



Speed Measurement and License Plate Detection of Vehicles using Image Processing

A Raja, Ummareddy Sravani, Durgapu Lokesh, Thota Mahesh Babu, Thiruvaipati Anand

Department of Electronics and Communication Engineering, Chalapathi Institute of Technology, Guntur, India.

To Cite this Article

A Raja, Ummareddy Sravani, Durgapu Lokesh, Thota Mahesh Babu, Thiruvaipati Anand, Speed Measurement and License Plate Detection of Vehicles using Image Processing, International Journal for Modern Trends in Science and Technology, 2024, 10(03), pages. 152-161. <https://doi.org/10.46501/IJMTST1003023>

Article Info

Received: 30 January 2024; Accepted: 22 February 2024; Published: 01 March 2024.

Copyright © A Raja et al;. This is an open access article distributed under the [Creative Commons Attribution License](#), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

ABSTRACT

Vehicle flow estimation is an important part of traffic management system. It plays an important role in tracking systems, automatic video surveillance and also to avoid collision. This paper proposes a method to estimate the speed of vehicles on the highways and city areas. The proposed method can be effectively implemented to control the over speed vehicles and to found guilty in leading to traffic accidents. Each vehicle in the video recorded by the camera is identified. A bounding box is created on the identified vehicle and its centroid coordinates are marked. The analysis of speed is done using mathematical formulae which are embedded in the software. The existing research in this field has certain limitations. The first limitation is consumption of a lot of memory to store videos in the hard drive. The second limitation is inaccuracy of the system in unpleasant weather conditions such fog, haze, rain, and heavy winds, etc. Some systems failed to crate proper bounding box as it is necessary for accurate analysis of the motion of the vehicle and its speed. Another disadvantage is that shadow produced by vehicles on the different lanes of the road creates a fuss and the system detects the shadow too as a different object and creates a bounding box over it. The objective of the proposed work is to develop a system which can provide the alternative to the We have evaluated the proposed method on various traffic videos and found that the proposed method accurately detects the speed of a vehicle and outperforms many state-of-the-art approaches.

Keywords: Haar Classifier, Object Detection, PPM (Pixel Per Meter), Speed Tracking.

1. INTRODUCTION

Intelligent video surveillance is a new research direction in the field of computer vision. It uses the method of computer vision and detects the movement target in the monitoring scene by automatic analysis the image sequence by the camera recording. And the research on moving target detection and extraction algorithm can be said to be key issues in intelligent

video. Its purpose is the detection and extraction of the moving targets from the scene of the video image sequence. Therefore, the effective detection of moving targets determines the system performance. Therefore, this article focuses on key technology in the moving targets detection and extraction. In this paper, firstly, it has a brief introduction of pretreatment of the video images. It reduces the error in the image processing after.

Secondly the paper focuses on analysis and comparison the two algorithms: the background subtraction and the frame difference. Lastly, this paper selects based on the background subtraction method to improve it and present a moving target detection algorithm based on the background which has dynamic changes.

In modern battles, long-distance attacking missile develops to intelligent, high precision and remote controllability. Midcourse guidance uses GPS/INS with terrain matching. Terminal guidance uses radar, infrared imaging technology or infrared imaging technology with data link. Infrared imaging guidance technology can auto search, auto-capture, auto-identify target, then can auto trace target because there are many features such as high precision, good anti-interference, good concealment capability and so on and it has been research hotspot in accurate terminal guidance field [1]. At present, the infrared seekers has been the second products whose type products are AAWS-M in America and Trigger belongs to German, France and Britain. The information captured by infrared seekers usually is serial image [2]. To treat infrared serial images intelligently is the precondition for accurate terminal guidance, and we can make infrared seekers have better tracing target ability. From martial application, region of interest (ROI) of target in serial images is the region in moving target. So the process of automatic extraction of

ROI in infrared serial images is the process of detecting moving target then extraction moving target region. It is a hotspot in computer vision fields that to trace target and to extract ROI from serial images with complex background. The technology used in missile guidance, video controller and traffic manager commonly while it also is an important issue for automatic extraction of ROI. There are two methods for extraction ROI: one is human detected regions of interest (HROI) which is selected according to ROI by human, and another is algorithmically detected regions of interest (AROI) which is selected according to characters of the image [3]. This paper mainly studied the target detection algorithm in static scenes and dynamic scenes, automatic extraction algorithm of ROI and image segmentation issues. The result can improve the efficiency of accurate guidance.

In a natural scene, objects of interest often move amidst complicated backgrounds that are themselves in motion e.g. swaying trees, moving water, waves and

