Traffic Rule Violation Detection in Traffic Video Surveillance

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***Abstract*—** The performance of a generic Traffic Rule Violation Detection system may drop significantly when it is applied to a specific scene due to the mismatch between the source training samples set and the target scene samples. To overcome this problem, this paper proposes an Optical Flow based Transfer Learning (OFTL) approach for detecting anomalies both in source and target scene without performing manual labeling. This work mainly focuses on accident detection. The proposed approach extracts motion pixels using optical flow, predicts, learns frequent & infrequent traffic flow patterns and detects traffic violation patterns. During the testing process, the proposed OFTL approach calculates energy levels at those motion pixels. The accident region is detected based on energy levels using Support Vector Machine (SVM) classifier. The proposed method has been validated on different data set and found to give better results in terms of detection accuracy.

***Keywords*—**Frequent pattern, SVM, Traffic Rule Violation, Transfer Learning.

I. Introduction

WITH increase in number of surveillance cameras at public places, the demand for automatic video content analysis is also increased among end users. One such application that received great interest is video traffic surveillance. The main aim of automated [14] systems is to detect the rule violations such as illegal U-turns, accident, Pedestrian Crossing. This kind of process is only possible when the video features extracted at the pixel level, object level and semantic level. The most important thing in transportation is the safety of vehicle drivers and pedestrian.

A recent survey suggests that in Sweden [4], accidents occurring at the junctions and intersections [1] make up 30% of high severity and 20% of fatal accidents. Traditional traffic monitoring system mainly relies on manual operator, for the supervision of traffic on the roads. The manual monitoring of traffic events requires high focus and there is always a chance of missing events.

The main objective of visual surveillance system is to track objects, analyze the behavior of the target, detect the anomalies, predict the future behavior and predict the potential abnormal event before they occur. The detection of anomaly and the prediction of behavior can be done based on the motion pattern analysis approach. In most of the cases, the object can't move randomly in the scene. Instead they regularly follow the specific type of motion patterns. The obtained motion patterns can be used as a reference for the detection of the anomalous object motion and behavior prediction.

There are two main categories to anomalous event detection depending on the features extracted. First category is based on low-level pixel features [17], while the second category is based on the high level features extracted from detection and tracking of the target [16]. Low level features are extracted using following techniques: background subtraction, tracklets, or optical flow. Events and activity are observed based on the motion patterns from these low-level features. Since tracking does not produce the meaningful results, the low-level feature approach provides a greater choice for extremely crowded or partially occluded scene. However, in these approaches, the individual objects are not identified & therefore detected anomalies cannot be matched to any particular objects.

The second approach extracts individual object trajectories by multi-object tracking [8] [16]. Tracking based methods have the advantage of detecting object related anomalies. Even though good performance has been obtained in different datasets using the above techniques, the main limitation is it's highly domain specific nature. To overcome these problems, this paper proposes Optical Flow based Transfer Learning (OFTL) approach (Fig.1), which extracts motion pattern, obtains infrequent pattern, gets the energy levels and finally uses SVM to detect the accidents occurred in a frame.

The remainder of this paper is organized as follows: Section II discusses about existing methods in the area of anomaly detection, followed by the proposed OFTL approach and its operational methodology in Section III. Section IV discusses about the experimental settings and results obtained in Matlab. Finally Section V presents the Conclusion.

II. Literature Survey

Kumar et al. [12] proposed a system that can handle both urban and highway scenes. This system has two disadvantages: Camera model needs elaborate & accurate manual tuning, lack of handling in sudden background variations. To overcome these problems, Vijverberge et al. [11] used trajectory feature and predefined violation for detection anomalies.

Lili Cui et al. [13] proposed an Anomaly detection system, in which Behavior modeling is performed based on these extracted trajectories. Benezeth et al.[2] used co-occurrence matrix for any two motion labels, used as a potential function in a Markov random field (MRF) model to detect abnormal patterns. Even though this method is widely used in several applications, it has some disadvantages: First, complex trajectory extraction. Second, is its inability to describe the partial moving vehicle or stopped vehicle.

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Boiman and Irani [3] constructed the library script with multiple features, for the normal events reconstruction. Irrelevant scenes are labeled as irregular event. All these leads to high computational time and memory space complexity. Collins et al. [5] classify the detected objects into different categories like human, group of human and vehicle.

