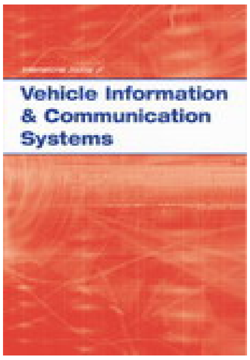

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An automatic moving vehicle detection system based on hypothesis generation and verification in a traffic surveillance system

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An automatic moving vehicle detection system based on hypothesis generation and verification in a traffic surveillance system

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Abstract: An intelligent transportation system has a major topic called traffic surveillance. In a complex urban Traffic Surveillance System (TSS), booming of vehicle detection and tracking is a dilemma. To overcome the problem, a two stage approach for moving vehicle detection system is proposed in this paper. The proposed system mainly consists of two stages namely, Hypothesis Generation (HG) and Hypothesis Verification (HV). At the first step, hypotheses are generated by shadows beneath the vehicles is darker than the road region concept. In the second step a generated hypothesis is verified as correct or not using Optimal Artificial Neural Network (OANN). The weights corresponding ANN is optimally selected using Grasshopper Optimisation Algorithm (GOA). Through experimental results, it is shown that the proposed moving vehicle detection system has better accuracy compared to other methods.

Keywords: traffic surveillance system; moving vehicle detection; tracking; hypothesis generation; hypothesis verification; feedforward neural network; grasshopper optimisation algorithm.

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1 Introduction

The main objective of Intelligent Transportation System (ITS) is to boost urban security, lower traffic congestion, enhance driving and transport info, develop cost nest egg for motor shippers and accident drivers, lower detrimental substantial brunt, etc. Owing to the increase in appeal of surface transportation system, the states, cities, and towns nationwide get help from the ITS automation. Based on the performance and extensiveness of vehicle detection technology, the capability of the ITS system is determined. Vehicle exposures as well as tracing are the ingredients for any vehicle detection technology, as it collects entire or a section of data from an active ITS (Chintalacheruvu and Muthukumar, 2012). It is the most moving undertaking to plan a framework that is fit for distinguishing vehicles ahead, moving in a similar course, for example, a car, by following them constantly with an in-vehicle camcorder. The major issue here is to recognise the vehicles in dynamic surroundings and brightness (Rosenberg and Weman, 1998).

Moreover, to reduce the traffic collision is the critical task which can be assumed by a vision-based vehicle detection framework under the automatic driving framework. Various vehicle under vision based are distinguished in proof systems using a single camera have been proposed and a run of the mill structure includes two phases, i.e., (HG and HV adventures to diminish computational time and achieve ongoing handling (Sun et al., 2002). Three techniques are been utilised by the HG step: strategy under information, strategy under stereo vision alternatively technique under movement. For identifying the hypotheses size in the area of object and protests, the strategy under learning utilises trademark data, e.g., symmetry (Kuehnle, 1991), corners (Jazayeri et al., 2011), shadows (Tzomakas and von Seelen, 1998), edges (Matthews et al., 1996), surfaces (Haralick et al., 1973), and beams of vehicle (Zhang et al., 2012). At present, two kinds of techniques under stereo in distinguishing vehicles. Among them one technique utilises a different map (Mandelbaum et al., 1998), where another strategy utilises an Inverse Perspective Mapping technique (Arrospide and Salgado, 2012). The strategy under movement removes the hypotheses utilising visual stream aside getting their respective movements: moving toward vehicles deliver separating stream during overwhelming vehicles create assemble stream (Sun et al., 2006).

