International Journal of Current Research and Modern Education (IJCRME)
ISSN (Online): 2455 – 5428 & Impact Factor: 3.165
Special Issue, NCFTCCPS - 2016

DETECTING AND TRACKING THE MOVING OBJECT IN TRAFFIC SIGNAL USING SPARSE IDENTIFICATION METHOD

R. Hema Priya*, R. Sabari Priya & K. Mouthami*****
Department of Information Technology, Dr. NGP Institute of Technology, Tamilnadu

Abstract:

Traffic management is difficult in the modern cities as well as rural areas due to the improvement in technologies. Due to traffic congestion and increase of users on road it is difficult to identify the people who are breaking the traffic rules. Sometimes by breaking the traffic rules it may lead to accidents. The aim of the system is to track the vehicle that violates the traffic rule. In the proposed system, the effective algorithms are developed that can aid in the semi- automatic interpretation and analysis of video data for surveillance. As a part of the first module, background subtraction is accomplished via the use of a Gaussian Mixture Model (GMM). The numbers of connected foreground pixels are calculated, and deem the connected segment to be a vehicle if this exceeds a threshold.

Index Terms: Blob Analysis, Gaussian Mixture Model & Gaussian Smoothening

1. Introduction:

Image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be model in the form of multidimensional systems. Traffic management is difficult in the modern cities as well as rural areas due to the improvement in technologies. Due to traffic congestion and increase of users on road it is difficult to identify the people who are breaking the traffic rules. Sometimes by breaking the traffic rules it may lead to accidents. The aim of the system is to track the vehicle that violates the traffic rule. The objective of this project is to identify unusual patterns such as traffic violation, accidents, unsafe driver behaviour, street crime and other suspicious activities. Drivers often experience uncertainty when traffic signals changes from green to yellow and they must quickly decide whether to stop at an intersection or continue driving. This situation is called the “dilemma zone”, and the great deal of research has been performed to minimize the uncertainty in that zone .The goal is to have the minimum number of vehicles caught in the dilemma zone and reduce red light runners while maximizing the green light period.

2. Methodology:

In the proposed system, videos are taken as inputs. The input video is then converted into frames which are further processed in the pre-processing phase .In the pre-processing phase, we reduce the noise of the video frame by Gaussian smoothing algorithm and for comparing each frame we use frame correlation .In the signal detector we will detect the color for the signal (i.e) red, green or yellow .The other algorithms that are deployed in the proposed system is Gaustian mixture Model.

3. Literature Survey:

3.1 An Algorithm for Identifying Red Light Runners from Radar Trajectory Data:

The existing idea presents an algorithm for identifying red light runners from radar trajectory data. The goal of this paper is to have the minimum number of vehicles caught in the dilemma zone and reduce red light runners while maximizing the green light period. In order to determine how well dilemma zone protection systems perform, we need to measure the frequency of red light runners. This frequency is closely correlated with crashes, but is difficult to collect. Recent algorithms utilize radar for dilemma zone protection. However, verification of the number of red light runners requires additional video detection. In this study, it proposes a new algorithm to predict red light runners and distinguish them from right turners on red. It used Canonical analysis to exclude right turners from red light runners.

3.2 Survey on Vision Based On-Road Vehicle Detection:

The existing system presents a review on the various techniques of On-Road Vehicle detection systems. When vehicles are fully stopped for epoch of time, this condition is known as a traffic jam. For this, we must need an efficient traffic control system. In this paper a Survey of previous and recent works is presented on vision-based vehicle detection using sensors and also gives a detailed discussion on two steps of vehicle detection which are hypothesis generation and hypothesis verification. In the first step, all vehicles are hypothesized and in the second step, all hypotheses are verified and classified into vehicle and non-vehicle classes.

3.3 A Car Monitoring System for Self Recording Traffic Violation:

The system consists of software techniques and hardware models to monitor and record samples of traffic law violations. These samples include, but are certainly not limited to speed violation and seat-belt violation. SRTV assists the department of traffic police in Egyptian ministry of interior by recording traffic violations automatically 24 hours/ 7days eliminating the human errors in recording violations as in Radar system. SRTV is designed to achieve its goals in three phases: Acquiring phase collects car speed; receive allowed speed from server, and seat-built status. Processing phase get all output data of acquiring phase and compare both car speed and allowed speed to determine if there is a speed violation or not (speed violation). Also it determines if the driver wears seat-built or not (seat-built violation). Recording phase is responsible for sending violations to server according to connection status between car and server (i.e. car located at the coverage area of any active spot of wireless connection system or not). If there is a connection, car will send violation immediately. In the case of losing connection, violations will be temporarily stored in a local database until connection is restored. Once the connection is restored, all violation in local database will be sent.