Davis et al. [6] proposed a system, in which a set of behaviors marching, walking, kicking are identified. In most of the application the object motion patterns might not be easily predefined. Johnson et al. [10] mentioned that, trajectory is generated from the object and the probability density function can be learned from the image sequence.

Zweng and Kampel [17] proposed a system which can study the abnormal behavior detection in crowded people. The potential of the local feature and the trained regular reference are found in abnormal event detection. Lili Cui et al. [13] proposed a system that depends on the local features which is different from existing methods. Their system has multiple classifiers, with focus on multiple training with different features.

Johnson [9] proposed the system which describes the advanced model with generation capabilities through the learned prediction superimposition technique. In Johnson method, the objects behaviors are not predicted and to identify anomalies, predict motions, the detection probability theory is not considered. In Stauffer and Grimson [15], online vector quantization is proposed based on trajectory features for learning motion patterns.

Though there are several methods available in the literature for abnormal event detection, still there is no efficient and perfect method. Hence there is a need to design an efficient traffic rule violation detection system.

III. Proposed OFTL Method

This paper proposes a novel OFTL method for traffic rule violation detection as shown in Fig 1. Existing models [9], [10] are based on learning pattern, which need long term data collection. Due to this, the installation process is costly and time consuming. In the proposed method, learnt motion models of source scenes are matched with the target data. The proposed approach is capable of detecting anomalies based on source motion patterns in the database, without the requirement of data collection, model training and labeling for each new target scene. The trained model in various source scenes is matched to unlabeled target scenes. Fig 2. shows the proposed system flow model.

A. Low Level 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 shortly. Abnormal regions are detected based on the optical flow in object regions. In this work, Lucas-Kanade[7] 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.

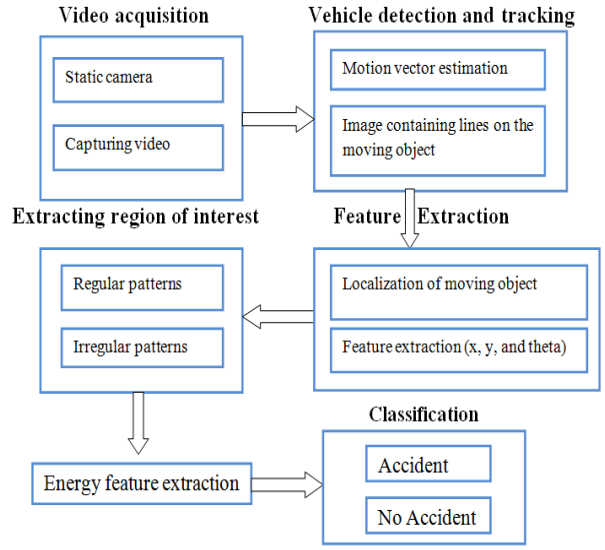


Fig. 1 Block Diagram of Proposed OFTL approach

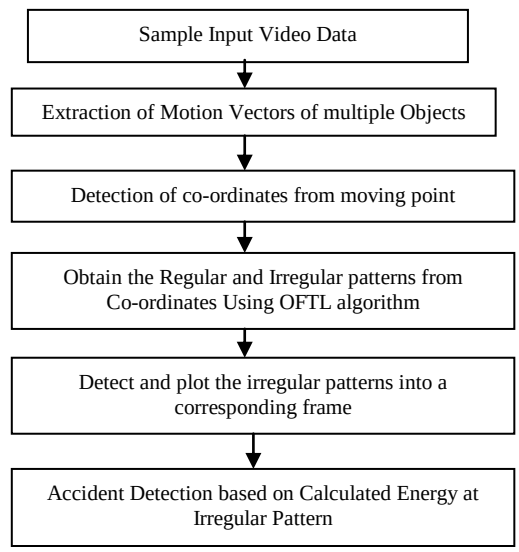


Fig. 2. Proposed OFTL system flow

Mixture of Gaussians (MoG) is used to model velocity distribution of object region. If vehicle moves straight, then velocity corresponding to different vehicle parts should be relatively same, and different when vehicle turns. For small regions, the velocities can be estimated by means of optical flow vectors.