rain. The visual system of animals is well adapted to recognizing the most important moving object (referred to henceforth as the "target"), in such scenes. In fact, this ability is central to survival, for instance, by aiding in the identification of potential predators or prey while ignoring unimportant motion in the background. Apart from the obvious importance in visual systems of the biological world, target detection is extremely useful for various computer vision applications such as object recognition in video, activity and gesture recognition, tracking, surveillance and video analysis. For instance, a robot or an autonomous vehicle could benefit from a module to identify objects approaching it amidst possibly moving backgrounds like dust storms, to do elective path planning. However, unsupervised moving target detection, often posed as the related problem of background subtraction, is hard to solve using conventional techniques in computer vision(see (Sheikh & Shah, 2005) for a review). Extracting the foreground object moving in a scene where the background itself is dynamic is so complex that even though background subtraction is a classic problem in computer vision, there has been relatively little progress for these types of scenes. A common assumption underlying many techniques for background subtraction is that the camera capturing the scene is static. (Stature&Grimson, 1999; Elgammal, Harwood, & Davis, 2000; Wren, Azarbayejani, Darrell, & Pentland, 1997; Monnet, Mittal, Paragios, & Ramesh, 2003; Tavakkoli, Nicolescu, & Bebis, 2006). However, this assumption places severe restrictions on the applicability of such techniques to real-world video clips, that are often shot with hand-held cameras or even on a moving platform in the case of autonomous vehicles. Conventional techniques to address this problem involve explicit camera motion compensation (Jung & Sukhatme, 2004), followed by stationary camera background subtraction techniques. But these methods are cumbersome and require a reliable estimate of the global motion. In extreme cases, when the background itself is highly dynamic, a unique global motion itself may not be possible to estimate. Another disadvantage of most current approaches is that they model the background explicitly and assume that the algorithm will initially be presented with frames containing only the background (Monnet et al., 2003; Stauer & Grimson, 1999; Zivkovic, 2004). The background model is built using this data, and regions

or pixels that deviate from this model are considered part of the target or foreground. Hence, these techniques are supervised, and the initial phase could be thought of as *training* the algorithm to learn the background parameters. The need to train such algorithms for each scene separately limits their ability to be deployed for automatic surveillance tasks, where manual re-training of the module to operate in each new scene is not feasible.

2. LITERATURE REVIEW

Aishwarya et al. [1] have created a unique method that might effectively detect speeding on roadways and encourage drivers to obey traffic laws by driving below the posted speed limitations. The proposed system includes RFID (Radio Frequency Identification), which allows the average speed to be 2023 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI) | 979-8-3503-1590-5/23/\$31.00 ©2023 IEEE | DOI: 10.1109/ACCAI58221.2023.10199888 calculated by measuring the time the vehicle needs to pass two consecutive readers, GSM (Global System for Mobile), which uses GSM technology to send the calculated speed and overspeed of the vehicle to the control room, and PIC (18F45K22). This method has delivered outcomes that are dependable, affordable, efficient, and timely. A reinforcement learning framework and a Kalman Filter that predicts positions were both supplied by Geist et al. [2]. The paper states that the issues of determining the precise location of bounding box in each frame for the stated item can be viewed as tracking the desired object inside the video material. By using video, Ginzburg et al. [3] created a technique for calculating the speed of autos. The created system has the following distinguishing characteristics: no accurate camera calibration is needed; minimal computing requirements for the computer evaluating the video sequence. This proposed system does not need to precisely detect the location of the camera in space, unlike other analogues. All that is needed is the camera suspension's measured height. The created system's ability to discern between the movement of just the vehicle's license plates rather than the full vehicle is one of its useful features. The study uses a system to identify moving items in videos, classify them, keep track of them, and determine their average speed. The system's error rate is 5%. A system for vehicle speed detection from video streams was created by

JozefGerat et al. [4] utilizing image processing techniques. It addresses the issue of vehicle speed detection using video record data and discusses the key techniques, including Gaussian mixture models, DBSCAN, Kalman filter, and optical flow. The architectural plan and a description of each segment's communication channels make up the implementation part. The conclusion includes testing of video recordings that were obtained utilizing various driving styles, vehicles, and vehicle positions at the recording. In order to overcome the object tracking issue, Kale et al. [5] combined a traditional optical-flow technique with motion vector estimates. Even without computing the quantitative characteristics, optical flow can provide important information about how an object moves. Motion vector estimation can be used to determine whether an object is present over multiple frames. This improves outcomes regardless of abnormalities like blurry images or busy backgrounds, which directly improves the algorithms' accuracy. A solid and dependable method for estimating vehicle speed was put out by Kassen N. et al. [6]. This provides the user with driving instructions and enables him to avoid being stuck in traffic. This strategy is RF-based. The generator of the radiofrequency current that is sent to the transmitting coil is a radiofrequency (RF) transmitter. In the frequency range from around 20 kHz to 300 GHz, radio frequency (RF) refers to the rate of oscillation of a magnetic, an alternating electric current or voltage, or of a mechanical system, or electromagnetic wave. Transmission rates range from 1 Kbps to 10 Kbps. An RF receiver, which uses the very similar frequency as the sender, receives the supplied data. In ordinary streets, this system has a speed estimation accuracy of 86% and a 78% average accuracy. A method to calculate the typical vehicle speed created for aerial video was put out by Ke et al. [7]. It tracks the object's movement between two succeeding frames using the optic flow method and the K-MEAN clustering algorithm. Using the data of the object's movement, the vehicle speed is calculated in picture scale before being translated to actual scale. and the length of one frame. This approach has a 12% error rate. For target detection, Li et al. [8] use the features fusion method. In their research, features are extracted from various PIR sensors (which employ a pair of pyroelectric sensors) utilizing symbolic dynamic filtering (SDF) are subsequently categorized as targets or