3.4 Automatic Traffic Estimation Using Image Processing:

This author proposed the system to avoid huge traffic in highways. To achieve this goal they were used image processing technique and MATLAB software. In this system, the video camera fixed in highways to record the traffic status. The recorded video is converted into continues pictures and then RGB to gray scale conversion is applied to the picture. This video to picture conversion and RGB to gray scale conversion is done by MATLAB software. After that the image processing technique such as 1) Image enhancement 2) Morphological operation is applied on the gray scale picture. Finally the gamma correction is applied to the picture for background elimination and lane masking to track the vehicles. End of the process the pictures were compared with the first picture to identify the number of vehicles in the highway. If the number of vehicles more than the threshold level the information sent to the traffic controller. Based on this information, the traffic is controlled by the traffic controller.

3.5 A Review of Computer Vision Techniques for the Analysis of Urban Traffic:

The author presents a comprehensive review of the state-of-the-art computer vision for traffic video with a critical analysis and an outlook to future research directions. This field is of increasing relevance for intelligent transport systems (ITSs).The decreasing hardware cost and, therefore, the increasing deployment of cameras have opened a wide application field for video analytics. Several monitoring objectives such as congestion, traffic rule violation, and vehicle interaction can be targeted using cameras that were typically originally installed for human operators. Systems for the detection and classification of vehicles on highways have successfully been using classical visual surveillance techniques such as background estimation and motion tracking for sometimes. There is no commonly used data set or benchmark challenge, which makes the direct comparison of the proposed algorithms difficult. In addition, evaluation under challenging weather conditions (e.g., rain, fog, and darkness) would be desirable but is rarely performed.

3.6 Online Detection of Unusual Events in Videos via Dynamic Sparse Coding:

This is fully unsupervised dynamic sparse coding approach for detecting unusual events in videos based on online sparse reconstructibility of query signals from an atomically learned event dictionary, which forms sparse coding bases. Based on an intuition that usual events in a video are more likely to be reconstructible from an event dictionary, whereas unusual events are not, our algorithm employs a principled convex optimization formulation that allows both a sparse reconstruction code, and an online dictionary to be jointly inferred and updated. Our algorithm is completely unsupervised, making no prior assumptions of what unusual events may look like and the settings of the cameras. The fact that the bases dictionary is updated in an online fashion as the algorithm observes more data, avoids any issues with concept drift. Experimental results on hours of real world surveillance video and several youtube videos show that the algorithm could reliably locate the unusual events in the video sequence, outperforming the current state-of-the-art methods.

3.7 Robust Face Recognition via Sparse Representation:

This system uses a general classification algorithm for (image-based) object recognition. This new framework provides new insights into two crucial issues in face recognition: feature extraction and robustness to occlusion. For feature extraction, we show that if sparsity in the recognition problem is properly harnessed, the choice of features is no longer critical. What is critical, however, is whether the number of features is sufficiently large and whether the sparse representation is correctly computed. Unconventional features such as down sampled images and random projections perform just as well as conventional features such as Eigen faces and Laplacian faces, as long as the dimension of the feature space surpasses certain threshold, predicted by the theory of sparse representation. This framework can handle errors due to occlusion and corruption uniformly by exploiting the fact that these errors are often sparse with respect to the standard (pixel) basis. The theory of sparse representation helps predict how much occlusion the recognition algorithm can handle and how to choose the training images to maximize robustness to occlusion. We conduct extensive experiments on publicly available databases to verify the efficacy of the proposed algorithm and corroborate the above claims.

4. Proposed System:

In this system we construct morphological structure element according with traffic moving target, and propose mathematical morphology analysis model for traffic video. Feature extraction based on mathematical morphology and tracking detection methods to establish typical violation pattern. Suppresses the background of image and remove the non uniform illumination and robustness of the proposed method to adverse imaging condition. After elimination of the effect of noise, blob analysis to identify the location of the moving vehicle. Interactions between distinct object trajectories are better captured and departures from expected "joint behavior".