B. Optical flow algorithm

Optical flow algorithm is used for the estimation of velocity of objects between two images as shown in Fig.3. There are three assumptions brightness constancy, spatial coherence, and temporal persistence.

Brightness constancy: $H(x,y) = I(x+u, y+v)$ (1)

Small motion: $I(x+u, y+v) = I(x,y) + u.\partial I/\partial x + v.\partial I/\partial y$ (2)

$$I(x+u, y+v) = I(x,y) + u.\partial I/\partial x + v.\partial I/\partial y + c \approx I(x,y) + u.\partial I/\partial x + v.\partial I/\partial y \quad (3)$$

Combining equations (1) and (2)

$$0 = I(x+u, y+v) - H(x, y) \tag{4}$$
$$\approx I(x, y) + I_x u + I_x v - H(x, y)$$
$$\approx (I(x, y) - H(x, y)) + I_x u + I_x v$$
$$\approx I_t + I_x u + I_x v$$
$$\approx I_t + \nabla I.\left[\frac{\partial x}{\partial t} \quad \frac{\partial y}{\partial t}\right]$$
$$0 = I_t + \nabla I.\left[\frac{\partial x}{\partial t} \quad \frac{\partial y}{\partial t}\right] \tag{5}$$

C. Foreground detection of object region

The motion pixels are detected by thresholding the velocity vectors from the optical flow algorithm. The sigma-delta improved version is proposed in [16] is used. It is known as background subtraction method. Each pixel background can be modeled and intensity variance is calculated and used as a threshold value for the extraction of foreground pixels. The foreground region in the current frame is detected based on the intensity variance.

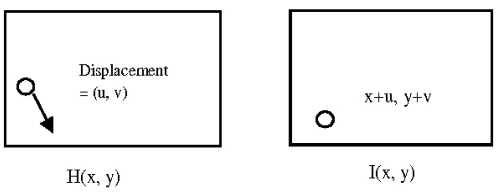


Fig.3 Velocity of Object

D. Morphological operations

The detected foreground region may have excessive noise regions, typically small in size. To overcome this problem, the morphologic operations are applied for smoothing out the noisy regions. In most scenarios, static camera is used for surveillance at fixed angle; objects nearer to the camera appear to be larger in the image. The objects size decreases when it is moving away from the camera. The structures of morphologic operations are different for different object sizes. Morphologic operations like open and close, on the smaller elements are eliminated as noise. Open operation are then used for smoothening the objects.

E. Regular and Irregular patterns

The features like location of moving points can be extracted from the segmented objects. The segmented objects can be obtained from the motion vectors. The segmented objects are in the form of zeros and ones (as shown in Fig.4).

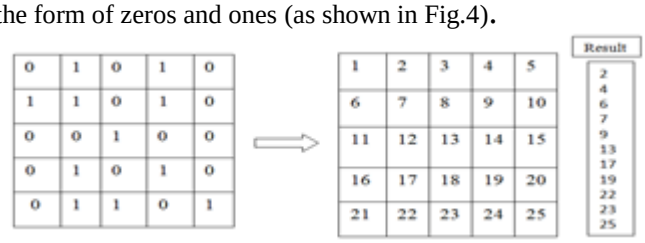


Fig.4. Location of Moving Pixels

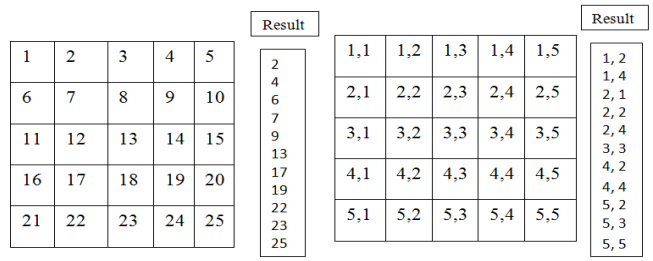


Fig.5. Location Mapping of moving Pixels

The result is 2,4,6,7,9,13,17,19,22,23,25. These values show the location of the moving points (Refer Fig.4). The result is (1,2), (1,4), (2,2), (2,4), (3,3), (4,2), (4,4), (5,3), (5,5). After finding the location of moving point, the abstract location is considered as the co-ordinate value as shown in Fig.5. These values show the x and y location. By using x and y location the theta value can be calculated with the help of following formula

$$P = a\tan 2(y, x) \tag{6}$$

The above equation is known as four quadrant inverse tangent. It returns an array P with x and y co-ordinated in element-by-element, four-quadrant inverse tangent (arctangent) of y and x, which must be real. Now the co-ordinates are x, y, θ. The co-ordinates for each and every moving point can be obtained and the maximum, minimum occurrence patterns are estimated using the count. The minimum occurrence patterns are considered as rare patterns. The energy feature is extracted from the rare moving points to check the abnormality i.e., violation or no violation with the help of SVM classifier. Energy can be calculated using gray level co-occurrence matrix.