Vehicle identification utilising passive optical sensors includes a few difficulties. Comparatively, with respect to body, capacity, and shading, the vehicles can vary. A particular vehicle existence may rely on its position and is influenced by close-by objects. Complex open-air situations (e.g., light conditions, the unpredictable interaction between traffic members, jumbled foundation) can't be controlled. On-board moving cameras make some entrenched procedures, for example, foundation subtraction, very unacceptable. Besides, onboard vehicle discovery frameworks have strict limitations on computational cost. They ought to have the capacity to process obtained pictures continuously or close to real-time, keeping in mind the end goal to spare more opportunity for driver's response (Jazayeri et al., 2011). The hypotheses are arranged as vehicle one or other, where hypotheses are produced in the initial step of HV step. Highlight extraction and classification are the two notable operations are required in the progression. HoG features (Yuan et al., 2011), Haar-like features (Sivaraman and Trivedi, 2010), edge features (Lin et al., 2012) and optical flow (Jazayeri et al., 2011) are some of the features to detect vehicle which was utilised by the current techniques.

The main objective of the proposed methodology is to moving vehicle detection system using two stages. In this first stage, generate hypotheses based on shadow under using shadows under vehicles is darker than the road region concept. After that, we verify the hypotheses generated objects are a vehicle or not using multiple stages. In this hypotheses verification, at first, select the features using two types of Histogram Orientation Gradients (HOG). After that, we train the feature vector using OANN classifier. Theweights corresponding FFNN is optimally select using Grasshopper Optimisation Algorithm (GOA). After the training process, the hypotheses generated objects are given to OANN classifier which will check the given object is vehicle or not. The main contribution of the work is summarised below;

- We perform hypotheses generation for real-time traffic video scene using shadow under the vehicle is dark and followed by intensity thresholding and morphological discrimination.
- We perform hypotheses verification using OANN classifier which provides better accuracy output.
- We design an OANN classifier with the help of Grasshopper optimisation algorithm which is optimally select the weight value in the training stage.
- We perform broad recreation on the proposed calculation, contrast and break down outcomes and existing and related calculations.

In Section 2, a short study related to object detection techniques is discussed in the rest of the paper. In Section 3, the proposed vehicle detection system is described and in Section 4, empirical conclusion and work appraisal have been discussed. In Section 5, the outcome has been summarised.

2 Literature survey

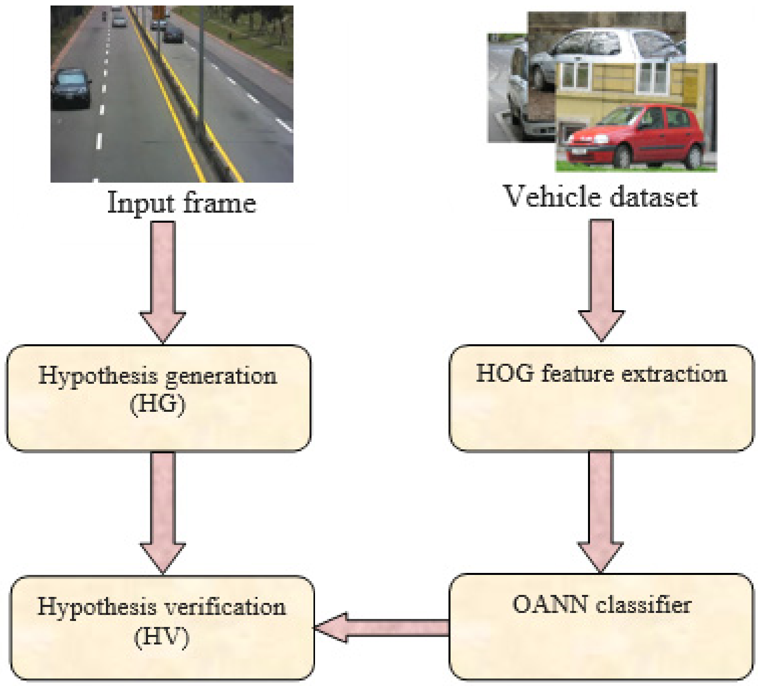
Several methods have been proposed by the related work over vehicle tracking. Following are the most recently published work over vehicle tracking; Kuo et al. (2011) explained the vision-based vehicle identification for driver assistance framework by utilising PC vision advancements. In addition, Wang et al. (2016) clarified a Vision-based two-step brake recognition technique for vehicle impact shirking. The brake behavior location of this work comprises of two methods, brake lights district identification and brake behavior decision. Moreover, Chong et al. (2013) explained Vehicle detection in the urban road by integrated real-time vision-based preceding. It shows that the answer calculation for the constant process of vision-based preceding vehicle location frameworks. The design has fundamental parts: Vehicle Discovery and Vehicle follow.