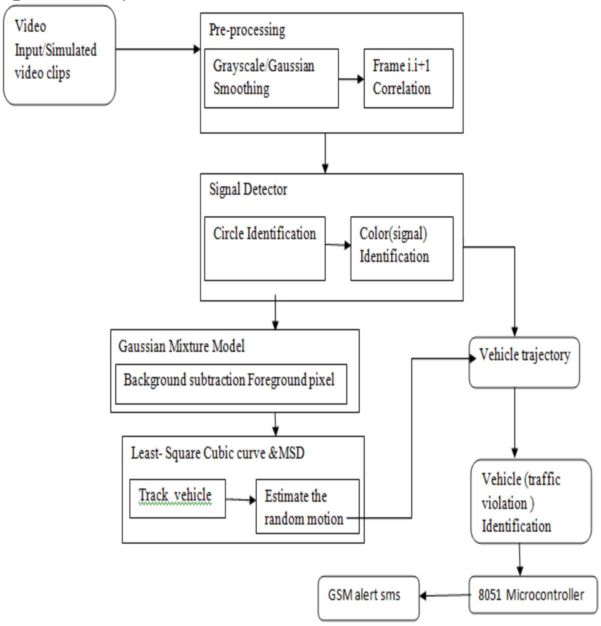

Figure 1: Block Diagram

4.1 Module Description:

In our proposed system we have the following modules:

- Preprocessing
- Gaussian smoothing
- Gaussian mixture model

4.1.1 Pre-processing:

Initially, there are two cameras set up, one facing the pedestrian crossing and the other, viewing the signal. In the initial process, the video input from the first camera, i.e., the camera facing the pedestrian crossing is being processed. The process begins with the collection of input videos that are to be processed. As the input video is drained from the camera, the video is now processed. By means of processing, here the video undergoes a conversion, where the input video is converted into frames. A set of codes is used to do this conversion process. During this process, the video gets converted into n possible frames. Further, these frames are being used in the identification of the vehicle that violates the red signal, by comparing these frames with the image obtained from the second camera, i.e., the one facing the signal, as well. This phase also used to reduce the noise of the video frame by Gaussian smoothing algorithm and for comparing each frame we use frame correlation.

4.1.2 Gaussian Smoothing:

In image processing, Gaussian blur is also known as Gaussian smoothing .It is the result of blurring an image by a Gaussian function. It is a widely used effect in graphics software, typically to reduce image noise and reduce detail. The visual effect of this blurring technique is a smooth blur resembling that of viewing the image through a translucent screen, distinctly different from the bokeh effect produced by an out-of-focus lens or the shadow of an object under usual illumination. Gaussian smoothing is also used as a pre-processing stage in computer vision algorithms in order to enhance image structures at different scales. The Gaussian blur is a type of image-blurring filter that uses a Gaussian function which also expresses the normal distribution in statistics for calculating the transformation to apply to each pixel in the image. The Gaussian blur is a type of image-blurring filters that uses a Gaussian function (which also expresses the normal distribution in statistics) for calculating the transformation to apply to each pixel in the image. The equation of a Gaussian function in one dimension is in two dimensions, it is the product of two such Gaussians, one in each dimension:

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}}$$

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Where x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis, and σ is the standard deviation of the Gaussian distribution

4.1.3 Gaussian Mixture Model:

In this phase an effective algorithms were developed that can aid in the semi-automatic interpretation and analysis of video data for surveillance. As a part of the first module, background subtraction is accomplished via the use of a Gaussian Mixture Model (GMM). The numbers of connected foreground pixels are calculated, and deem the connected segment to be a vehicle if this exceeds a threshold. In the background averaging method, all video frames are summed up. The learning rate specifies the weight between a new frame and the background. This algorithm has little computational cost. However, it is likely to produce tails behind moving objects due to the contamination of the background with the appearance of the moving objects. The Kalman filter can be used to estimate the background image, where the colour of each pixel is temporally modelled by one filter. The foreground can be interpreted as noise for the filter state. However, illumination changes are non-Gaussian noise and violate basic assumptions for the use of Kalman filters.

5. Implementation and Results:

5.1 Preprocessing:

```
vid=VideoReader('input.avi');
numFrames = vid.NumberOfFrames;
n=numFrames;
for i = 1:2:n
frames = read(vid,i);
mkdir('dataset')
imwrite(frames,strcat('C:\Users\umasubbu\Documents\code\dataset','\',int2str(i),'.jpg'))
;
im(i)=image(frames);
end
```