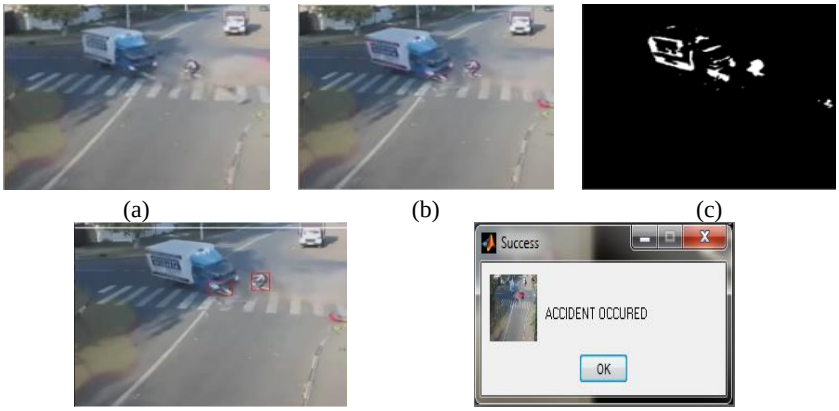
$$Energy : E = \sum_{\substack{0 \le i \le m \\ 0 < j < n}} P(i, j)^2 \tag{7}$$

where P-pixel, i-rows, j-columns.

IV. Results And Discussion

The platform used for this work is Matlab 7.3.0. The input accident videos are collected from the YouTube. The results provided below are belongs to the particular frame of the input video.

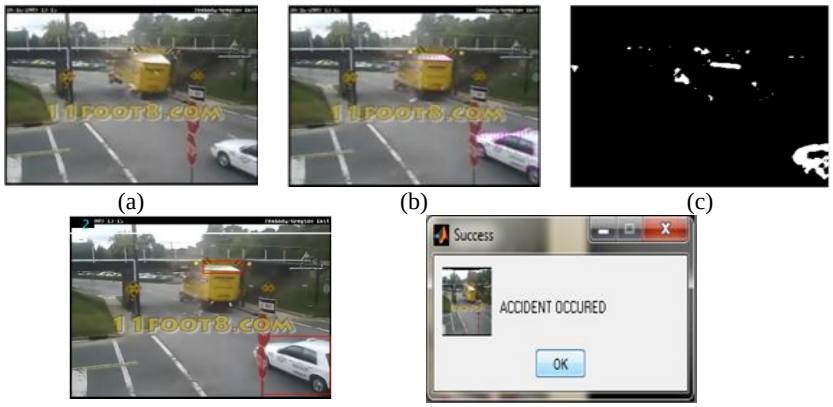
Fig. 6(a) shows the original frame, its motion pixels indicated in Fig.6 (b) and its corresponding motion values are tabulated in Table I. Fig 6(c) shows that the segmented results of the moving object from 6(b), 6(d) highlights the segmented portion in the original frame, 6(e) shows that whether accident occurred or not.



(a) (b) (c)

(d) (e)

Fig. 6-(a) Original frame (b) Motion values (c) Segmented objects (d) Object detection (e) Classification result



(a) (b) (c)

(d) (e)

