OFFPM) based on low level pixel features. OFFPM employs temporal pattern analysis for detecting abnormal events from the sequences of video streams. Optical flow method is used to determine the spatial information and direction of moving pixels. In addition to the spatial and direction information, temporal information is also determined for every window of sequences. OFFPM relies mainly on extracting spatial and temporal information of motion pixels and mining frequent temporal patterns in a sequence of video frames. Frequent pattern mining is applied to discover regular patterns of normal events. The irregular patterns of events are classified as anomalies. Experiments are conducted on the Queen Mary University of London (QMUL) traffic junction & Roundabout dataset and results show the proposed method accurately detects abnormal traffic events.

Key words: Motion pixels, optical flow, regular and irregular patterns, temporal pattern analysis.

1. Introduction

Detecting anomalous events in traffic video plays an important role in many real time activities such as traffic congestion recognition, crash detection etc. The continuous monitoring is difficult for human operator to detect anomalies. Thus, there is a need for developing intelligent video anomaly detection systems. However, robust and accurate detection of abnormal events in a traffic video still remains a difficult problem due to variations in illumination, background and object appearance. All the traffic anomalies arise mainly due to uneven spatial motion patterns within the time period. The main objective of ITS system is to effectively detect anomalies using efficient event modeling technique based on the spatial and temporal constraints.

Most of the existing works in anomaly detection systems are based on object trajectories, where objects are first detected and tracked to get features. However, the main limitations are sensitive to occlusion and tracking errors especially in dense traffic scenes where multiple activities occur simultaneously. This paper proposes Optical Flow based Frequent Pattern Mining (OFFPM), which works on low level features to effectively detect abnormal events in traffic junction videos. The proposed OFFPM consists of two phases: Training Phase & Testing Phase. In training phase, Motion pixel's spatial information, directions are extracted using optical flow technique and regular motion patterns are extracted. Then temporal relations between the motion patterns are analyzed and are stored as normal regular pattern. In testing phase, the same process of visual feature extraction and aggregation is performed to find out the motion pattern in the test sequence. The test motion pattern is compared with the stored regular pattern to find out abnormal pattern in the test sequence. The use of optical flow[1] avoids the need to identify individual objects and thus eliminates combinatorial complexity. The proposed technique is validated using QMUL traffic & Roundabout junction datasets and is found to provide good detection accuracy.

The rest of this paper is organized as follows: Section 2 presents the Literature Survey in the area of video anomaly detection systems. Section 3 gives the complete information about the steps carried out in the proposed OFFPM. Section 4 discusses the results and implementation details for the Anomalous event detection method. Section 5 presents the conclusion of the proposed work and its future directions.

2. Literature Survey

Currently, there are two different categories of approaches to abnormal event detection depending on the features used [2]. First category employs high-level features by performing target detection and tracking [3]-[7]. While the other category of approaches uses low-level image features[8]-[10]. Track based methods have also been extensively studied for anomaly detection and employs motion tracks of individual objects by multi-target tracking [4], [5], [7]. Motion pattern or path models are usually learned beforehand from large volumes of training data, which is then clustered into particular templates of motion events such as turn-left or go-back. New trajectories can be classified by matching against the event-templates, or evaluated for abnormality by the likelihood under the entire model [5], or the distance to the closest template. The main limitations in these approaches are occlusion and tracking errors. Low-level feature approaches employ, for example, background subtraction [10], granular particles [11], tracklets [7] or optical flow [2], [9], [12]. Then activity patterns are learned from these features. The major advantage of a low level feature based method is that it provides uniform computational loading. It treats every pixel in a similar way irrespective of the number of objects.

At feature level, both pixel and object level are used in recent works. In Han Li *et al.* (2013)[13], used spatio-temporal trajectory features of the multiple objects and motion model parameters are estimated using gray model. With this high level object level feature, anomalies with respect to individual vehicles are easily found out. But the main problem lies in accurate tracking results due to partial occlusion. Mau-Tsuen Yang *et al.* (2013) [14] proposed a real-time cost-effective traffic monitoring system for traffic flow estimation and vehicle classification. In their work, pixel-wise weighting scheme is used for foreground detection and a spatial–temporal profile image is collected over a series of image and finally with post processing operations vehicles are classified. But this work didn't consider illegal U turns which is most common in traffic scenarios.

