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Road Traffic Congestion (TraCo) Estimation Using Multi-Layer Continuous Virtual Loop (MCVL)

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ABSTRACT

Any road traffic management application of intelligent transportation systems (ITS) requires traffic characteristics data such as vehicle density, speed, etc. This paper proposes a robust and novel vehicle detection framework known as multi-layer continuous virtual loop (MCVL) that uses computer vision techniques on road traffic video to estimate traffic characteristics. Estimations of traffic data such as speed, area occupancy and an exclusive spatial feature named as corner detail value (CDV) acquired using MCVL are proposed. Further, the estimation of traffic congestion (TraCo) level using these parameters is also presented. The performances of the entire framework and TraCo estimation are evaluated using several benchmark traffic video datasets and the results are presented. The results show that the improved accuracy in vehicle detection process using MCVL subsequently improves the precision of TraCo estimation. This also means that the proposed framework is well suited to applications that need traffic characteristics to update their traffic information system in real time.

KEYWORDS

Area Occupancy, Computer Vision, Corner Detail Value, Intelligent Transportation Systems, Multi-Layer Continuous Virtual Loop, Speed, Traffic Congestion

1. INTRODUCTION

Any Intelligent Transportation Systems (ITS) is dependent on reliable and real-time traffic details. Traffic Congestion (TraCo) information becomes the most essential and primary requirement for any ITS service application. Irregular events such as accidents, faulty traffic signals, breakdowns etc., cause unintended delay and congested scenario for commuters. Traffic congestion has also been a major problem affecting human daily lives, stabilizing economic and social developments (Reddy, 2018; Document on Transportation, 2020). It also tends to increase the pollution emission, fuel consumption, travel time, driver stress etc., (Kong 2016, Amudapuram, 2012). These situation causes higher real-time and reliable demand of TraCo information for ITS applications that monitor road traffic. Additionally, TraCo information becomes essential to applications that evaluate the performance or decide appropriate mitigation measures to aid comfortable commutations (Reddy, 2018). The congestion information can be enumerated from traffic status of a road segment that is described using vehicle traffic density, volume, speed, occupancy etc., (Duc-Binh 2018; Kong, 2016;

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ke, 2018; R.Wang, 2019; Wan-Xiang, 2018; Todd Litman, 2019). There are two major challenges in estimating traffic congestion. The first challenge is to facilitate the estimation over a large scale of road network. Several researches are attempting to address this issue and are divided into two categories (Kong, 2016; Duc-Binh, 2018). They include estimations of traffic status using infrastructure based technologies and Vehicular Adhoc Network (VANET) technology. Many congestion estimation and prediction algorithms have been adopted based on the data formalisation using either of the above two technology. The former approach include data acquisition methods using infrastructures such as the Global Positioning System (GPS), (Duc binh, 2018, Kong, 2016), sensor systems such as inductive loop detectors, infrared detectors (Bhaskar, 2015; Al-Naima) and traffic video archives (Reddy, 2018; Ke, 2018; Amudapuram, 2012). And later approach utilises Vehicle to Vehicle (V2V) communications from smart vehicles to gather traffic data (Duc-Binh, 2018; R.Wang, 2019; Badeddine, 2019; Manipriya, 2020). Infrastructure-based technologies have been the most easily available procurement process among the two technologies. Although VANET based methods have gained popularity in this research area and incorporated in various application, it is not widely available and has feasibility issues for heterogeneous traffic scenario. Also it has network related limitations such as redundancy, bandwidth and reliability issues, coverage, delay and inaccurate estimates which lead to inadequate precision and failure prone congestion estimations (Duc-Binh, 2018).

The second challenge in TraCo estimation is to ensure the quality of congestion information that depends on the accuracy, reliability and consistency of acquired data. Although infrastructure and VANET-based solutions have equal challenges in collecting and transferring data safely, sensor integration, overhead issue during rise in number of vehicles, etc., it is important to provide a simple and efficient solution to handle the problem to obtain precise congestion information. The existing systems do not address or resolve these shortcomings efficiently or systematically. Among many infrastructures available for traffic status enumeration, the use of the current traffic monitoring cameras serves several objectives without additional cost of installation, maintenance or equipment (Impedovo, 2019). Even though the data acquisition from traffic videos has been explored by researches over the past three decade, there are still challenges such as appropriate feature extraction, methods for detection and classification, video and camera specifications and properties etc., that need to be accomplished during vehicle detection (Zi Yang, 2018; Hanif, 2018; Boukerche, 2017;T. Bouwmans, 2019). This paper proposes a Traffic Congestion (TraCo) estimation process from traffic surveillance cameras using novel data acquisition from Multi-layer Continuous Virtual Loop (MCVL) framework or model. The proposed MCVL provides traffic status of the road segment focused by the surveillance camera using computer vision/ image processing techniques. The enumerated traffic statuses from MCVL are adapted in a fuzzy logic based method to address non deterministic problem of TraCo determination. The proposed system attempts to contribute successfully to enumerate traffic status required for ITS application with robust detection process for heterogeneous traffic condition and camera properties. The proposed work shows that the precision of the congestion information depends on the data acquired and has improved accuracy using MCVL.

The remainder of the paper is structured as follows: Section 2 briefly describes the relevant works of the proposed work. Section 3 discusses the proposed traffic congestion estimation using novel MCVL. The details of implementation and result analysis are demonstrated in Section 4. Finally, the paper is concluded in Section 5.

2. RELATED WORKS

There are many ITS applications that aid in communicating the safety, current travel environment related information in real time to travellers (Manipriya, 2020). The most significant requirement for many applications is to obtain real time traffic states and characteristics either in quantitative macroscopic, mesoscopic or microscopic forms (Duc Binh, 2016). The traffic status information has to be utilised to acquire higher level of traffic composition narrative. The universally existing next level of traffic characteristics descriptive is Traffic Congestion (TraCo) information. Such information is enumerated from a combination of several traffic parameters such as density, speed, travel time, length of queue, time of arrival, occupancy area, travel time etc. (R Wang, 2019; Kong, 2016; Reddy, 2018). Apart from these traffic parameters few mobility and reliability related measures for congestion indicators are road saturation degree, Level of Service (LOS), commute duration, travel efficiency, low speed propagation, buffer time index, volume to capacity ratio, planning time index (Wan Xiang, 2018; Todd Litman, 2019; Amudapuram, 2012). Choosing the right traffic flow parameters can accurately characterize the traffic state. Several detailed proposals for traffic congestion prediction and estimation using traffic data from floating car trajectory, Internet of Vehicles or Vehicular ADHOC Network (VANET), RFID, GSM, traffic video etc., are proposed (Al Naima, 2012; Kong, 2016; Badreddine, 2019; Reddy, 2018). There are numerous soft computing techniques available to test these parameters and estimate traffic related statistics such as Support Vector Machine, K-Nearest Neighbour (KNN), Neural Network, Genetic Algorithms, Gaussian Radial Basis Function (RBF) kernel, Classifiers, Bayesian Networks, Clustering Algorithms Neuro Fuzzy logic, Chaotic Cloud Particle Swarm Optimization algorithm etc., (Kong,2016; Reddy, 2018; ke, 2018; Duc binh, 2018). Therefore, TraCo estimation techniques are proposed as the combination of the appropriate sensors, desired traffic data acquired from sensors and soft computing techniques used on traffic data.

Kong (2016) extracts road saturation, density and speed form floating car trajectory and estimates TraCo using fuzzy logic controllers. In Duc Binh (2018), macroscopic traffic parameters that include volume, density and speed of vehicles from internet of vehicles are acquired and used in fuzzy logic controllers for TraCo information. It also proposes the Traffic Congestion Condition Verification Operation that verifies the estimation. KNN and SVM computing techniques for TraCo estimations are analysed by using area occupancy, speed and corner values from traffic video archive in Reddy (2018). Also their traffic parameters are enumerated using image processing techniques like background subtraction, optical flow tracking and corner detection algorithm. In Ke (2018) traffic feature including traffic density, traffic speed, traffic occupancy, and traffic flow are calculated from traffic videos using Gaussian based Convolution Neural Network. The traffic congestion is estimated using heuristic approach. Similarly, Al Naima (2012) uses RFID to extract time spent to travel the road segment and speed to estimate TraCo with set rules or thresholding. Four traffic characteristics such as average travel speed, road saturation degree, travel efficiency, low-speed propagation are enumerated from traffic video and are used in fuzzy logic to calculate congestion index in Wan Xiang (2018). The major drawback in the above-mentioned methods is that they have not considered the spatial information of the roads for evaluation that are meant to contribute effectively to determine traffic status in a visual context. Moreover, there is a lack of a comprehensive approach for addressing precision, instantaneity and stability. Among the diverse technology traffic state estimations using traffic videos is a vital one. In specific, using surveillance based traffic videos which already exist to solve other purpose has advantageous benefits. They can provide real time information without any alteration in the road infrastructure and overrides the issues of deployment as in GPS, RFID, VANET communications etc., Using traffic videos from such technologies becomes very challenging to have a unique robust method to tackle the video content to extract traffic related information (Kastrinaki, 2003; Impedovo, 2019; T Bouwman, 2019). The core process in acquiring any traffic characteristics data from traffic video is the vehicle detection.