no-targets using several methods, including hierarchical agglomerative clustering, as K-means clustering, and spectral clustering. The literature extensively studies the classification of the PIR sensor readings using various machine learning methods. Because to their simplicity, the techniques support vector machines (SVM), K-nearest neighbors, and naive Bayes have drawn the attention of numerous academics. A machine learning strategy for object recognition that can analyze images very quickly and achieve greater detection capability than other strategies is described by Madasu et al. [9]. using digitized video taken with a stationary camera, to forecast traffic speed, the proposed method compares the vehicle position between the current frame and the previous frame. The camera device was calibrated using geometric equations. It demonstrated an overall accuracy of 83%. A brand-new vibration sensor device was put forward by Malik et al. [10], and it was mounted on the car. Vibration is activated in the event of a collision, and an infrared finder is used to locate the car. In order to retrieve the accident and find the culprit using a GPS locator, the incident was promptly documented to Patrol and Life Support. Researchers estimated vehicle speeds by incorporating accelerometer (measures vibration or acceleration of motion of a structure) readings over time and determining acceleration faults. Extensive testing was conducted to ensure that sensor speed is precise and strong in real-world driving environments. A method that uses a toolbox for image and video processing to determine vehicle speed was developed by Rad A. G. et al. [11]. Video sequences and photos with different resolutions might both be used by this system. A collection of workflow software and industry-standard algorithms for image analysis, evaluation, visualization, and algorithmic development is called the Image Processing Toolbox. In order to increase perspective vision and prepare the image for machine application, it is used to enhance visual input such as clarity, color, and brightness. An speed limit error of +7 km/h and -7 km/h was the outcome. Researchers Rangan P.R. et al. [12] created an Automatic Speed Detection System to assess a vehicle's speed and, if over-speeding occurs, retrieve the specific vehicle's plate number, and mail it to the toll booth for a fee. The speed in this case is computed using the observable Doppler Effect. If excessive speed is estimated, a camera will take a photo of the car and

employ. Using DIP (Digital Image Processing) methods, the license plate number is removed. Results demonstrated that the suggested designed system performs excellently, detects over-speeding vehicles, obtains the license number, and may be utilized to keep an eye out for them on roadways. A system to spot reckless driving on the highways and to notify the traffic authorities of any violations has been presented by Shabibi L. A. et al. [13] Many strategies demand human attention and involve numerous, difficult-to-implement tries. A buzzer, a control circuit, and an IR transmitter and receiver are required for the entire implementation. The voltage and resistivity of the photo-output diode vary proportionally to the quantity of IR light received. Some of the radiation that the IR transmitters emits is reflected back towards the Infrared sensor after the target is hit. With an IR Sender and IR Receiver, remote controllers are commonly used to remotely control electronic devices. If the car violates the traffic regulations, a buzzer sound alerts the police. For permanent magnet synchronous, Shedbalkar K. et al. [14] created a speed estimate method based on an enhanced Kalman filter. System is created using the SIMULINK model Blockset in MATLAB. A technique for solving the continuous form of Hidden Markov Models is the Kalman Filter. Latent variables are the subject of Hidden Markov. A Kalman filter is an algorithm that uses current position to forecast positions in the future. A method based on the optical flow method was developed by Shukla and Patel et al. [15] to identify the direction of object motion in video taken by a camera mounted above the road. Here, image processing is applied to all related frames as well as the generated displacement vectors. The center mass coordinates of each moving object are thus discovered. The gathered data is further examined before the estimated object motion is calculated. The height and tilt angle of the camera suspension must be determined prior to processing. The system determines the velocity of moving objects using computer vision technologies. This tactic has an 82% accuracy rate. In a sample movie, Wang [16] developed a method for moving target recognition based on which the relationship between actual distance and expressed in terms of pixels. This technique for recognizing moving targets is quite trustworthy. To extract features from the moving automobiles in the video, the system used background and three-frame

differencing. The vehicle centroid feature extraction technique was then used to track and position the vehicle.

3. PROPOSED METHODOLOGY

The proposed method is an approximate median filter-based method in Daubechies complex wavelet domain. It uses frame differencing for obtaining video object planes which gives the changed pixel value from consecutive frames. First, we decompose two consecutive frames (I_{n-1} and I_n) using complex wavelet domain and then apply approximate median filter based method to detect frame difference. Figure 1 shows the process steps in the proposed method.

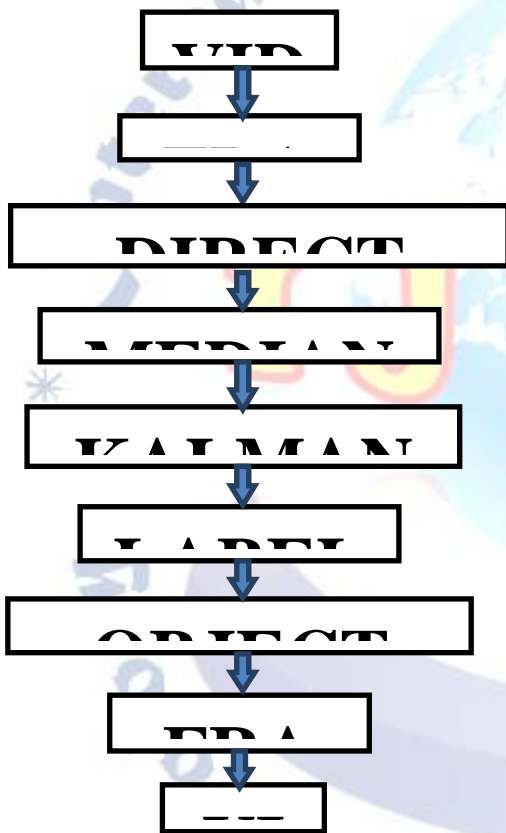


Figure 1: Process steps in the proposed method

Frame subtraction method:

We decompose two consecutive frames (I_{n-1} and I_n) using complex wavelet domain and then apply approximate median filter based method to detect frame difference For every pixellocation (i, j) _ the co-ordinate of frame of frame $I_n(i, j)$ and $I_{n-1}(i, j)$ respectively

$$FD_n(i, j) = WI_n(i, j) - WI_{n-1}(i, j) \quad (1)$$

Approximation median filter:

Median filtering is similar to using an averaging filter, in that each output pixel is set to an average of the pixel values in the neighborhood of the corresponding input pixel. However, with median filtering, the value of an output pixel is determined by the median of the neighborhood pixels, rather than the mean. The median is much less sensitive than the mean to extreme values (called outliers). Median filtering is therefore better able to remove these outliers without reducing the sharpness of the image.

Segmentation:

Discrete wavelet transforms

The continuous wavelet transform was computed by changing the scale of the analysis window, shifting the window in time, multiplying by the signal, and integrating over all times. In the discrete case, filters of different cutoff frequencies are used to analyze the signal at different scales. The signal is passed through a series of high pass filters to analyze the high frequencies, and it is passed through a series of low pass filters to analyze the low frequencies. The procedure starts with passing this signal (sequence) through a half band digital lowpass filter with impulse response $h[n]$. Filtering a signal corresponds to the mathematical operation of convolution of the signal with the impulse response of the filter. The convolution operation in discrete time is defined as follows:

$$x[n_2] * h[n_2] = \sum_{k=-\infty}^{\infty} x[k] \cdot h[n_2 - k]$$

Having said that, we now look how the DWT is actually computed: The DWT analyzes the signal at different frequency bands with different resolutions by decomposing the signal into a coarse approximation and detail information. DWT employs two sets of functions, called scaling functions and wavelet functions, which are associated with low pass and high pass filters, respectively. The decomposition of the signal into different frequency bands is simply obtained by successive high pass and lowpass filtering of the time domain signal. The original signal $x[n]$ is first passed through a half band high pass filter $g[n]$ and a lowpass filter $h[n]$. After the filtering, half of the samples can be eliminated according to the Nyquist's rule, since the signal now has a highest frequency of $\pi/2$ radians

instead of \otimes . The signal can therefore be subsampled by 2, simply by discarding every other sample. This constitutes one level of decomposition and can mathematically be expressed as follows:

$$y_{high}[k] = \sum_n x[n] \cdot g[2k - n]$$

$$y_{low}[k] = \sum_n x[n] \cdot h[2k - n]$$

where $y_{high}[k]$ and $y_{low}[k]$ are the outputs of the high pass and lowpass filters, respectively, after subsampling by 2.

This decomposition halves the time resolution since only half the number of samples now characterizes the entire signal. However, this operation doubles the frequency resolution, since the frequency band of the signal now spans only half the previous frequency band, effectively reducing the uncertainty in the frequency by half. The above procedure, which is also known as the subband coding, can be repeated for further decomposition. At every level, the filtering and subsampling will result in half the number of samples (and hence half the time resolution) and half the frequency band spanned (and hence double the frequency resolution). Figure 2 illustrates this procedure, where $x[n]$ is the original signal to be decomposed, and $h[n]$ and $g[n]$ are lowpass and high pass filters, respectively. The bandwidth of the signal at every level is marked on the figure as "f".

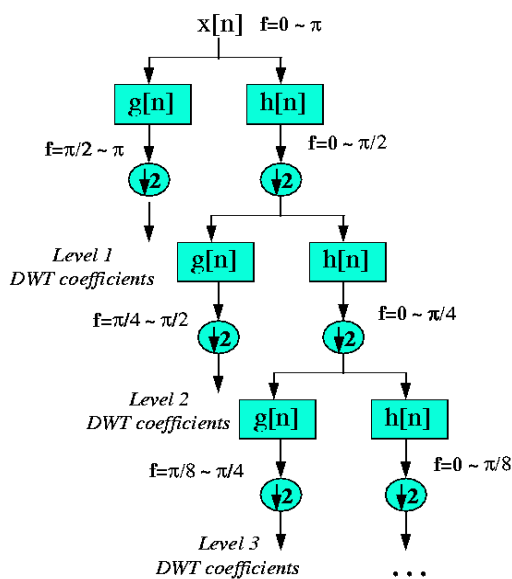


Figure 2: The Decomposition Process

The Subband Coding Algorithm

As an example, suppose that the original signal $x[n]$ has 512 sample points, spanning a frequency band of zero to π rad/s. At the first decomposition level, the signal is passed through the high pass and lowpass filters, followed by subsampling by 2. The output of the high pass filter has 256 points (hence half the time resolution), but it only spans the frequencies $\pi/2$ to π rad/s (hence double the frequency resolution). These 256 samples constitute the first level of DWT coefficients. The output of the lowpass filter also has 256 samples, but it spans the other half of the frequency band, frequencies from 0 to $\pi/2$ rad/s. This signal is then passed through the same lowpass and high pass filters for further decomposition.