At event modeling level, we can see probabilistic, graphical, soft computing approaches used in traffic modeling. Muhammad Tayyab Asif *et al.* (2014) [15] proposed unsupervised learning methods, such as k-means clustering, principal component analysis, and self-organizing maps, to mine spatiotemporal performance trends at the network level and for individual links. They used prediction purposes. But in traffic videos, anomalies depend on spatial and temporal parameters. Weixin Li *et al.* (2010) [16] proposed a joined detector of spatial and temporal anomalies. They used novel video representation that accounts for both appearance and dynamics and their framework detects anomalies at multiple spatial and temporal scales. To improve accuracy, contextual information plays a major role in anomalous detection systems. Fan Jiang (2011) [1] proposed a context-aware approach to identify abnormalities. They used hierarchical data mining approach is used for detecting anomalies at three levels: point anomaly, sequential anomaly, co-occurrence anomaly pertaining to objects.

Though there are several methods available in the literature for abnormal event detection, still there is a need for better schemes to improve accuracy. So, in this paper, OFFPM is proposed to detect the anomalous events in traffic junction.

3. Proposed Optical Flow based Frequent Pattern Mining for Anomaly Detection

Fig. 1 shows the flow diagram of the proposed OFFPM. It consists of two phases :1) Training Phase and 2) Testing Phase. In Training phase, features are extracted for each set of frames with the help of optical flow technique. This feature consists of pixel direction, spatial location and temporal information. The temporal information contains frame number indicating the pixel occurrence with in each set of frames. Finally, the OFFPM is applied to discover regular spatial-temporal patterns in the frame sequence. In testing phase, motion patterns are extracted for each sequence of frames. The extracted test feature set is compared with stored regular motion patterns to detect anomalies present in the frame sequence.

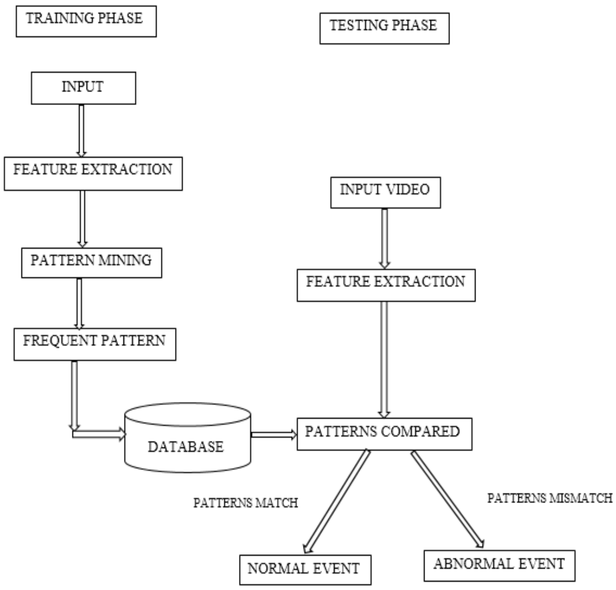
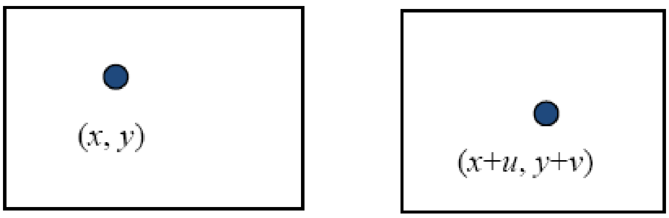


Fig. 1. Proposed OFFPM model.



(a) $H(x.y)$ (b) $I(x,y)$

Fig. 2. shows new and old location of point P(x,y).

The proposed OFFPM workflow contains three major components: 1) Feature Extraction-Extracting spatial direction and temporal information from video. 2) Frequent Pattern Mining-Identifying frequently occurring patterns 3) Pattern Matching-Comparing patterns and features from training and testing videos to detect abnormality.