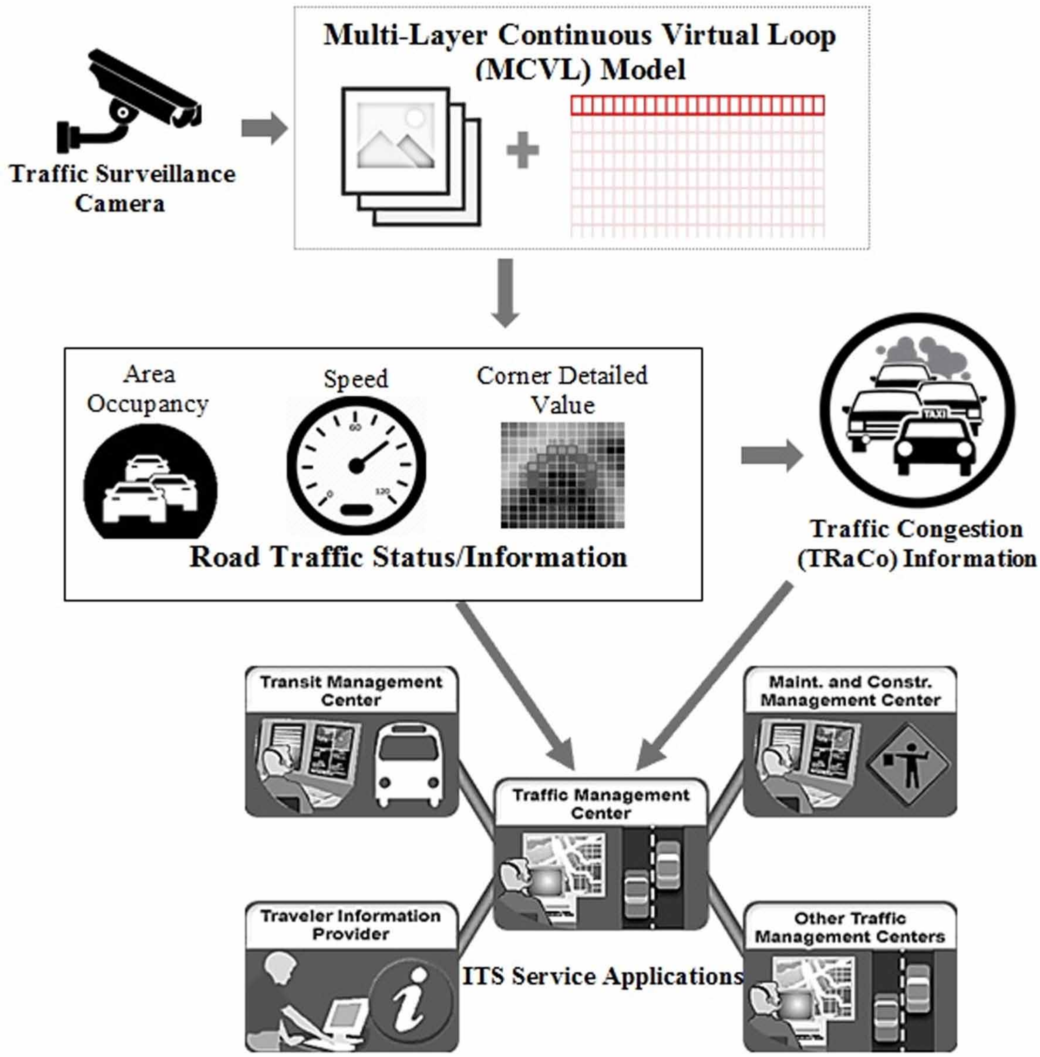
From the existing literature, the common pipeline process adopted for using computer vision techniques in estimating any traffic state information in videos as in Impedovo, 2019 include (i) Pre-processing the video to elevate the important object (vehicle) that has to be detected (ii) Extracting the features of the vehicle that describes the traffic characteristics. Common low-level vehicle visual features extracted are colour, texture, shape, corners, edge, shadows, etc. and high-level features such as Scale Invariant Feature Transform (SIFT), Haar-like features, Gradient Histogram (HOG), Gabor features and fused features are used to identify vehicles from videos. (Zi Yang, 2018; Arróspide, 2014; M. Manana, 2017; Pae, 2018, Song H, 2019, Nseenouvong, 2016; Z.Huo, 2016; Arróspide, 2014). (iii) Implementation of one or more techniques or methods to identify and classify vehicles and traffic state. Over more than two decades several techniques for detecting vehicle from videos have been introduced to assess traffic parameters. These techniques are categorised based on appearance or feature, motion or tracking, illumination, weather (Raad Ahmed, 2014, Zi Yang, 2018; Hanif, 2018; Boukerche, 2017; Kastrinaki, 2003). The common technique is to extract features and use machine learning process to detect vehicle. In this approach the method of identifying and validating moving object is through training with prior knowledge of the characteristics of the vehicles. Some of the methods include K-Nearest Neighbour (KNN), Neural Network (NN), Random forest, Ada Boost, Support Vector Machine (SVM) etc., (Reddy, 2018; Impedovo, 2019; Song, 2019; Z Huo, 2016; M. Manana, 2017) Other common approach include motion based techniques known as Background Subtraction (BS) that separate background and foreground content of the video using pixel intensities and properties to and the process is known as Background Subtraction (BS). Few of the popular techniques of BS include Running Average Method, Gaussian Mixture Models, Fuzzy integrals, Codebook Method, Adaptive learning, Kernel Density Method etc., (T. Bouwmans, 2019; Barnich, 2011; M piccardi, 2004; Pae, 2018).

The driving disparity of the environment is the main reason for a variety of computer vision algorithms and methods. Any vehicle detection algorithm using computer vision techniques is the combination of aforementioned features and the detection technique (Impedovo, 2019; T Bouwman, 2019; Zi Yang, 2018). It becomes difficult to identify and adopt the best suitable methods and features as they are often dependant on camera properties and its testing conditions. Also, they are developed and designed as an independent process to extract the best outcome. However, in reality the detection of vehicles for traffic information is an integral and inevitable process of any ITS applications. Consequently, it is necessary to identify the suitable techniques that overcome the challenges of having a successful operational system. This paper proposes such a framework known as Multi-Layer Continuous Loop (MCVL) that chooses the best suitable process to balance all the requirement of an efficient detection process for any service applications related to traffic management. Also the most common parameters encountered in literature to enumerate TraCo are speed and density. Therefore in this work, new methods for extracting area occupancy (an alternate for density) and speed parameters from the novel MCVL framework are proposed. Being vision based estimations, additionally the parameter known as Corner Detail Value (CDV) with spatial information that shows substantial difference in traffic states is proposed. The main motivation of this work is to provide the finest techniques with the proposed novel detection framework to ensure significant robustness, accuracy with minimal computational complexity to estimate traffic flow characteristics in real-time. Subsequently, there is certainty that such traffic information improves the quality of any ITS service application provider utilizing it.

3. TRAFFIC CONGESTION (TRACO) ESTIMATION USING MULTI-LAYER CONTINUOUS VIRTUAL LOOP (MCVL)

The significant requirement for most of the applications of ITS especially traffic monitoring or traveller information updating applications is to identify or detect the presence of vehicle in the traffic scene. This paper aims to utilise the already existing traffic surveillance cameras installed in road segments and/or intersections for the above purpose. This eliminates a number of other detection techniques disadvantages such as installation costs, maintenance costs, environmental conditions etc., (Impedovo, 2019; T Bouwman, 2019). However, while installing any traffic surveillance cameras are installed based on the location, target coverage, road infrastructure, camera properties etc., which leads to diverse complications such as background, lighting, shadows etc. A novel Multi-layer Continuous Virtual Loop (MCVL) is proposed in this work to improve the quality of the existing process of traffic data acquisition by considering the real life complications described above. It uses with optimal combination of computer vision or image processing methods and techniques that provides a balance

Figure 1. Functional Diagram of TraCo Estimation using MCL



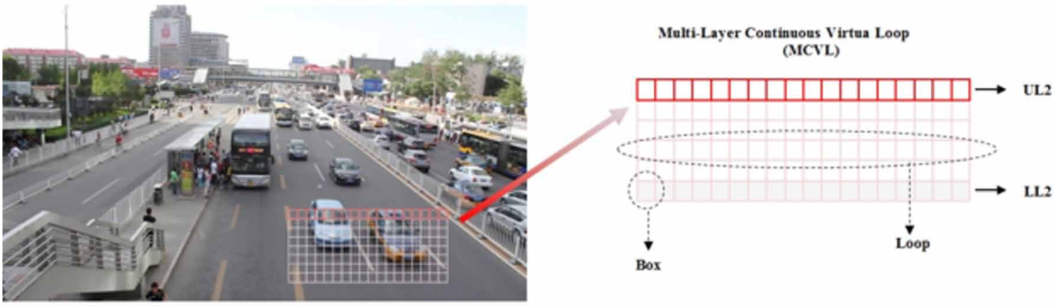
between accuracy as well as computation cost is presented in this work. The framework of MCVL allows accurate estimation of traffic parameters such as speed, area occupancy etc. Additionally, this paper presents estimation of Corner Detail Value (CDV) as a parameter that describes the traffic status. These parameters can be utilised with several application of ITS. Traffic flow status such as Traffic Congestion (TraCo) information which is an integral requirement and part of ITS applications are derived using these parameters and presented in this wok. The functional diagram of the proposed work is shown in Figure 1.

The subsection includes the details of MCVL for vehicle detection, traffic data collection for TraCo estimation, fuzzy logic based TraCo information processing.

3.1. Operational Design of Multi-Layer Continuous Virtual Loop (MCVL)

The Multi-Layer Continuous Virtual Loop (MCVL) framework for vehicle detection is the extension of the work from Manipriya (2019) which describes in detail the function of individual modules

Figure 2. Multi-Layer Continuous Virtual Loop (MCVL) Framework



of the detection process. With few changes in the structure of MCVL, the overall essence of the work is briefed. This paper focuses primarily on the algorithms and methods used to extract traffic parameters from MCVL and use the same for the operation of the service such as traffic congestion. The framework of MCVL model is shown in Figure 2.