The output of the second lowpass filter followed by subsampling has 128 samples spanning a frequency band of 0 to $\pi/4$ rad/s, and the output of the second high pass filter followed by subsampling has 128 samples spanning a frequency band of $\pi/4$ to $\pi/2$ rad/s. The second high pass filtered signal constitutes the second level of DWT coefficients. This signal has half the time resolution, but twice the frequency resolution of the first level signal. In other words, time resolution has decreased by a factor of 4, and frequency resolution has increased by a factor of 4 compared to the original signal. The lowpass filter output is then filtered once again for further decomposition. This process continues until two samples are left. For this specific example there would be 8 levels of decomposition, each having half the number of samples of the previous level. The DWT of the original signal is then obtained by concatenating all coefficients starting from the last level of decomposition (remaining two samples, in this case). The DWT will then have the same number of coefficients as the original signal.

Kalman Filter:

Kalman filtering, also known as linear quadratic estimation (LQE), is an algorithm that uses a series of measurements observed over time, containing statistical noise and other inaccuracies, and produces estimates of unknown variables that tend to be more precise than those based on a single measurement alone. The Kalman filter has numerous applications in technology. A common application is for guidance, navigation and control of vehicles, particularly aircraft and spacecraft. Furthermore, the Kalman filter is a widely applied concept in time series analysis used in fields such as

signal processing and econometrics. Kalman filters also are one of the main topics in the field of robotic motion planning and control, and they are sometimes included in trajectory optimization. The Kalman filter has also found use in modeling the central nervous system's control of movement. Due to the time delay between issuing motor commands and receiving sensory feedback, use of the Kalman filter provides the needed model for making estimates of the current state of the motor system and issuing updated commands.

The Kalman filters are based on linear dynamic systems discretized in the time domain. They are modelled on a Markov chain built on linear operators perturbed by errors that may include Gaussian noise. The state of the system is represented as a vector of real numbers. At each discrete time increment, a linear operator is applied to the state to generate the new state, with some noise mixed in, and optionally some information from the controls on the system if they are known. Then, another linear operator mixed with more noise generates the observed outputs from the true ("hidden") state

The Kalman filter model assumes the true state at time k is evolved from the state at $(k - 1)$ according to

$$\mathbf{x}_k = \mathbf{F}_k \mathbf{x}_{k-1} + \mathbf{B}_k \mathbf{u}_k + \mathbf{w}_k$$

Where \mathbf{F}_k is the state transition model which is applied to the previous state \mathbf{x}_{k-1} ; \mathbf{B}_k is the control-input model which is applied to the control vector \mathbf{u}_k ; \mathbf{w}_k is the process noise which is assumed to be drawn from a zero mean multivariate normal distribution with covariance \mathbf{Q}_k .

$$\mathbf{w}_k \sim \mathcal{N}(0, \mathbf{Q}_k)$$

At time k an observation (or measurement) \mathbf{z}_k of the true state \mathbf{x}_k is made according to

$$\mathbf{z}_k = \mathbf{H}_k \mathbf{x}_k + \mathbf{v}_k$$

where \mathbf{H}_k is the observation model which maps the true state space into the observed space and \mathbf{v}_k is the observation noise which is assumed to be zero mean Gaussian white noise with covariance \mathbf{R}_k .

$$\mathbf{v}_k \sim \mathcal{N}(0, \mathbf{R}_k)$$

Many real dynamical systems do not exactly fit this model. In fact, unmodelled dynamics can seriously degrade the filter performance, even when it was supposed to work with unknown stochastic signals as inputs. The reason for this is that the effect of unmodelled dynamics depends on the input, and, therefore, can bring the estimation algorithm to instability (it diverges). On the other hand, independent white noise signals will not make the algorithm diverge. The problem of separating between measurement noise and unmodelled dynamics is a difficult one and is treated in control theory under the framework of robust control.

Bounding Box Creation

we find the cluster of the moving pixels. Afterwards, we surround that moving cluster into bounding box for each moving vehicle in each frame as shown in figure we generate the centroid for every bounding box detected. Centroid will help us to reference each vehicle

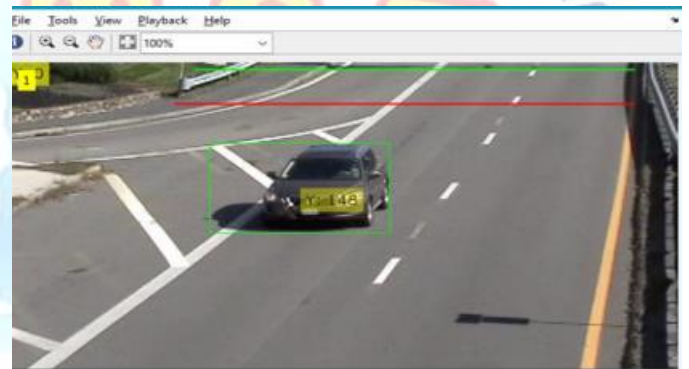


Figure 3: Bounding Box Creation over detected object

Speed Calculation

In the proposed method, first we have to identify each vehicle in the video and then find their corresponding distance covered in consecutive frames. The proposed method tracks each vehicle and traces their centroid in upcoming frames to get the distance travelled by that vehicle. When vehicles arrive into the region of interest, in the video, their corresponding bounding boxes are created and then centroid of the each bounding box is generated. For every new vehicle arrival, we store its centroid value to the track. In addition, we update its centroid value in upcoming frames, and keep on updating its tracked value of centroid until that vehicle passes out by the video. We track all vehicles in a video