3.1. Feature Extraction

In the proposed work, the motion feature is considered as the local feature. Optical flow algorithm is used to estimate the movement of objects. In this work, Lucas-Kanade [15] method is used to get spatio-temporal smoothness in the region and optical flow is estimated in the detected area. A dense mesh grid is placed on each frame and optical flow is calculated at each grid point to find motion pixels.

The proposed system uses Optical flow algorithm [1] to estimate the motion vectors from the input video. Given two frames, it estimates the apparent motion between the sequences of frames. There exist few assumptions in the algorithm.

1) Brightness constancy: projection of the same point looks the same in every frame.

$$H(x,y) = I(x+u, y+v) \tag{1}$$

2) Small motion: points do not move very far.

$$I(x+u, y+v) = I(x,y) + u.\partial I/\partial x + v.\partial I/\partial y \tag{2}$$

$$\begin{aligned} I(x+u, y+v) &= I(x,y) + u.\partial I/\partial x + v.\partial I/\partial y + c \\ &\approx I(x,y) + u.\partial I/\partial x + v.\partial I/\partial y \end{aligned} \tag{3}$$

Combining equations (1) and (2)

$$\begin{aligned} 0 &= I(x+u, y+v) - H(x,y) \\ &\approx I(x,y) + I_x u + I_x v - H(x,y) \\ &\approx (I(x,y) - H(x,y)) + I_x u + I_x v \\ &\approx I_t + I_x u + I_x v \end{aligned} \tag{4}$$

$$\begin{aligned} &\approx I_t + \nabla I . \left[\frac{\partial x}{\partial t} \quad \frac{\partial y}{\partial t} \right] \\ 0 &= I_t + \nabla I . \left[\frac{\partial x}{\partial t} \quad \frac{\partial y}{\partial t} \right] \end{aligned} \tag{5}$$

When u and v are zero, it indicates no motion. When values are present for u and v then vectors are computed using Taylor's expansion. Coordinates are then generated for plotting motion vectors.

The motion vectors are returned in complex form $(x + yi)$ after applying optical flow. From those vectors direction is computed as

$$\theta = tan^{-1}(y/x); \tag{6}$$

x is the coefficient of imaginary part

y is the coefficient of real part

In the feature construction phase, the location (x, y) of the moving pixels from the frame and direction in (θ) which the motion takes place are concatenated to form novel feature set for each frame. Most of the anomalous events are based on temporal information. So for each set of frames, feature set are extracted and aggregated over a set of frames to extract temporal information. This information specifies the period of occurrence of that spatial feature over time. The temporal information along with the spatial information constitutes the proposed novel feature set (x, y, θ, *sf*, *ef*) where *sf* and *ef* represents the start frame and end frame number of the feature point.

3.2. Frequent Pattern Mining

In data mining literature, the term frequent pattern is defined as a pattern (a set of items, sub-sequences, substructures, etc.) that occurs frequently in a data set. Given a set of input patterns, this technique enables to identify the frequently occurring pattern. The algorithm for finding regular patterns are shown in Table 1.

Table 1. Proposed Frequent Pattern Mining Algorithm

Input: Data Stream S_n, support threshold *Sup*
Output: The set *D* Frequent Temporal Patterns in a Sequence of frames.

Begin
  For each Sequence S_i, i=0 to L, **do**
    For each frame F_i, i=0 to end_of_video, **do**
      $f_i = \{(x_n, y_n, \theta_n, s_f, e_f)\}$, $n = 1,2,...N$;// Updating with stored patterns
    end for
    If T_i exists in ($T_j \in$ D) **Then**
      $Sup(T_i) = Sup(T_i)+1;$
      //existing Temporal Pattern T_j is retained. Count of the pattern T_j is incremented.
    end if
    else if $T_j \supset (T_j, \forall D)$ **Then**
      $T_j = T_i$; // T_j is replaced with T_i
      $Sup(T_j) = Sup(T_j)+1;$; //count of the Frequent Pattern T_j is incremented.
    else if // Store new patterns in *D*
      add-entry(T_i,1) to D;
    end
    $D_i = \{T_i \mid Sup_i\}$, $i = 1,2,..m$ // set of patterns
    For every w sequences(bucket),
      Delete T_j ; $\forall$ T_j where $S_i < \varepsilon$, Threshold
    End for
  End for
    Output T_j; // Displays Regular Spatial-TemporalPatterns.
End