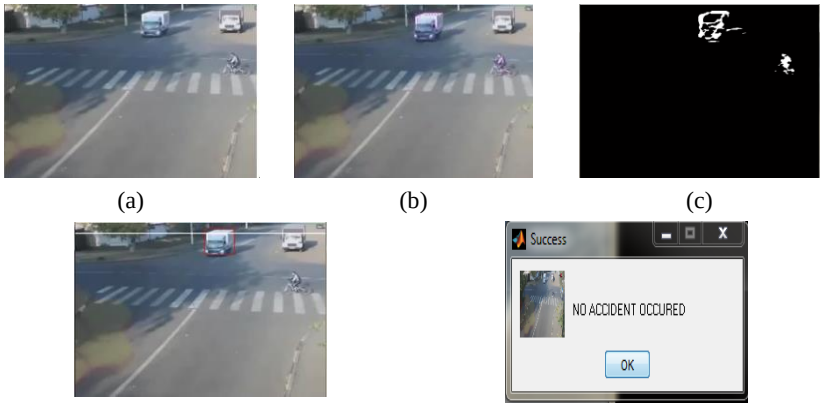
Fig. 7(a) Original frame (b) Motion values (c) Segmented objects (d) Object detection (e) Classification result

TABLE I
MOTION VALUES OF THE SUB BLOCK OF SIZE 10×4 IN THE FIG. 6

M \ N	1	2	3	4	5
1	0.5882	0.6157	0.5412	0.5098	0.4902
2	0.5490	0.5294	0.4824	0.4902	0.4471
3	0.5176	0.4980	0.4667	0.4471	0.4627
4	0.5373	0.5176	0.4863	0.4706	0.4667
5	0.5804	0.5529	0.5176	0.4902	0.4706
6	0.6039	0.5804	0.5412	0.5176	0.4824
7	0.5647	0.5333	0.5176	0.5216	0.4941
8	0.5137	0.4902	0.4824	0.4941	0.4941
9	0.5098	0.5020	0.4902	0.4941	0.5059
10	0.5176	0.5373	0.5412	0.5294	0.5333

Fig. 7(a) shows the original frame, in which moving pixels are plotted on the original frame which is indicated by the pink color in Fig.7 (b). Table III shows the motion values of the sub block of size 10×4 in the Fig.7 (b). Fig. 7(c) shows that the segmented results of the moving object from fig.7(b). Fig. 7(d) highlights the segmented portion in the original frame, 7(e) shows that whether accident occurred or not. Table IV shows the minimum occurrence pattern and energy in the Fig.7. The count values are used to indicate the infrequent pattern.

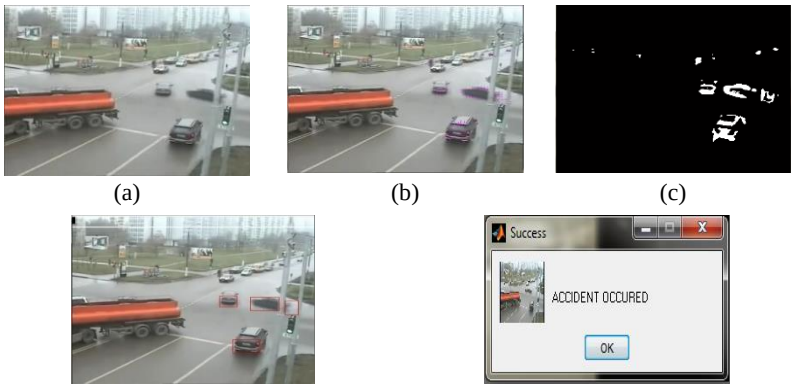
Figs 8(a) & 8(b) shows the original frame and its corresponding plotted moving points. Motion values of the colored pixels are tabulated in Table V. Fig. 8(c) shows that the segmented results of the moving object from 8(b), 8(d) highlights the segmented portion in the original frame, 8(e) shows that whether accident occurred or not. Table VI .shows the minimum occurrence patterns and energy in the Fig. 8. The count values are used to indicate the infrequent pattern.



(a) (b) (c)

(d) (e)

Fig. 8(a) Original frame (b) Motion values (c) Segmented objects (d) Object detection (e) Classification result



(a) (b) (c)

(d) (e)

Fig. 9(a) Original frame (b) Motion values (c) Segmented objects(d) Object detection (e) Classification result

TABLE II
INFREQUENT PATTERN AND ENERGY FOR FIG. 6

X	Y	θ	Count	Energy
5	265	90	1	47037
25	255	0	2	47436
35	175	90	2	47264
45	55	0	1	343
55	335	90	2	838
65	325	0	1	737
75	135	90	2	696
105	325	0	1	1005
155	425	90	2	965
195	505	0	2	893

Fig. 9(a) shows the original frame and fig. 9(b) shows that the moving points plotted on the original frame & its motion values are tabulated in Table VII. Fig.9(c) shows that the segmented results of the moving object from fig. 9(b). Fig. 9(d) highlights the segmented portion in the original frame.