As an initial step, the first frame of the video is provided to the user to select the Significant Area of the Video (SAV) which becomes the detection zone. This process ensures that the computational cost is immensely reduced and a complex and chaotic video can be reduced to a static background processing which reduces the false positives of enumerated traffic data (Manipriya, 2020). The SAV is now converted into Multiple Layer of Continuous Virtual Loop (MCVL). It comprises of several layers of segments with grid like pattern that are consecutive and connected. Individual segments are denoted as box and continuous sequence of box forms a loop. The topmost and bottommost loops are defined as Upper Layer Loop (UL2) and Lower Layer Loop (LL2) respectively. One of the most efficient aspects of the proposed work is that the entire detection process is done only for UL2 which aids in reducing the computational cost significantly.

In this paper, the Background Subtraction (BS) based detection is evaluated to detect the moving vehicles in the proposed MCVL model among several detection techniques that exist for vehicle detection. BS detects object movements by observing the pixel properties of the Background Image (BI) and comparing subsequent Foreground Image (FI) against them. The main stage in any BS is to design the BI requiring replication according to the changes in the scene (Zi Yang, 2018; Bouwmans, 2019; M. Piccardi, 2004; Reddy, 2018). The detection process using MCVL considers each UL2 box denoted as individual image. As a pre-requirement, *B* boxes are converted to HSV color format defining the Hue, Saturation and Value element which shows a significant difference in lighting changes required to identify the moving object in the outdoor image sequence (Manipriya, 2014). BS process is done by histogram comparison and by using Earth Movers Distance (EMD) for the respective B boxes of UL2 to identify the dissimilarity between BI and FI. The BI is updated using running average frequently to replicate the real time background of the video (Manipriya 2020; Manipriya 2015). The running average to model updated BI and BS process using EMD is given in Equation 1, 2 and 3. Equation 4 gives the number of boxes that are candidates of vehicle presence.

$$H_{C,t}\left(UBI\right)_B = \alpha H_{C,t-1}\left(UBI\right)_B + \left(1-\alpha\right) H_{C,t}\left(FI\right)_B \tag{1}$$

$$Ind_{C,t,B} = Index_{EMD}\left(H_{C,t}\left(FI\right)_B,\ H_{C,t}\left(UBI\right)_B\right) \tag{2}$$

$$R_{B,t} = \begin{cases} 1, \ if \ Ind_{C,t,B} > Th_C \\ 0, \ Otherwise \end{cases} \tag{3}$$

$$NB_{k,t} = B_{la}\left(k\right) - B_{fi}\left(k\right) + 1 \tag{4}$$

$\boldsymbol{H_{C,t}\left(UBI\right)_B}$ *is the histogram of the Updated Background Image of color component Cϵ {Hue(H),Value(V)} for the Bt^h box of UL2 at time t.*

$\boldsymbol{H_{C,t}\left(FI\right)_B}$ *is the histogram of Foreground Image of color component C{Hue(H),Value(V)} for B^{th} box of UL2 at time t*

$\boldsymbol{R_{B,t}}$ *is the result of binary value that indicates the movement of vehicle in B^{th} box of UL2 at time t.*

α is the weightage given to FI.

$\boldsymbol{Th_C}$ *is the EMD threshold for color component Cϵ{Hue(H),Value(V)} i.e.* Th_H & Th_V

Index$_{\mathbf{EMD}}$() is the similarity index estimation function across two histograms using Earth Mover's Distance Method

$\boldsymbol{Ind_{C,t,B}}$ *is the histogram similarity index of color component C{Hue(H),Value(V)} for B^{th} box of UL2 at time t.* $\boldsymbol{B_{fi}\left(k\right)}$ *is the first box of the k^{th} set of consecutive candidate boxes of loop*

$\boldsymbol{B_{la}\left(k\right)}$ *is the last box of the k^{th} set of consecutive candidate boxes of loop*

$\boldsymbol{NB_{k,t}}$ *is status vector to maintain the boxes that has candidacy of the k^{th} vehicle in UL2 at time instant t*

The accuracy and false positives of the detection of vehicles primarily depend on user specified SAV and number of lanes occupied in SAV. Contributing these two values aids is using the proposed MCVL in any traffic video irrespective of the camera properties. The total Number of Boxes i.e. *NB*, total Number of Loops i.e. *NL* and number of boxes that constitute single Passenger Car Unit (PCU) i.e. NB_{pcu} can be an optional choice for user selection. The more boxes per lane used, the better the accuracy. The number of boxes that define PCU helps in solving various image/pixel to real life measurements. However, this dependency of SAV, *NB* and NB_{pcu} on camera properties is very challenging to automate and considered for future scope. Ideally 8 boxes for a lane, 8 loops and size of each box is congruent to 3.5 meter of road coverage are the optimal values found by trial and error.

3.2. Traffic Data Collection for TraCo Estimation Using MCVL

Among several applications of ITS the most common requirement is the macroscopic traffic flow details or their derivatives such as traffic congestion information. Among several existing literature the most significant parameters for traffic congestion estimation using diverse detection technique are density and speed values (R Wang, 2019; Kong, 2016; Reddy, 2018; Duc Binh, 2018). This paper uses MCVL to convert the visual interpretations of traffic into digital traffic parameter readings such as speed and area occupancy. Area occupancy is assumed as the replacement of density or volume estimation that reduces the cost of processing. The traffic information from proposed MCVL model is used to obtain these two parameters easily without any difficulty. Apart from these two parameters, being visual representation, the Corner Detail Values (CDV) is added as an extra parameter specifically for traffic congestion estimation.

This section aids in briefing the process of enumerating speed, area occupancy and CDV from proposed MCVL model.

3.2.1. Traffic Speed Estimation

The speed parameter is the most common characteristics for evaluating the quality of travel. The speed is generally defined in terms of distance travelled in unit time. In this paper, speed information is extracted using optical flow technique with feature tracking (Reddy, 2018). In Equation 5 to 13, novel speed detection techniques are proposed using the optical flow concept with the proposed MCVL model. The dimension features from Equation 4 i.e. $NB_{k,t}$ is used to track the movement of *k* vehicles. The number of frames for the k^{th} vehicle in SAV to travel from ULP to LLP is tracked using the optical flow. The optical flow identifies the displacement of vehicles across video frames. Here the histogram of the box is used as the feature to analyze the displacements. The displacement of the histogram is represented in Equation 5. Considering Taylor series approximation on RHS in Equation 5 and dividing the terms with δt, the resultant solved equation is given in Equation 6, 7, 8. Solving the values of V_x and V_y in sets of Equation 8 provides the solution for movement over time. In this work, the adjacent histograms of $NB_{k,t}$ for k^{th} vehicle are used to solve using the Lucas-Kanade method. Also the angle (direction) of flow and the distance (magnitude) of flow are identified by histogram of hue and value of HSV color representation respectively by using Farneback method (S. Hua, 2018; Adrian, 2019; Chuan, 2019). The entire displacement is tracked until x+δx, y+δy reach the LL2 of MCVL. A vector is maintained for k *v*ehicles and their corresponding number of frames N *t*aken to reach LL2 is calculated. The time travelled across SAV is obtained from Equation 9. From NB_{PCU}, the width of the car ($Wpcu$) is defined. The approximate real world width of PCU ranges from 1.54m to 1.77m (Mardani, 2015). This value helps in identifying the equivalent size or width of a box that is of square dimension in real world. Subsequently, the size of the SAV chosen by the user and its equivalent real world measurement is extracted from Equation 10. As per definition of speed, the distance travelled i.e. the size of SAV in Equation 11 and the time travelled i.e. number of frames in Equation 9 are now available. From these two values the spot speed of the vehicles at time *t* moving across the fixed length of SAV is calculated in Equation 12. The average space mean speed of SAV is for *k* vehicles at time *t* detected from MCVL is enumerated using Equation 13.

$$H(x,y,t,) = H(x+\delta x, y+\delta y, t+\delta t) \tag{5}$$

$$\frac{\partial H}{\partial x}u+\frac{\partial H}{\partial y}v+\frac{\partial H}{\partial t}=0,\ V_x=\frac{dx}{dt},\ V_y=\frac{dy}{dt} \tag{6}$$

$$H_x=\frac{\partial H}{\partial x},\ H_y=\frac{\partial H}{\partial y},\ H_t=\frac{\partial H}{\partial t} \tag{7}$$

$$H_x(B_{fi}(k))V_x+H_y(B_{fi}(k))\,V_y=-\,H_t(B_{fi}(k)) \tag{8}$$

$$H_x(B_{la}(k))V_x+H_y(B_{la}(k))\,V_y=-\,H_t(B_{la}(k))$$

$$T(k) = \frac{N\left(V_x, V_y\right)_{LL2}}{FPS} \tag{9}$$

$$S\left(B\right) = \frac{Wpcu}{NB_{pcu}} \tag{10}$$

$$D\left(k\right) = S\left(B\right) \times NL \tag{11}$$

$$spot\left(k,t\right) = D\left(k\right) / T\left(k\right) \tag{12}$$

$$Sp\left(t\right) = \frac{\sum_{i=1}^{k} q_i}{\sum_{i=1}^{k} \frac{q_i}{Spot\left(i,t\right)}} \tag{13}$$

where

$H\left(x, y, t\right)$ *is the histogram of* k^{th} *vehicle at* x^{th} *row and* y^{th} *column of loop for* $x \epsilon NB$, $y \epsilon NL$