Table 2. Algorithm for Pattern Matching

Begin
  For each sequence S_i, i=0 to L, up to End-of-Video, do
    For each frame, F_i, i=0 to EOS **do**
      T_i = Feature-Extraction(f_i)
    End for
      Compare(T_i ,Stored-D);//compare with Stored patterns
  End for
End

First, Input features are extracted from each frame F_i using optical flow technique as described in Section 3.1. These features are aggregated for each set of input frame sequence S_i to form aggregated feature set. During the process of aggregation, redundant features are removed and the parameter *ef* is updated in sync with frame number. This set of feature represents a spatial pattern related to the particular type of scene and Support count is maintained for each Sequence S_i. This whole process of feature set aggregation is performed over set of frames $f_1, f_2, \ldots f_n$. If the pattern matches with the existing stored patterns, then its support count parameter sup(T_i) is updated. If it is new one other than the stored pattern, the stored pattern set is updated and its support count sup(T_i) is maintained. If the pattern is found to be subset of the stored pattern then support count sup(T_i) of the stored pattern is updated. If the pattern is found to be superset of the stored pattern then stored pattern is replaced with new pattern and support count sup(T_i) is updated.

3.3. Pattern Matching

In testing phase, Feature Extraction as discussed in Section 2 is performed for sequence. These patterns are compared with the stored patterns for the detection of anomaly. The algorithm used is brute force method and is shown in Table 2. In this algorithm, comparison is made pattern by pattern basis. If Test pattern is subset or superset, then it is classified as Normal regular pattern, else it is classified as irregular Pattern and the sequence is said to have anomalous event. The anomaly region is found out with the help of embedded location in the feature.

4. Results and Discussion

The proposed work is implemented using Matlab and the observations are discussed in this Section. In this experiment, pixels are sampled at every 5 units along X and Y direction and velocity vectors are found out in these locations only. The direction is also quantized into four directions (90°, 180°, 270°, 360°).

4.1. Feature Extraction Using Optical Flow Technique

Optical flow technique is applied to sampled points in each frame to detect motion pixels (as shown in Table 3). Table 4 shows a subset of coordinates extracted from the motion vector in the 56th frame and direction as 90° and 360° in the QMUL dataset.

Table 3. Velocity Vectors

0.000569453404750675 - 0.000214162602787837i
0.000569803640246391 - 0.000109621010778937i
0.000405998784117401 - 0.000203157032956369i
0.000449552870122716 - 0.000334141834173352i
0.000260501343291253 + 1.27985776998685e-5i

Table 4. Coordinates for 56th Frame

X	Y	θ
5	95	360
45	115	360
55	115	360
75	115	360
75	135	360

4.2. Frequent Pattern Mining Implementation

The extracted visual features are aggregated over each sequence S_i to form temporary feature set T_i. The sequence length is taken as L=10 frames. For each unique feature set T_i, separate support count sup(T_i) is maintained. The support threshold 's' is taken as 0.1% of w=100 sequences and error threshold 'ε' as 0.01% of w=100 sequences. Infrequent feature set is deleted based on sup(T_i)<(s-ε). Table 5 shows the max frequent patterns that is obtained using OFFPM algorithm for one particular instance of regular traffic flow.

Table 5. Max Frequent Pattern Set

X	Y	Theta	Start frame	End frame
15	5	90	2	3
15	15	90	1	3
15	25	90	1	4
15	35	90	1	2
15	45	90	3	5
15	215	90	2	2
15	225	90	3	7

Table 6. Infrequent Pattern Set

X	Y	Theta
15	45	360
15	165	90
25	35	90
25	85	90
25	95	90
25	105	90
25	175	90

4.3. Pattern Matching Using Brute Force Method

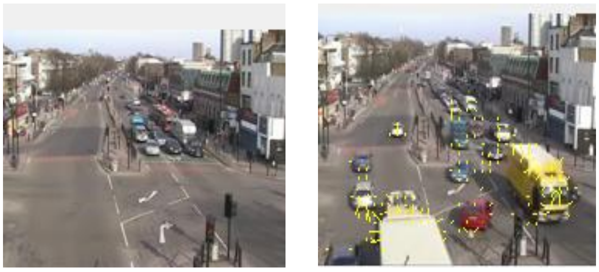
In each sequence, the spatial location (x, y) and direction of every feature extracted from the test video is compared with x, y and direction of every frequent pattern stored in the database using the following condition.