simultaneously. Moreover, we store their centroid values into the track structure that we have created. The speed of each identified vehicle is calculated as:

$$\text{Speed} = \frac{\text{Observed Distance}}{\text{framecount} / \text{fps}}$$

Total_frames are the number of frames traversed over the distance. The speed is calculated in the number of pixel travelled per second unit, and then we change it into the km/hr unit by taking the actual distance measure of the area covered by the camera view.

4. RESULTS & DISCUSSION

The area where system has to be installed needs to be first analyzed and the physical distance between initial entering position (the first frame where the camera detects the vehicle) and final exiting position (the last frame of detection) needs to be calculated and stored in the system's. The proposed system requires configuring of inputs such as camera height, initial position from camera, final position from object and speed detection by used MATLAB 8.10 v

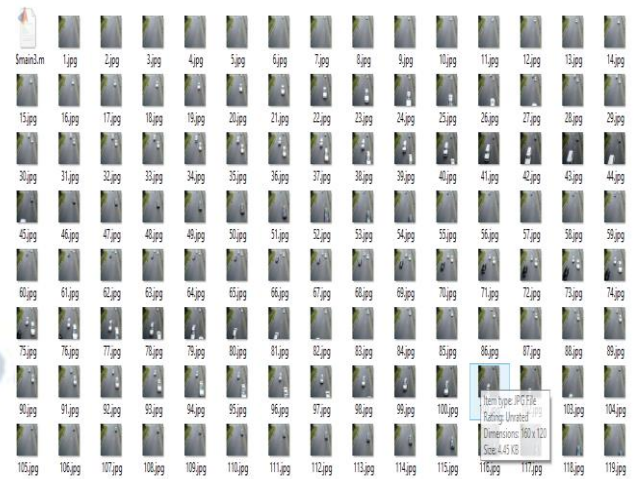


Figure 5: Video divided into frames

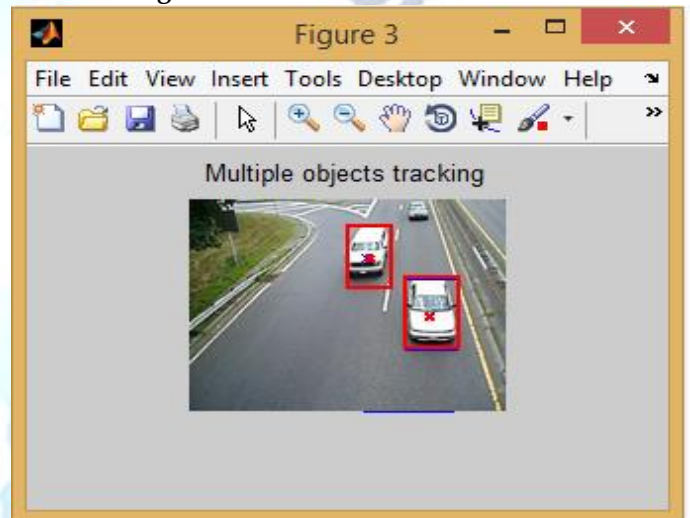


Figure 6: Labeling the detected car and show the number of the cars

After detection of the cars the calculation of speed will start considering two different factors. The first factor is the position of the car, position of the car means the car localize in specific track.