δx, δy, t are displacement factors

$\frac{\partial H}{\partial x}, \frac{\partial H}{\partial y}, \frac{\partial H}{\partial t}$ *are the histogram gradient along the row, column and time of loop*

V_x, V_y *are the movements over time across the loop*

$N\left(V_x, V_y\right)_{LL2}$ *is the number of frames the movement is determined up to LL2*

***FPS** is the number of frames per second in the traffic video*

NB_{pcu} *is the number of boxes that define one Passenger Car Unit(PCU)*

NL is the total number of loop of MCVL

S(B)is the size equivalent to real world measurement of a box

***Wpcu** is the width of Passenger Car Unit (PCU)*

D(k) is the total length/distance covered by MCVL in real world

Spot(k, t) is the spot speed of the k^{th} vehicle at time t

q_i *is the number of vehicles having speed* $Spot\left(i,t\right)$ *where i=1 to k*

Sp(t) is the average spaces mean speed of vehicles at time t

3.2.2. Area Occupancy Estimation

Area occupancy defines the usage of road space by the vehicle. It indicates the road traffic concentration with volume of vehicles as it measures the usage of the road space. It is defined as the proportion of time taken by the vehicle to occupy the unit area or a detection zone (SAV) of the road segment (Reddy, 2018; Thamizh, 2009). During visual feature extraction, the area occupancy becomes a replacement to volume or density values for traffic flow. In MCVL, the resultant binary image from Equation 3 indicates the presence of vehicle in SAV. Thus the pixel value of 1 at time t to the total number of pixels in SAV indicates the occupancy of the area at time t. The generalized equation of area occupancy *AOcc* is given in Equation 14. The modified percentage of area occupied using MCVL is proposed in Equation 15 and 16.

$$AOcc = \frac{\sum_{i=1}^{k} a_i t_i}{AT} \tag{14}$$

$$AOcc_{MCVL} = \frac{TB_t}{NB} \times 100 \tag{15}$$

$$TB_t = \sum_{i=1}^{B} R_{B,t} \tag{16}$$

where

a_i *is the area of the k^{th} vehicle entering the detection zone*

t_i *is the time taken by the k^{th} vehicle to occupy the detection zone*

A *is the total area of the detection zone*

T *is the constant observation time*

$AOcc_{MCVL}$ *is the percentage of area occupied by vehicles in MCVL*

TB_t *is the total number of boxes that indicates the binary value from Equation 3 at time t*

NB *is the total number of boxes in MCVL*

3.2.3. Corner Detail Values (CDV) Estimation

It becomes necessary to have a third parameter to intuitively reflect the actual road condition especially during extreme conditions. The consecutive frames of the traffic videos with nil traffic or completely jammed conditions do not have any significant movement and becomes difficult to differentiate using image processing techniques. Hence along with the other two parameters this paper uses corner detection process in every box of MCVL. The pixel intensity gradients along the perpendicular direction of an image indicate corner features. Corners can also be defined as the intersection of two edges (Junqing Wang, 2018; Reddy, 2018). Therefore the post processing of edge detection in computer vision technique helps in identify the corner values. Among several corner detection process in literature, FAST (Features from Accelerated Segment Test) is considered for corner detection using MCVL (Edward, 2010). FAST are computationally better for real time application with least processing time. Each p pixel with neighbouring 16 pixels and their intensities are used for identifying the gradient difference with a threshold value Th_{FAST}. The high speed of the algorithm is due to the stepwise comparison of 2 and 4 pixels among the surrounding 16 pixels of p. When the difference in intensity is very high or too low they are considered as candidate pixel for corners. Each value of vector P can have only one of the values in Equation 17. Finally using Boolean and ID3 algorithm the pixel p is classified as corner. Although FAST is considered to be the fastest of all corner detection but the accuracy of it depends on $Th_{FAST.}$ This value is updated dynamically for detection using MCVL with the intensity values of UBI and the values are modified as in Equation18:

$$F_{(B,i,p)} = \begin{cases} D, & I_{(B,p,i)} \leq I_{(B,p)} - Th_{B,FAST} \\ S, I_{(B,p)} - Th_{FAST} < I_{(B,p,i)} < I_{(B,p)} + Th_{B,FAST} \\ L, & I_{(B,p)} + Th_{B,FAST} \leq I_{(B,p,i)} \end{cases} \tag{17}$$

$$Th_{B,\ FAST} = \sum_{a=1}^{M}\sum_{b=1}^{N} I_{(a,b),B}\left(UBI\right) \forall B \in \left\{1 to NB\right\} \tag{18}$$

where

$\boldsymbol{F}_{(\boldsymbol{B},\boldsymbol{i},\boldsymbol{p})}$ is the feature values of i^{th} pixel surrounding p^{th} pixel of B^{th} box of MCVL $\forall i \in \left\{1 to 16\right\}$
$\boldsymbol{I}_{(\boldsymbol{B},\boldsymbol{p})}$ is the intensity of the p^{th} pixel of B^{th} box of MCVL
$\boldsymbol{I}_{(\boldsymbol{B},\boldsymbol{p},\boldsymbol{i})}$ is the intensity of i^{th} pixel surrounding p^{th} pixel of B^{th} box of MCVL

D, S, L is the feature vector values p^{th} pixel of B^{th} box of MCVL that denotes darker, similar and lighter intensity respectively
$Th_{B,FAST}$ is the threshold value for the B^{th} box of MCVL for FAST corner detection

$I_{(a,b),B}\left(UBI\right)$ is the intensity of B^{th} box of MCVL of Updated Background Image with dimension of a×b $\forall a \in \left\{1 to M\right\}, b \in \left\{1 to N\right\}$.

3.3. Traffic Congestion (TraCo) Estimation Using Fuzzy Logic

In this section, the proposed TraCo estimation for a road segment covered by traffic surveillance camera using Mulit-Layer Virtual Loop (MCVL) model is presented. There are no guidelines or statistics to work with the non-deterministic complex problem of identifying traffic congestion on a specific segment of road. These problems can be efficiently solved by fuzzy rule based approach (Wan Xiang, 2018; Duc Binh, 2018, Kong, 2016; R Wang, 2019). This paper further proposes a fuzzy rule based traffic congestion estimation that uses area occupancy, speed and Corner Detail Value (CAV) from MCVL model as input parameters. The initial step to this comprehensive method is to determine the membership functions or fuzzification of inputs. The input parameters values of speed, area occupancy and CDV and resultant traffic level of congestion values are transformed to fuzzy sets. The relationship between the values and sets are established through membership functions. Table 1 displays the set of parameters and their respective fuzzy sets used in the fuzzy system.

Table 1. List of Fuzzy sets

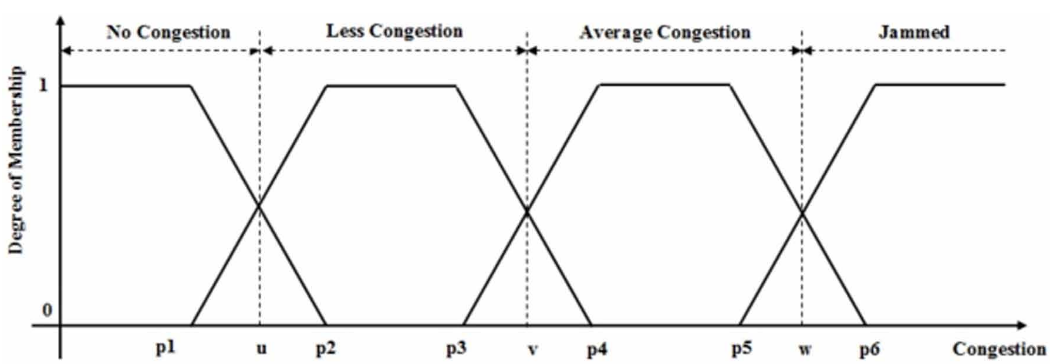
	Parameters	Fuzzy sets
Input Parameter (L)	Average Speed (l_1)	Low, Medium, High
	Area Occupancy (l2)	Low, Medium, High
	CDV (l3)	Few, Average, High
Output Parameter (K)	TraCo	No congestion (k1), Less Congestion(k2), Average Congestion(k3), Jammed(k4)

The whole range of the resulting parameter is [0,1] where 0 refers to no congestion and 1 refers to a state that is absolutely jammed. Congestion values in-between are lower and average conditions. In the next step, for each parameter are confined to the membership functions of the fuzzy sets and TraCo membership function is shown in Figure 3 and represented in Equation 19 to 22. Similar to these member functions the other input parameters values are also confined to a membership function.

$$\mathrm{K1(l)} = \begin{cases} 1, & l \le p1 \\ \dfrac{p2 - l}{p2 - p1}, & p1 < l < p2 \\ 0, & l \ge p2 \end{cases} \tag{19}$$

$$\mathrm{K2(l)} = \begin{cases} \dfrac{l - p1}{p2 - p1}, & p1 < l < p2 \\ 1, & p2 < l < p3 \\ \dfrac{p4 - l}{p4 - p3}, & p3 < l < p4 \\ 0, & l \ge p4 \end{cases} \tag{20}$$

Figure 3. Membership function of TraCo estimation



$$\mathrm{K3(l)} = \begin{cases} \dfrac{l - p3}{p4 - p3}, & p3 < l < p4 \\ 1, & p4 < l < p5 \\ \dfrac{p6 - l}{p6 - p5}, & p5 < l < p6 \\ 0, & l \geq p6 \end{cases} \tag{21}$$

$$\mathrm{K4(l)} = \begin{cases} 0, & l \leq p1 \\ \dfrac{1 - p5}{p6 - p5}, & p5 < l < p6 \\ 1, & l \geq p6 \end{cases} \tag{22}$$

where

p1, ***p***2, ***p***3, ***p***4, ***p***5, ***p***6 are the linear congestion values with threshold u, v and w