$$if\left(\left(A(i,1)==B(j,1)\right)\&\&\left(A(i,2)==B(j,2)\right)\&\&\left(A(i,3)==B(j,3)\right)\right)$$

Features which do not match with any of the values in frequent patterns stored in the database are termed as abnormal and plotted in the corresponding frame based on the frame number using a red rectangular box indicating an abnormal event had occurred in video.

4.4. Result of Abnormality Detection Method

Abnormality is represented by plotting the infrequent points obtained from pattern matching over the corresponding frame. During training phase, input frame (as shown in Fig. 1(a)) is applied to optical flow algorithm to find out the motion pixels as shown in Fig. 1(b). Morphological Operations are applied to remove edge pixel motions. The proposed OFFPM algorithm is applied with support '*S*' taken as 0.1% and error threshold '*ε*' of 0.01% of number of sequences in a bucket width '*w*' of sequences and the resultant motion patterns are shown in Fig. 2. Vertically moving upward object's motion pattern is shown in Fig. 2(a), while vertically moving downward object's pattern is shown in Fig. 2(b). In testing phase, the typical anomalies found out in this junction video are illegal U turns. Fig. 3(a), 3(b) and 3(c) show the frames of QMUL dataset in which a truck, blue sedan and white hatchback car is marked as red rectangular box. These marked regions indicate abnormal because of the infrequent path taken by the corresponding vehicle in left direction.



(a) (b)

Fig. 1. (a) Motion vector detected (b) Traffic junction.

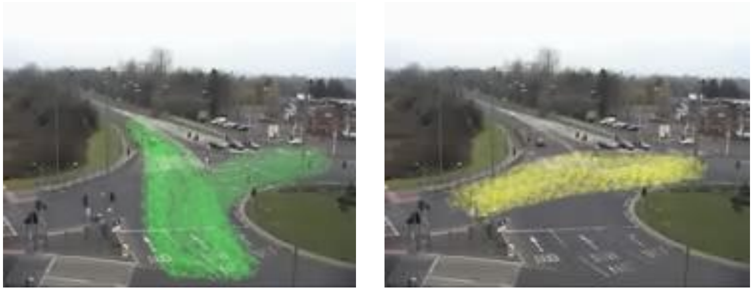
(a) (b)

Fig. 2. (a)-(b) Frequent pattern in left and right lane.

(a) (b) (c)

Fig. 3. (a) Abnormality scenario1, (b) scenario2, (c) scenario3.

Similarly, OFFPM is applied to QMUL round about junction dataset. During testing phase, regular motion patterns obtained are shown in Fig. 4(a) and Fig. 4(b) represented in green and yellow colors bands respectively. Those bands indicate the most common path taken by the vehicles in the video. In testing phase, motion patterns are extracted and compared with stored regular patterns to get anomalies. Fig. 5(a), 5(b) and 5(c) show the frames of the video in Roundabout dataset in which three heavy vehicles are marked inside a red rectangular box indicating an infrequent path opted by them.



(a) (b)

Fig. 4. (a) Frequent pattern1, (b) Frequent pattern2.

(a) (b) (c)

Fig. 5. (a) Abnormality scenario1, (b) Abnormality scenario2, (c) Abnormality scenario3.

5. Conclusion and Future Work

Detection of anomalous events in traffic videos have always been challenging tasks owing to various factors such as large variations in background, effects of illumination that impede the accurate detection. An efficient method for identifying abnormal events using optical flow and Frequent Pattern Mining algorithm is proposed and implementation results are presented. This method efficiently detects vehicles moving on the wrong trajectories. In future, the method can be enhanced by integration of multiple cameras to incorporate advanced features like number plate recognition of vehicles those violate rules.

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