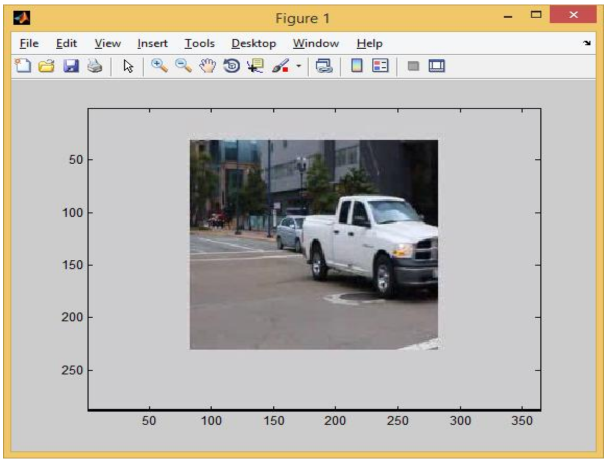

Figure 2: Collection of dataset

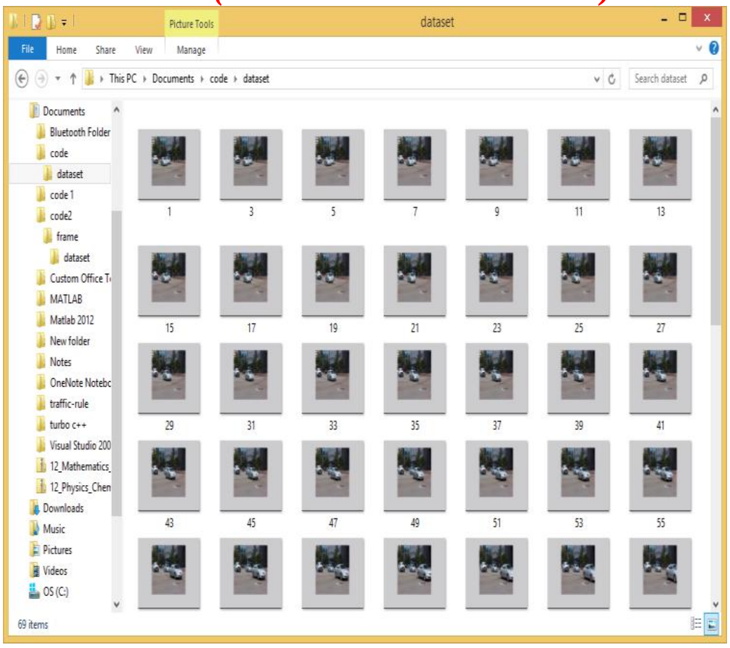

Figure 3: Converting video into Frames

5.2 Gaussian Smoothening:

```
vid = VideoReader('input.avi');
numFrames = vid.NumberOfFrames;
n= numFrames;
for i = 1:n
frames1 = read(vid,i);
G1 = fspecial('gaussian',[5 5],2);
Ig1 = imfilter(frames1,G1,'same');
im(i)=image(Ig1);
end
```