K1(l), K2(l) K3(l) K4(l) denotes the four traffic congestion levels that lies in the range of [0,1]

As the next step the relation between the input parameters and the result congestion states are established by fuzzy rules. The sets of inputs $L= \{l_1, l2, l3\}$ corresponds to density, speed and CDV. The resultant traffic congestion levels are expressed as sets $K= \{k1, k2, k3, k4\}$ that corresponds to no traffic, less congestion, average congestion and jammed traffic congestion level. The relation between the sets L and K i.e. *l1®{k1,k2,k3,k4}, l2®{k1,k2,k3,k4}, l3®{k1,k2,k3,k4}* etc. and all the individual and combined fuzzy member set of *L* is given a relation to the discrete resultant set of K. Sample of few rules is shown in the Table 2

Once the rules are established among the input and resultant fuzzy sets, the fuzzy compositional operation and evaluation is carried out. The comprehensive evaluation of the rules is represented by a matrix for the rules with i^th^ input parameter and j^th^ resultant states are represented as $S_i= \{s_{i1}, s_{i2}, s_{i3}, s_{i4}\}$ (Kong, 2016). The evaluation matrix is shown in Equation 23 and 24:

$$S = \begin{pmatrix} s_{11} & s_{12} & s_{13} & s_{14} \\ s_{21} & s_{22} & s_{23} & s_{24} \\ s_{31} & s_{32} & s_{33} & s_{34} \end{pmatrix} = \left\{c_1, c_2, c_3, c_4\right\} \tag{23}$$

Table 2. Sample fuzzy rules for TraCo estimation

		Average Speed Fuzzy sets		
		Low	**Medium**	**High**
Area Occupancy Fuzzy sets	**Low**	No Congestion	Less Congestion	Less Congestion
	Medium	Average Congestion	Average Congestion	Less Congestion
	High	Jammed	Average Congestion	No Congestion

$$c_j = \sum_{i=1}^{n} s_{ij} \quad \forall i = 1,2,3\ldots 6; j = 1,2,3,4 \tag{24}$$

$$C = Max\left\{c_1, c_2, c_3, c_4\right\} \tag{25}$$

c_j is the fuzzy comprehensive evaluation index which signifies that the evaluation object is member of j^{th} congestion level. Based on the maximum membership of the congestion level as in Equation 25 the final congestion state C is calculated.

4. EXPERIMENTAL RESULTS

The performance of the proposed Multi-Layer Continuous Loop (MCVL) model traffic congestion is evaluated from traffic videos taken at various camera angles and under different environmental conditions. The state-of-the art datasets such as DETRAC, Urban Tracker, KoPER were used in the analysis. Videos have featured different traffic densities of varied backgrounds. The videos were of different resolution such as 640x480; 720x480; 960x480; 1280x1024 etc. The algorithms were implemented with the OpenCV and OpenMP library files in Visual Studio C++. (Background Subtraction, 2019; Adrian, 2019).

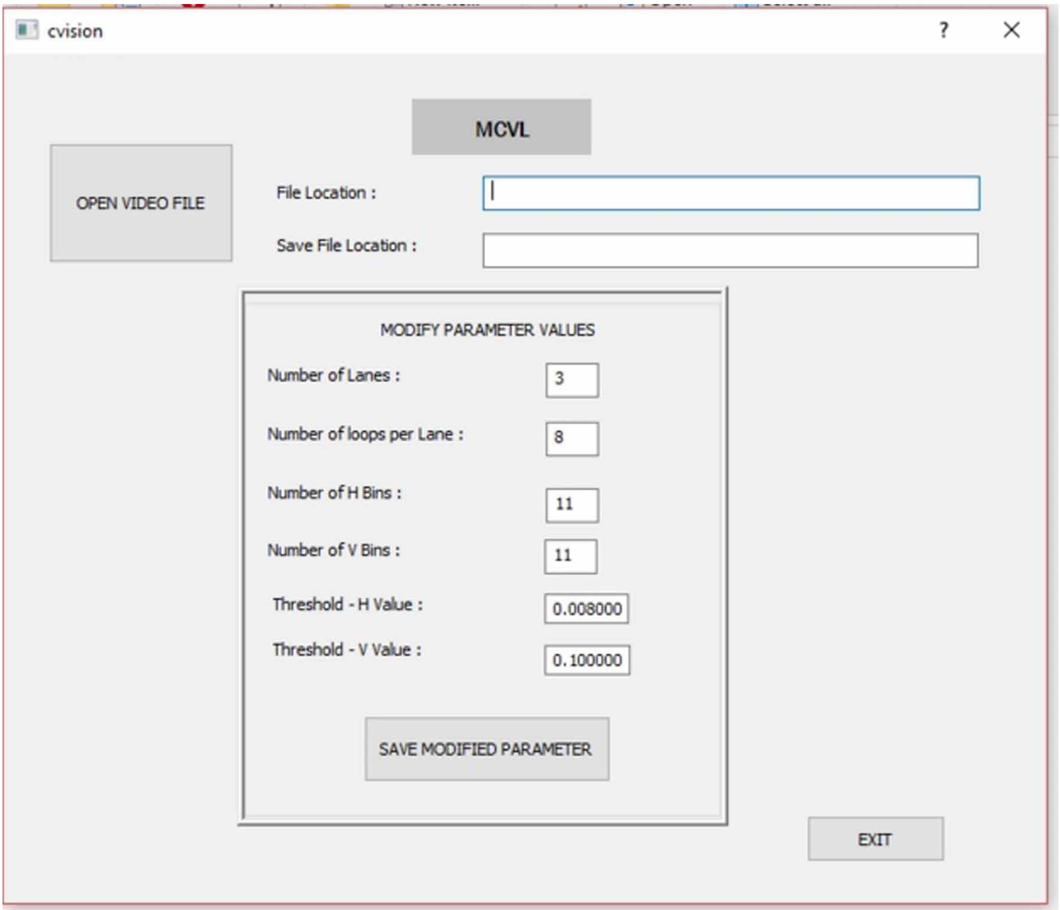
The results are analysed based on Mean Absolute Percentage Error (MAPE) (Manipriya 2015; Reddy, 2018) for the enumeration of the traffic characteristics from several videos using the proposed MCVL model. The overall efficiency and computational complexity of the same are evaluated and presented. Finally, the traffic congestion estimated with MCVL using fuzzy logic is presented.

The screenshots of user preference modifications in Graphical User Interface (GUI) console for MCVL is shown in Figure 4. The screenshots of the vehicle detection process and the results of detection using MCVL are shown in Figure 5 and Figure 6. To analyse efficiency using histogram comparison of MCVL, other algorithms that are native to OpenCV and those available as open source are used. Some of them are: Mixture of Gaussian (MOG), K-Nearest Neighbour (KNN), fuzzy integral, VIBE and HSV based Running Average (Background Subtraction, 2019). The resultant binary image of Significant Area of Video (SAV) of the video for few traffic videos are shown in Figure 7 for visual interpretation.

Figure 8 shows the average processing time taken per frame for the above mentioned detection techniques. It is seen that the HSV color model based running average detection techniques takes the least time to process among all as it takes pixel comparison time only. Therefore the proposed model uses HSV running average detection technique. While doing this process for the Upper Layer Loop (UL2) in MCVL there is further drastic reduction in computation where most of the existing works considers processing entire selected region or image.

Some of the other frameworks such as grids, selected region and entire image (Manipriya, 2020) used for detection with running average, MoG and KNN techniques are analysed. Figure 9 illustrates the average detection rate of moving object using multiple videos with different scenarios such as rainy, cloudy, sunny, night time etc. The detection percentage of entire image in all the detection technique is higher compared to other frameworks. This does not mean that all the detected objects are vehicles. Hence the false positives obtained for the same videos used for Figure 9 are analysed in Figure 10. It is seen that detection using entire image has the highest false positive detection. The other frameworks show drastic reduction in false positives and the proposed MCVL based detection shows the least. This is mainly due to the reduction of the complex background while choosing SAV in MCVL based detection.

Figure 4. GUI of User preference Modification using MCVL



The proposed model MCVL is also assessed with other state-of-the art techniques such as, SSD,

Figure 5. Screenshot of MCVL Vehicle Detection Process

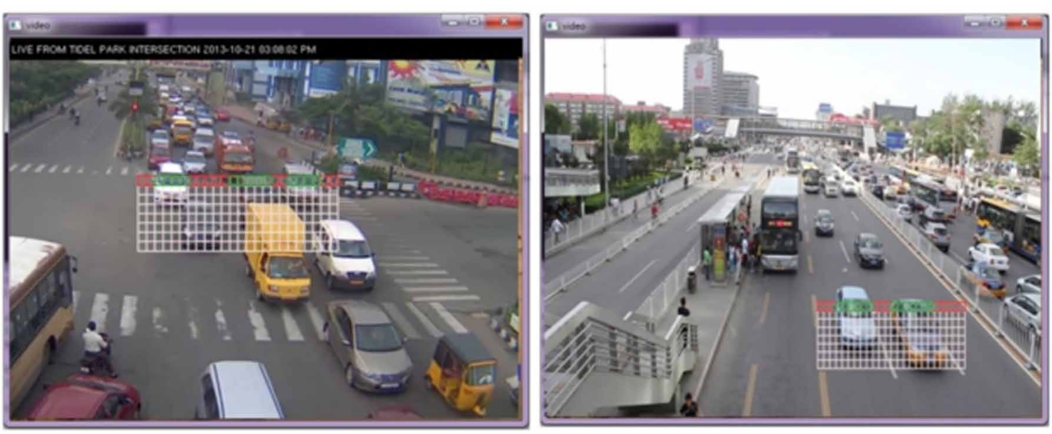
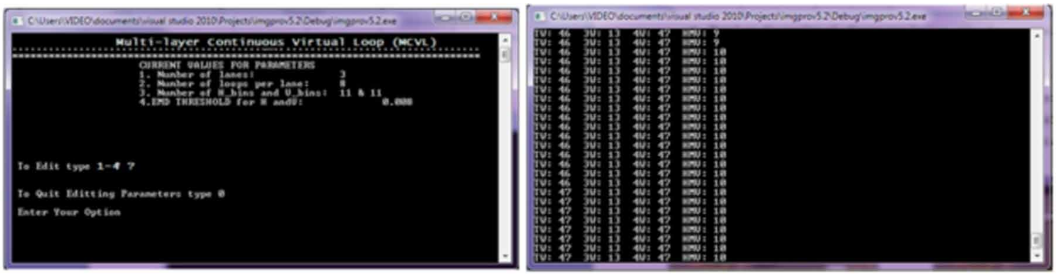