Kumar and Kushwaha (2016) clarified identification rate of motion appraisal moving the vehicle by utilising a solitary camera in sunlight or legitimately enlightened condition. This approach distinguishes and follows the vehicle going over observation region; in addition, the document of vehicle area is maintained. Besides, Wong et al. (2016) clarified moving objects discovery for vehicles utilising movement vector calculation. Moving things were perceived by surveying the planar parallax residuals of macroblocks in the video. Also, Zhang and Knoll (2016) clarified Based on Probability Hypothesis Density Filter Vehicle Discovery. By using cameras, vehicles were recognised by the Regions of Interest (ROI) in complicated situations. Besides, Tian et al. (2014) clarified back view vehicle discovery and following by consolidating various parts for complex urban reconnaissance. Rear-view vehicle identification and following strategy in view of various vehicle striking parts utilising a static camera. They demonstrate the dimensional displaying vehicle parts were pivotal as general execution. To begin with, the vehicle was dealt with as a protest made out of different notable parts, including the tag and backlights. The above mentioned methods are good for moving vehicle detection system. Even though, these methods have some of the common difficulties such as results in less accuracy, reliability, illumination factors and misclassification. To overcome the problem, an efficient automatic moving vehicle detection system is proposed to improve the classification accuracy which is used to reduce the traffic and accident.

3 Proposed moving vehicle detection system

The main objective of this paper is to detect the moving vehicles to reduce the traffic and accident on roads. Vehicle location in rush hour gridlock scenes is a significant issue in driver help frameworks and independently directed vehicles. To overcome the issue, the two-stage approach for the vehicle detection system has been proposed in this paper. HG and HV are the two stages in the proposed system. Two phases are significant and challenging. In the main stage, potential vehicles are guessed and in the second stage, all speculations are checked and grouped into vehicle or non-vehicles. The point of our proposed vehicle location framework is to avoid car crashes by distinguishing encompassing vehicles in street pictures taken by a camera introduced in a moving vehicle. The general design of our projected methodology was given below.

Figure 1 Proposed moving vehicle system



3.1 Hypothesis generation

In vehicle detection system Hypothesis Generation (HG) is the main process. The principle reason for the HG is to remove vehicle hypotheses from street pictures. In the HG step, speculations that are competitor vehicles are extricated from a street picture utilising shadow locales showing up under vehicles. From this paper, at first, to generate the hypothesis of vehicle areas outside of the road picture, shadow regions should be extracted. Here, hypotheses are generated under the basis of the screened region below the road extent the vehicle has lack of light forever. After detecting the lack of light underneath a vehicle, a region above the lack of light is considered as an ROI. One more important thing is illumination significantly affect the shadows because in bright and hazy the gray level of the shadow may differ. To set an adaptive threshold is essential for extracting the extent of shadow region. There is no lower limit for the force of the shadow underneath a vehicle yet dependent on the power dispersion of the street surface, an upper limit can be characterised for it, despite the fact that it won't be fixed. The estimation of this limit relies upon the shade of the outside of the street and its light. After the vehicle recognition, we apply the Sobel activity for extricating the edges of the ROI and after that expelling the zones legitimately over the edges. The rest of the district of the picture is the free road region. A Gaussian distribution is satisfied by assuming distribution of the gray level of the road which is given in equation (1). Here, by setting the upper bond of the shadow to $Th = \mu - 3\sigma$. The ROI $R(x, y)$ is extracted using equation (2).