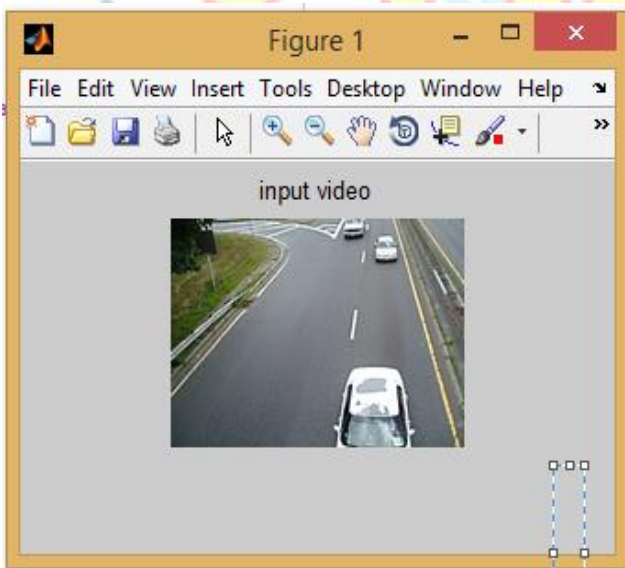


Figure 4: Input video Consider one input video in the traffic

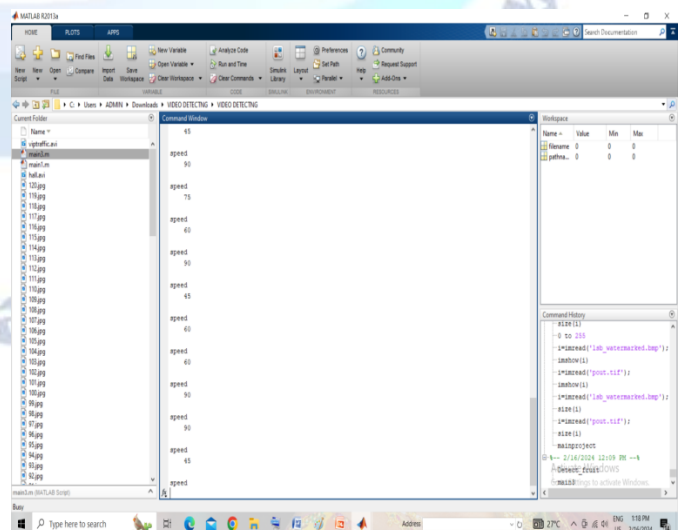


Figure 7: Speed calculation by using static frame rate for moving of object

The accuracy of detection calculated according to the comparison the human decision and the result of the program. The accuracy is given according to the formula:

$$accuracy = \frac{\text{calculated speed}}{\text{actual speed}} * 100\%$$

The second calibration test is to optimize the parameters to increase the accuracy of the measurement the speed of the car, that test consider three different parameters the first parameter is the distance that the car passed and the second parameter is the execution time of processing and the third on is the accuracy of the speed measurement. Table 1 shows the relation between the three parameters.

Table 1: Parameters analysis for speed measurement

Distance	Execution Time	Actual speed (km/h)
3 meters	0.051	65
3.5 meters	0.061	65
4 meters	0.063	65
5 meters	0.069	65
5.5 meters	0.072	65
6.5 meters	0.062	65
7 meters	0.068	65
8 meters	0.058	65

The accuracy of speed measurement calculated according to the comparison the speed of the car using proposed algorithm with the real speed of the car.

4. CONCLUSIONS

A speed detection camera system has been developed to measure the speed of vehicles on the highways. The proposed system is capable to identify target vehicles in the presence of partial occlusions and ambiguous poses, and the cluttered background. The proposed method is capable to detect multiple vehicles simultaneously by drawing the surrounding bounding box. Experimental results show that the proposed model gives relatively good performance. The accuracy of counting vehicles is 94%, although the vehicle detection was 100% in the

presence of partial occlusions. The proposed method has a limitation that it fails when two vehicles are merged together and system treat them as a single entity. The future work will focus to overcome this limitation and to estimate speed on real-time live video sequences.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

REFERENCES

- [1] Aishwarya et al. S. R. (2015), "An IoT Based Accident Prevention & Tracking System for Night Drivers", International Journal of Innovative Research in Computer and Communication Engineering, 3 (4), pp. 3493-3499.
- [2] Geist M., O. Pietquin, and G. Fricout. Tracking in reinforcement learning. In International Conference on Neural Information Processing, pages 502–511. Springer, 2009.
- [3] Ginzburg, C., Raphael, A., Weinshall, D., 2015. A cheap system for vehicle speed detection. arXiv: 1501.06751. Google Colab, 2020. Available at: <https://colab.research.google.com/> (accessed May 21, 2020).
- [4] JozefGerat, Dominik Sopiak, M. Oravec, J. Pavlovičová Computer Science "Vehicle speed detection from camera stream using image processing methods" 2017 International Symposium ELMAR 2017.
- [5] Kale K., S. Pawar, and P. Dhulekar. Moving object tracking using optical flow and motion vector estimation. In Reliability, Infocom Technologies and Optimization (ICRITO) (Trends and Future Directions), 2015 4th International Conference on, pa1–6. IEEE, 2015.
- [6] Kassem N, A. E. Kosba and M Youssef (2012), " RF-Based Vehicle Detection and Speed Estimation, ", IEEE 75th conference on Vehicular Technology, pp-1-5.
- [7] Ke, R., Kim, S., Li, Z., Wang, Y., 2015. Motion-vector clustering for traffic speed detection from UAV video. 2015 IEEE First International Smart Cities Conference (ISC2). Guadalajara, Mexico, 1–5. DOI: 10.1109/ISC2.2015.7366230.
- [8] Li, C.; Xu, P. Application on traffic flow prediction of machine learning in intelligent transportation. Neural Comput. Appl. 2021, 33, 613–624.
- [9] Madasu V and M. Hanmandlu, "Estimation of vehicle speed by motion tracking on image sequences," in IEEE Intelligent Vehicles Symposium, 2010, pp. 185–190.
- [10] Malik et al. (2014), "Automated Over Speeding Detection and Reporting System", IEEE Xplore, pp. 1-7.
- [11] A. G. Rad, A. Dehghani, and M. R. Karim. Vehicle speed detection in video image sequences using cvs method. International Journal of Physical Sciences, 5(17):2555–2563, 2010.
- [12] Rangan P. R. (2017), "Vehicle Speed Sensing and Smoke Detecting System", International Journal of Computer Science and Engineering, pp.27-33.
- [13] Shabibi L. A., Jayaraman N. and Vrindavanam J. (2014), "Automobile Speed Violation Detection System using RFID and