Figure 6. Screenshot of MCVL Vehicle Detection Results



YOLO, Faster-RCNN, CompACT, DPM and EB by using DETRAC dataset (Longyin, 2020; Z Huo, 2016) and the results of MAPE for detection are presented in Table 3. It is noted that the detection happens based on the user selection of SAV in the video and may vary for different SAV. The data set is categorized according to various traffic composition and weather conditions as shown in Table 3. It shows an overall detection of 82.3% with a processing speed of 19 frames per second. The overall performance is affected by the MAPE of highly traffic condition and visually challenging night time videos. However, the accuracy of detection for other type of videos is significantly better comparing to other methods. The most advantageous of the proposed MCVL is the reduced computation time as the entire process occurs only in UL2. From the performance of the proposed model it is seen that the detection of vehicles based on the combined visual feature of histogram of hue, saturation and values shows significant and substantial results. The novel structure of MCVL also enables to a reduced computation region leading to an increased processing speed per image of the video.

As MCVL detection process is one among the composite module of an ITS, it does not choke the respective application. Hence an optimal detection process such as MCVL provides an appropriate balance between computational complexity and accuracy.

Figure 7. Resultant Binary Image of BS Methods

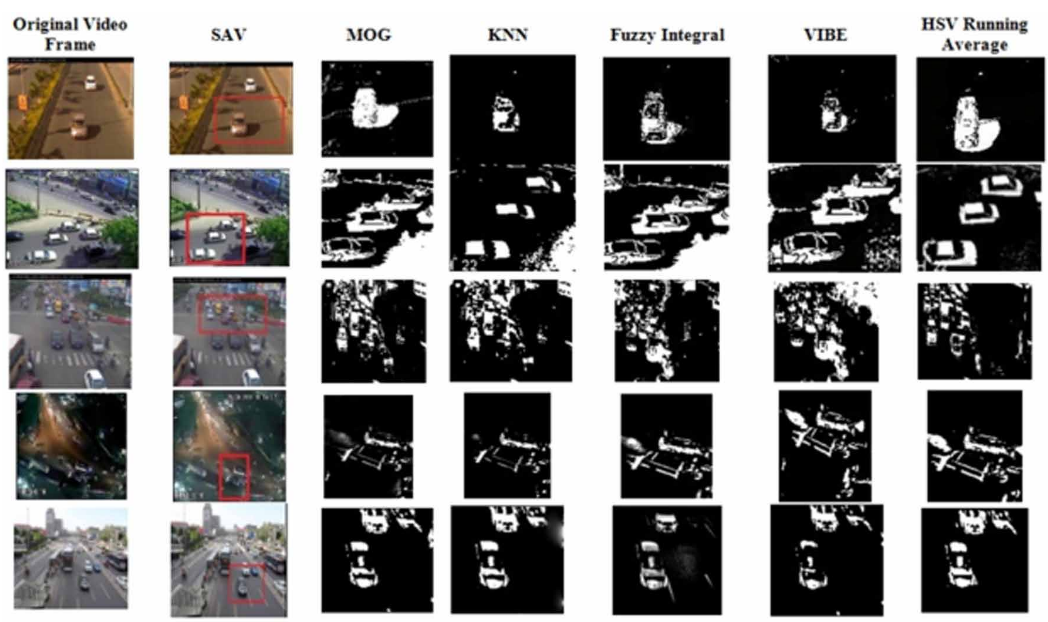


Figure 8. Processing Time of Vehicle Detection Process using BS Methods

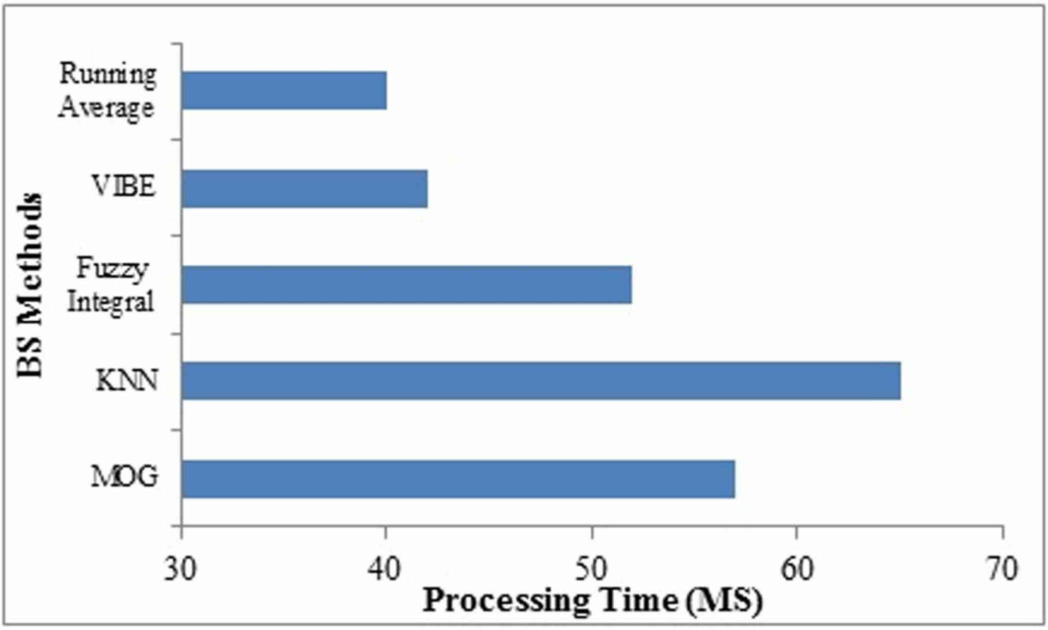


Figure 9. Detection Rate of Frameworks

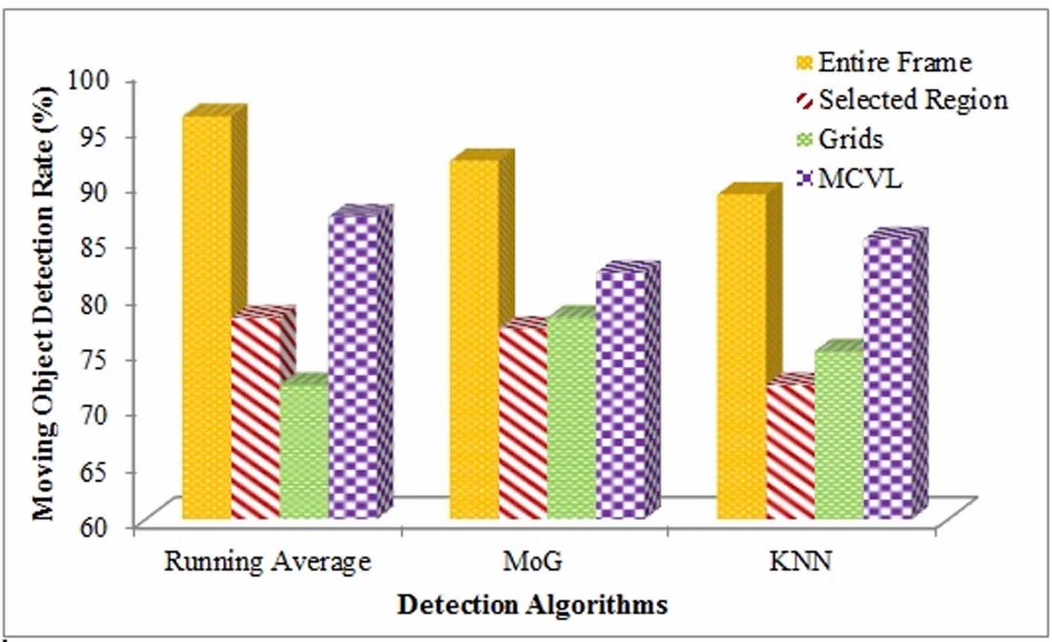


Figure 10. False Positive Rates Frameworks

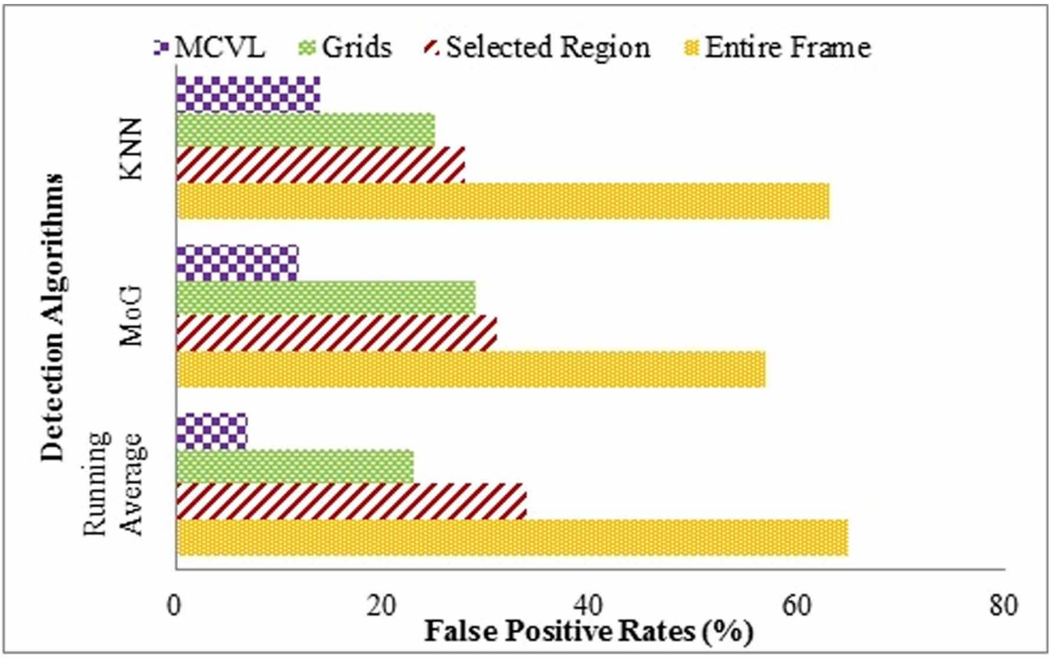


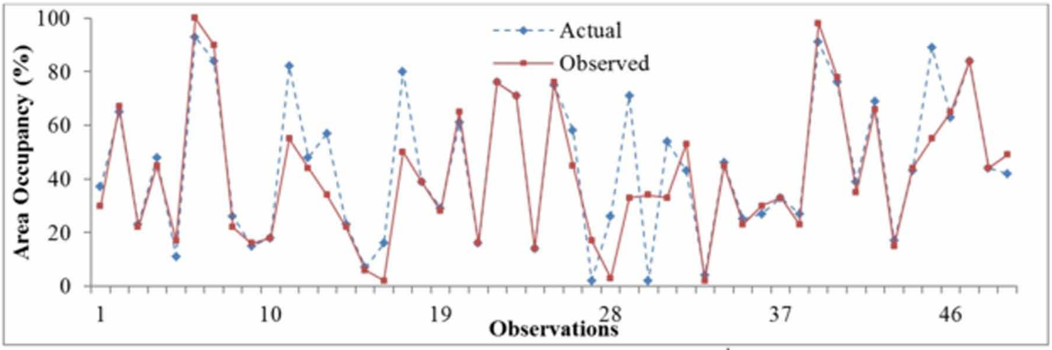
Table 3. Detection Accuracy and Processing Time Using DETRAC Dataset

Technique	Overall	Static Background	Moderate Background	Dynamic Background	Gloomy	Night	Rainy	Afternoon	Processing Time (FPS)
E B	32.1	10.4	26.9	46.4	27.6	26.1	46.6	16.3	10
YOLO	42.3	16.8	37.8	57.6	42.1	35.5	52.2	30.3	-
SSD	17.4	5.4	10.3	29.4	10.2	17	26.7	11.9	2
DPM	74.3	65.6	69.8	82.4	75.3	69.1	74.5	68.3	0.17
Faster RCNN	41.6	17.3	37	55.8	33.8	30.2	54.9	37.7	11.1
Comp ACT	46.8	35.2	41.3	56.9	36.8	53.7	55.8	28.9	0.22
MCVL	17.7	6.7	13.7	24.6	18.4	33.5	17.6	5.6	19

4.1. Evaluation of Estimation of Area Occupancy using MCVL

The precision of any ITS application depends on the accuracy of traffic data acquisition and in this paper the accuracy of MCVL model based acquisition is evaluated using vehicle occupancy detection for any given traffic video. Several observations of occupancy estimation on different illuminations, camera angle and properties are shown in Figure 11. For reference the total number of vehicles is obtained manually at an interval of 20 seconds. It shows percentage of vehicles occupied in the MCVL framework detected against actual vehicles. The occupancy for static and well illuminated traffic videos shows better results with MAPE of 8.3%. However, few videos with background disturbances showed error up to 13 to 15% Therefore for running average based BS process in MCVL establishes an overall 90.3% of accuracy in determining the area occupancy.