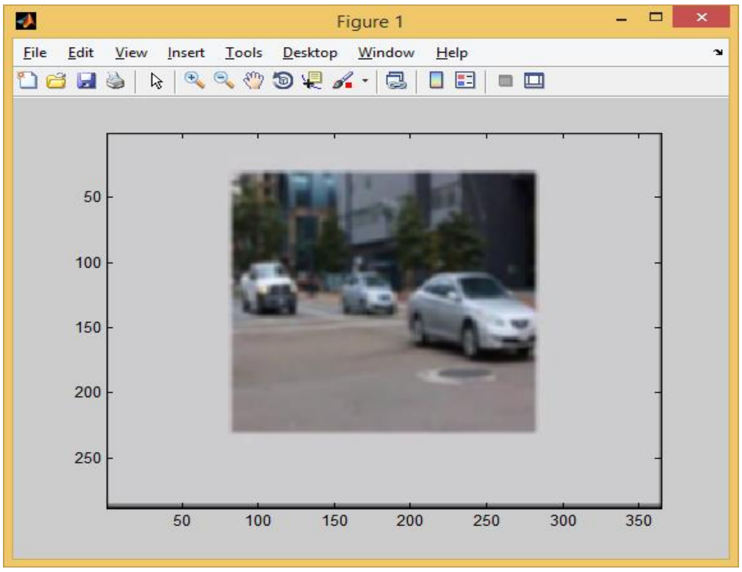

Figure 4: Blurring the Video

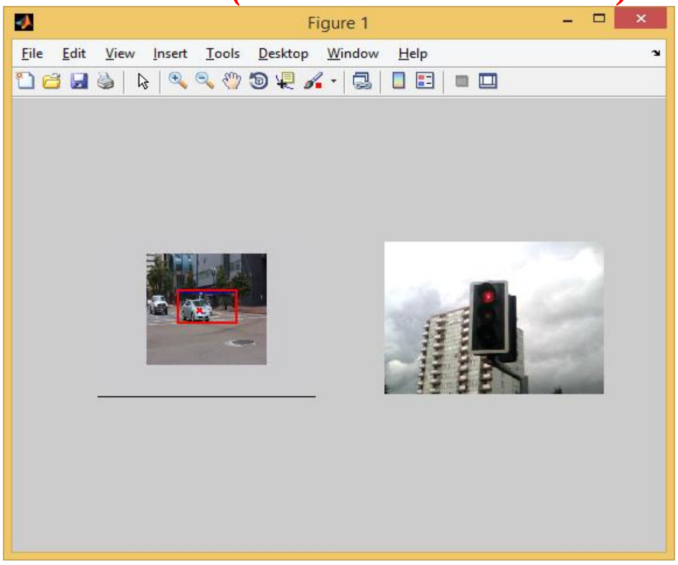

Figure 5: Detecting the violating vehicle

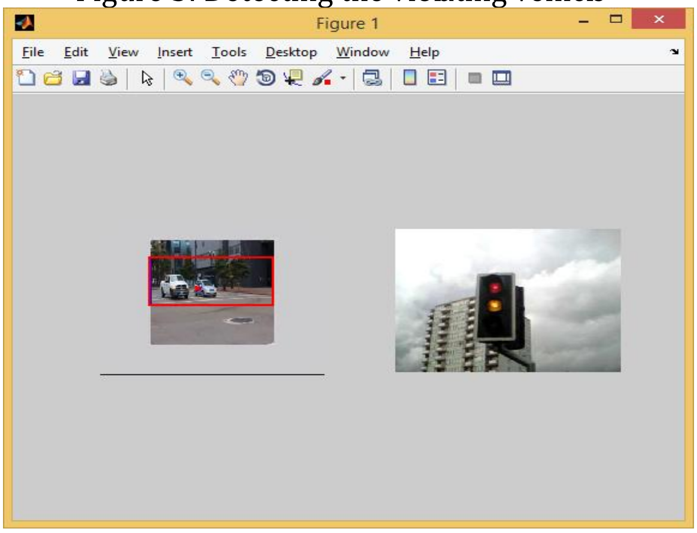

Figure 6: Transition in signal

6. Conclusion:

The traffic violation detection process was helpful in identifying and penalizing the vehicles that violated the red light at any of the traffic signal junction. This has lead to the reduction of traffic signal jumping which was the major reason for most of the accidents that had occurred. The system helps in identifying the violators within a short duration.

7. Future Enhancements:

The system can be further updated with an enhancement in identifying the vehicles while violating traffic signal with the license plate registration using image processing, and to send messages along with license plate registration number.

8. References:

1. Supriya Sawwashere , Ashutosh Lanjewar, "Automated accident intimation and rescue system for vehicles",International journal of Application or Innovation in engineering and management (2015).
2. Rana Biswas,Romit S.Beed,Dibyabiva Seth,Proyag Pal,Kaustav Basu,Triparna Mukherjee, "Traffic Rule Violation Information System TRuVis", International Journal of Advanced Research in Computer Science and Software Engineering .
3. Satadal Saha, Subhadip Basu, Mita Nasipuri, Dipak Kumar Basu, "Development of

an automated Red Light Violation Detection System (RLVDS) for Indian vehicles", IEEE National Conference on Computing and Communication Systems (COCOSYS).

4. Mona Saini, "Survey on Vision Based On-Road Vehicle Detection", International Journal of u-and e-Service, Science and Technology Vol.7, No.4 (2014), pp.139-146.
5. Ahmed M. Elmahalawy "A Car monitoring system for self recording traffic violation", Journal of traffic and logistic engineering(2014).
6. Dr.Rajendra R.Dube, Sushma S.Pawar " Design and implementation of traffic monitoring system based on embedded web technology", International journal of science and research.
7. Pejman Niksaz "Automatic Traffic Estimation Using Image Processing", International Journal of Signal Processing, Image Processing and Pattern Recognition 2012.
8. Norbert Buch "A Review of Computer Vision Techniques for the Analysis of Urban Traffic", IEEE Transaction on Intelligent Transportation systems (2011).
9. B. Zhao, L. Fei-Fei, and E. Xing, "Online detection of unusual events in videos via dynamic sparse coding," in Proc. IEEE Conf. Computer Vision Pattern Recognition (2011).
10. J. Wright, A. Yang, A. Ganesh, S. Sastry, and Y. Ma, "Robust face recognition via sparse representation," IEEE Trans. on Pattern Analysis and Machine Int. (2009).