- GSM Technologies", *International Journal of Applied Information Systems*, Vol. 7, No. 6, pp. 24-29.
- [14] Shedbalkar K, A P Dhamangaonkar and A B Patil," Speed estimation using extended Kalman filter for PMSM", *IEEE conference on Emerging Trends in Electrical Engineering and Energy Management (ICETEEEM)*, 2012, pp-433 to 435.
- [15] Shukla, D., Patel, E., 2013. Speed determination of moving vehicles using Lucas-Kanade algorithm. *International Journal of Computer Applications Technology and Research* 2 (1), 32–36. DOI: 10.7753/IJCATR0201.1007.
- [16] Wang J.-x. Research of vehicle speed detection algorithm in video surveillance. In *Audio, Language and Image Processing (ICALIP)*, 2016 International Conference on, pages 349–352. IEEE, 2016.
- [17] Ravikiran, D. N., & Dethe, C. G. (2018). Improvements in Routing Algorithms to Enhance Lifetime of Wireless Sensor Networks. *International Journal of Computer Networks & Communications (IJCNC)*, 10(2), 23-32.
- [18] Ravikiran, D. N., & Dethe, C. G. Fuzzy Rule Selection using LEACH Algorithm to Enhance Life Time in Wireless Sensor Networks. *Advances in Wireless and Mobile Communications*. ISSN, 0973-6972.
- [19] Rajesh, G., Thommandru, R., & Subhani, S. M. DESIGN AND IMPLEMENTATION OF 16-BIT HIGH SPEED CARRY SELECT PARALLEL PREFIX ADDER.
- [20] Polanki, K., Purimetla, N. R., Roja, D., Thommandru, R., & Javvadi, S. Predictions of Tesla Stock Price based on Machine Learning Model.
- [21] Thommandru, R. A PROSPECTIVE FORECAST OF BRAIN STROKE USING MACHINE LEARNING TECHNIQUES.
- [22] Rajesh, G., Raja, A., & Thommandru, R. OPTIMIZATION OF MINIATURIZED MICROSTRIP PATCH ANTENNAS WITH GA.
- [23] Vellela, S. S., & Balamanigandan, R. (2022, December). Design of Hybrid Authentication Protocol for High Secure Applications in Cloud Environments. In *2022 International Conference on Automation, Computing and Renewable Systems (ICACRS)* (pp. 408-414). IEEE.
- [24] Vellela, S. S., & Balamanigandan, R. (2024). Optimized clustering routing framework to maintain the optimal energy status in the wsn mobile cloud environment. *Multimedia Tools and Applications*, 83(3), 7919-7938.
- [25] Praveen, S. P., Sarala, P., Kumar, T. K. M., Manuri, S. G., Srinivas, V. S., & Swapna, D. (2022, November). An Adaptive Load Balancing Technique for Multi SDN Controllers. In *2022 International Conference on Augmented Intelligence and Sustainable Systems (ICAISS)* (pp. 1403-1409). IEEE.
- [26] Priya, S. S., Vellela, S. S., Reddy, V., Javvadi, S., Sk, K. B., & Roja, D. (2023, June). Design And Implementation of An Integrated IOT Blockchain Framework for Drone Communication. In *2023 3rd International Conference on Intelligent Technologies (CONIT)* (pp. 1-5). IEEE.
- [27] Vellela, S. S., & Balamanigandan, R. An intelligent sleep-awake energy management system for wireless sensor network. *Peer-to-Peer Netw. Appl.*(2023).
- [28] Addepalli, T., Babu, K. J., Beno, A., Potti, B. M. K., Sundari, D. T., & Devana, V. K. R. (2022). Characteristic mode analysis of two port semi-circular arc-shaped multiple-input-multiple-output antenna with high isolation for 5G sub-6 GHz and wireless local area network applications. *International Journal of Communication Systems*, 35(14), e5257.
- [29] Srija, V., & Krishna, P. B. M. (2015). Implementation of agricultural automation system using web & gsm technologies. *International Journal of Research in Engineering and Technology*, 04 (09), 385-389.
- [30] Potti, D. B., MV, D. S., & Kodati, D. S. P. (2015). Hybrid genetic optimization to mitigate starvation in wireless mesh networks. *Hybrid Genetic Optimization to Mitigate Starvation in Wireless Mesh Networks*, *Indian Journal of Science and Technology*, 8(23).
- [31] Potti, B., Subramanyam, M. V., & Prasad, K. S. (2013). A packet priority approach to mitigate starvation in wireless mesh network with multimedia traffic. *International Journal of Computer Applications*, 62(14).
- [32] Potti, B., Subramanyam, M. V., & Satya Prasad, K. (2016). Adopting Multi-radio Channel Approach in TCP Congestion Control Mechanisms to Mitigate Starvation in Wireless Mesh Networks. In *Information Science and Applications (ICISA) 2016* (pp. 85-95). Springer Singapore.
- [33] S Phani Praveen, Sai Srinivas Vellela, Dr. R. Balamanigandan, "SmartIris ML: Harnessing Machine Learning for Enhanced Multi-Biometric Authentication", *Journal of Next Generation Technology* (ISSN: 2583-021X), 4(1), pp.25-36 . Jan 2024.