Figure 11. Area Occupancy Estimation using MCVL



4.2. Evaluation of Estimation of Average Speed using MCVL

The detection of vehicle suffers a bit of hindrance during highly congested and night time traffic videos. Traffic videos from several locations are used for analysing the estimation of speed of vehicles using MCVL. The actual values of speed are obtained manually from videos. The manual calculation is done using the Upper Layer Loop (UL2) and Lower Layer Loop (LL2) as reference points and timestamp of vehicle crossing them. The estimated average speed of the vehicles using MCVL is averaged for every 20 seconds and the results for several instances across diverse videos are presented in Figure 12.

During free flow conditions the speed estimations were good and showed an average error of 10.6%. The speed detection accuracy was reduced during situations of slow moving vehicles at peak hours, complex road structure and surrounding disturbances. However the average MAPE was 19.6%. It is seen that during completely jammed and empty road conditions at any time of the day the average speed were accurately detected as nil and MAPE were near to 0%. The difference of traffic situation during these extreme conditions was difficult to capture and were significantly identified using the Corner Detail Values (CDV) proposed in this work.

4.3. Evaluation of Corner Detail Value (CDV) Estimation

Corner Detail Values (CDV) is other parameter that is essential for traffic congestion to differentiate vehicle availability during completely halted and empty condition. This section analyse the correctness of identifying the extreme conditions of traffic using proposed Equations 17 and 18 with the novel

Figure 12. Average Speed Estimation using MCVL

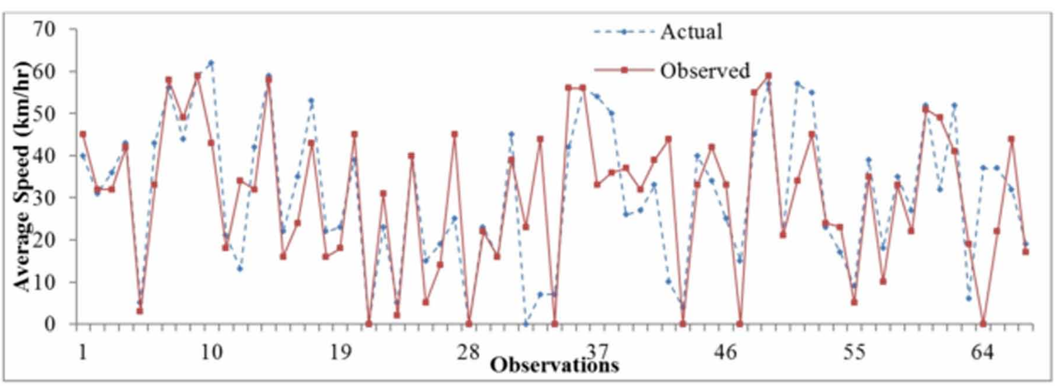


Table 4. Confusion Matrix of CDV Estimation using MCVL

Description		Observed			Total
		Few	Average	High	
Actual	Few	67	9	4	80
	Average	17	137	16	170
	High	5	23	72	100
Total		89	169	92	350

MCVL framework. The correctness is expressed with the confusion matrix in Table 4. The CDV for 200 instances each obtained for the interval of 20 seconds are presented. The actual reference values are obtained through subjective manual analysis. The number of corners in each box are categorised into few, average and high based on the number of corners detected. The threshold to decide this categorisation is subjective and depends on the size of the box defined in MCVL.

It shows from the Table 4 that proposed CDV uisng MCVL estimates and detects the extreme conditions appropriately. The overall accuracy of detection of traffic state into three classes is 92%. While building up the fuzzy rule base for traffic congestion estimation the values for the extreme condtions aids in distinguishing the traffic state accurately.

From the above three real time parameter enumeration from traffic videos the TraCo level of the road segments are estimated.

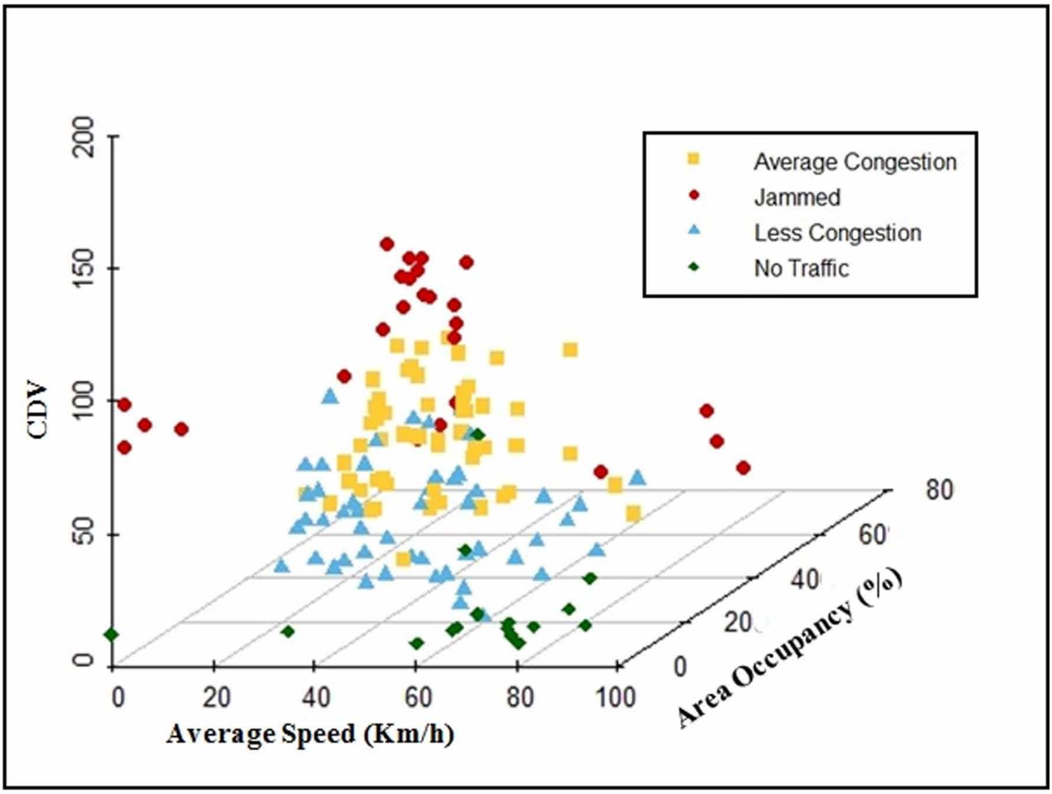
4.4. Traffic Congestion (TraCo) Estimation Using MCVL