Fig. 9(e) shows that whether accident occurred or not. Table VIII shows the minimum occurrence patterns and energy in the Fig. 9.The count values are used to indicate the infrequent pattern.

TABLE III
THE MOTION VALUES OF THE SUB BLOCK OF SIZE 10×4 IN THE FIG. 7.

N / M	1	2	3	4	5
1	0	0	0	0	0.0078
2	0.0275	0.0078	0	0.0039	0.0078
3	0	0.0196	0	0.0275	0.0353
4	0	0.0039	0.0039	0.2000	0.2392
5	0.0039	0.0235	0.0235	0.4471	0.6745
6	0.0039	0	0	0.3098	0.6706
7	0.0039	0	0	0.2824	0.7059
8	0	0	0.0824	0.6980	0.8824
9	0	0	0.0471	0.3333	0.3647
10	0	0	0	0.0314	0.0235

TABLE IV
INFREQUENT PATTERN AND ENERGY FOR FIG. 7

X	Y	θ	Count	Energy
15	225	90	2	15912
45	195	90	2	15902
75	125	90	2	15768
95	125	0	2	1
115	285	90	2	18
135	85	0	2	33
145	265	90	2	38
185	205	90	2	49
195	35	0	1	63
225	295	90	2	102

TABLE V
THE MOTION VALUES OF THE SUB BLOCK OF SIZE 10×4 IN THE FIG. 8.

M \ N	1	2	3	4	5
1	0.5882	0.5843	0.5765	0.5725	0.5686
2	0.6078	0.5922	0.5804	0.5765	0.5647
3	0.6196	0.6078	0.5882	0.5765	0.5529
4	0.6275	0.6118	0.5922	0.5804	0.5569
5	0.6196	0.6118	0.6000	0.5882	0.5686
6	0.6118	0.6078	0.6078	0.6000	0.5843
7	0.5961	0.5961	0.6000	0.6000	0.5882
8	0.6078	0.6078	0.6039	0.6039	0.6039
9	0.5961	0.5961	0.5961	0.5922	0.5922
10	0.5843	0.5843	0.5843	0.5804	0.5725

TABLE VI
INFREQUENT PATTERN AND ENERGY FOR FIG. 8

X	Y	θ	Count	Energy
5	495	90	2	788
65	385	90	2	915
85	605	0	1	992
125	595	90	1	1284
145	635	0	2	1320
225	195	0	2	1358
235	615	90	2	1489
285	235	0	2	1577
285	235	90	2	1583
355	635	90	1	1751

TABLE VII.
THE MOTION VALUES OF THE SUB BLOCK OF SIZE 10×4 IN THE FIG. 9.

M \ N	1	2	3	4	5
1	0.0353	0.0353	0.0118	0.0118	0
2	0.0353	0.0353	0.0118	0.0118	0
3	0.0353	0.0353	0.0118	0.0118	0
4	0.0353	0.0353	0.0118	0.0118	0
5	0.0353	0.0353	0.0118	0.0118	0
6	0.0353	0.0353	0.0118	0.0118	0
7	0.0353	0.0353	0.0118	0.0118	0
8	0.0353	0.0353	0.0118	0.0118	0
9	0.0314	0.0314	0.0118	0.0118	0
10	0.0314	0.0314	0.0118	0.0118	0

TABLE VIII
INFREQUENT PATTERN AND ENERGY FOR FIG. 9

X	Y	θ	Count	Energy
35	295	90	2	43227
95	375	90	2	43087
105	195	0	2	42652
145	205	0	2	2638
175	445	90	1	2083
185	175	0	2	1713
245	195	90	1	1043
255	275	0	1	642
265	265	0	2	247
355	185	90	1	111

V. CONCLUSION

The proposed system detects the Traffic Rule Violation by combining the optical flow method, transfer learning approach and classifier which is not an existing one. It provides an improved result in terms of detection accuracy. By using this optical flow method, motion vectors are extracted and transfer learning algorithm is used to detect the co-ordinates from the different videos. Finally, SVM Classifier is applied for accident detection. From the simulation results, it is found that the proposed OFTL method detects the accidents accurately.

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