The TraCo is estimated using fuzzy logic with traffic characteristics; area occupancy, speed and CDV estimated from MCVL model. As in subsection 3.3, the estimated congestion values for few observations are shown in the scatterplot in Figure 13 for visual interpretation. The Figure 13 shows the resultant membership functions of the traffic congestion level which is the output parameter of the fuzzy logic controller. It shows that few observations predict the congestion range appropriately. Few extreme outliers are obtained from the videos with extreme illumination issues and complex road properties. The other values especially the extreme cases were suggestively differentiated from other congestion level during very low speed values mainly due to the CDV. As its values differed significantly during no traffic and jammed conditions. Hence along with other two parameters, CDV plays an important role in the proposed fuzzy based traffic congestion estimation. The Figure 14 shows the linear relation between speed and area occupancy acquired efficiently using MCVL. This also expresses the robustness aspect of the proposed detection framework that ensures improved accuracy establishing its linear relationships among its respective parameter values.

Due to the non-deterministic nature of the congestion estimation problem, defining the specific boundary for the output membership function is difficult and not explicitly available especially for heterogeneous traffic conditions. For result evaluation purpose, subjective weighing along with the consideration of Greenshields' linear speed-density relationship the rule based implications are done with value (Reddy, 2018) presented in Table 5.

The improvements of fuzzy logic based congestion using MCVL are presented by associating the estimated values along with values from Table 5. The performance of TraCo estimations in several traffic videos categorized by difference in illumination and environment are presented in the Receiver Operating Characteristics (ROC) curve space as shown in Figure 15. It shows that congestion estimation during night and hard level of traffic scenarios have less accuracy in prediction compared to other traffic videos. The videos with appropriate illuminations and easy detection have an accuracy of 98.4% in estimating the TraCo values. Whereas the overall accuracy of TraCo estimates is 90.3%,

Figure 13. TraCo Estimation from MCVL



regardless of the type of video. As this accuracy depends on the estimation from the MCVL the improved detection rate consequently reflects in the TraCo estimation accuracy.

Although there are several video based vehicle detections using image processing techniques being extensively explored in the past three decades, an optimal process that balances accuracy and computational complexity is not yet presented. Also, the detection process is part of or one of the modules of ITS application related to traffic monitoring or traveller information updating systems that needs to be simple and comprehensible. Therefore from the results it is seen the proposed TraCo estimations for any ITS application using MCVL provides an ideal balance by improved precision with minimal processing time compared to other high end state of the art detection process. Consequently, using traffic status information from MCVL improves the congestion estimation process of ITS applications.

5. CONCLUSION

Any application of Intelligent Transportation Systems (ITS) that involves monitoring or updating traffic and travel information requires traffic parameters and their derivatives for its real time operations. The most common and useful derivatives for such applications are the road Traffic Congestion (TraCo) information. Real time estimation of parameters to enumerate TraCo for a road segment is challenging. This paper proposes an estimation technique using the existing and available traffic surveillance camera to estimate the necessary parameter for TraCo estimation. A novel framework known as Multi-Layer Continuous Virtual Loop (MCVL) for estimation of parameters such as area

Figure 14. Linear Relation with Speed and Area occupancy

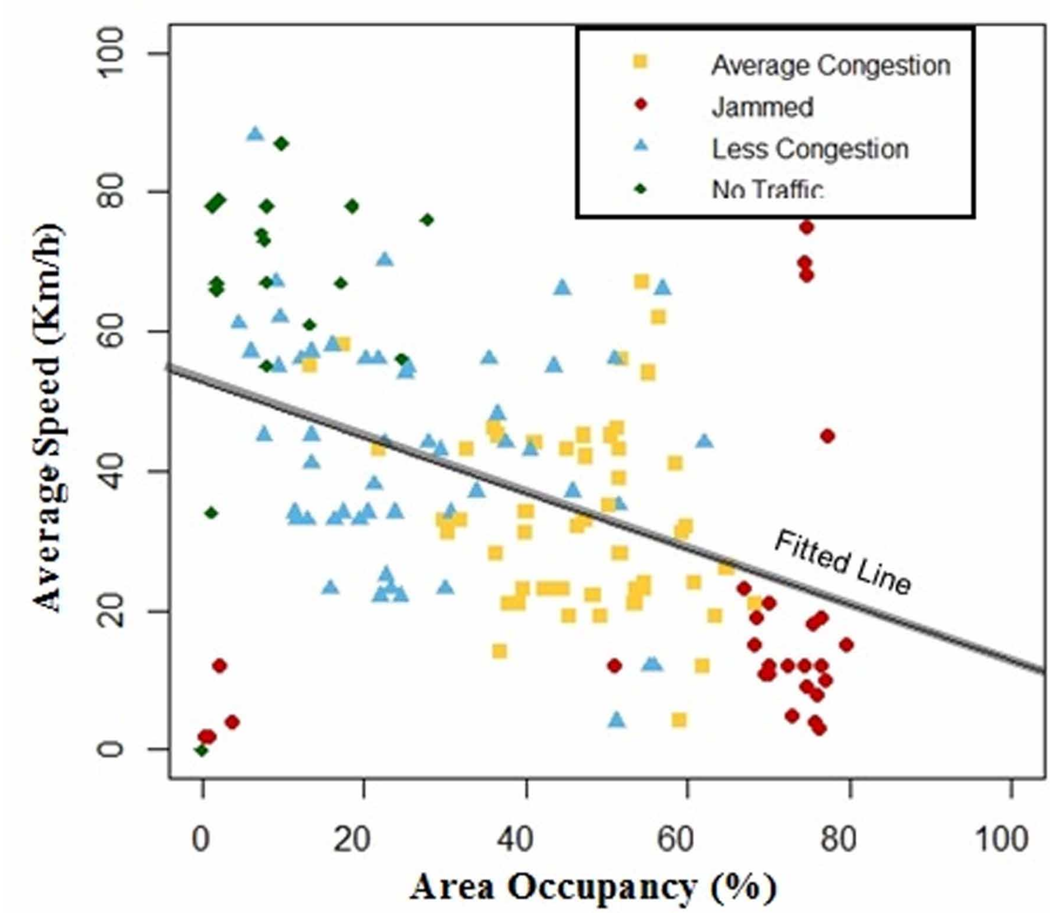
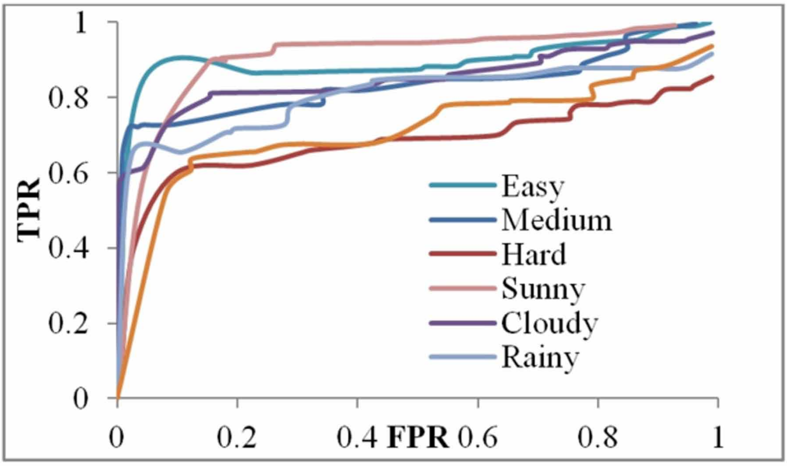


Table 5. Fuzzy set values for Area occupancy and Average Speed

Congestion Levels	Area Occupancy (%)	Average Speed (Km/hr)
No Congestion	5.5	45
Less Congestion	12.6	30.1
Average Congestion	20.1	21.5
Jammed	30	10

occupancy and speed is proposed. Further it also presents the process of estimating Corner Detail Value (CDV), a novel parameter that shows significant difference in the traffic status. The overall accuracy in enumeration of the traffic parameters such area occupancy, speed and CDV using MCVL are 90.3%, 84.9% and 92% respectively. The estimation of TraCo using these real time traffic data contributes an accuracy of 90.3% irrespective of the camera properties and real life environment. As a result, the proposed work shows that the precision of the congestion information depends on the data acquired and has improved accuracy using MCVL.

Figure 15. ROC Curve for Traffic Videos using MCVL



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