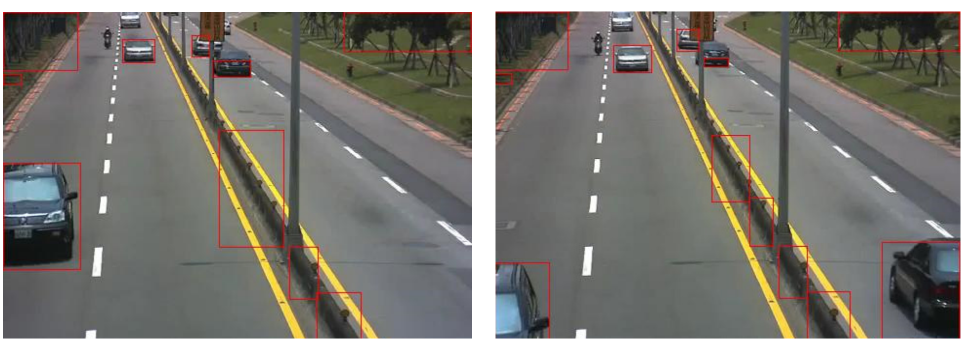
$$f(x)=\frac{1}{\sqrt{2\Pi}\,\sigma}e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{1}$$

$$R(x,y)=\begin{cases}1\ , & I(x,y)>T_h\\ 0\ , & else\end{cases} \tag{2}$$

where the standard deviation is σ, the average of gray values is μ, the input image is $I(x,y)$. After by extracting the process, we have to apply the morphological method to $R(x,y)$ which makes the shadow areas more notable.

Figure 2 Shadow-based Hypothesis generation (1) input frame and (2) detected an object

(1)

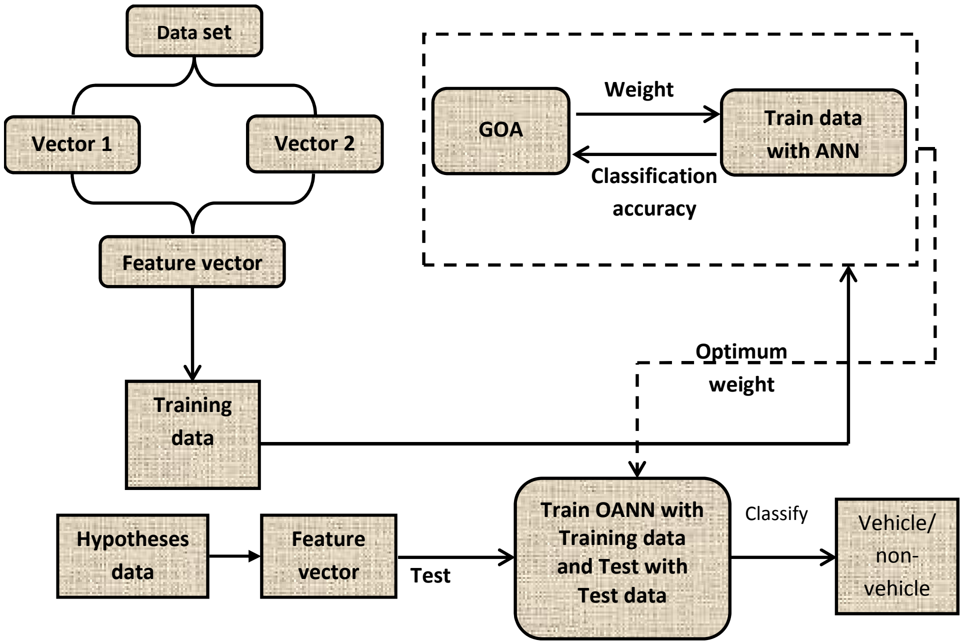


(2)

3.2 *Hypothesis verification*

In the HV steps, hypotheses separated in the HG step are checked as either to those are vehicles instead of by using a classifier and feature vectors. The hypotheses verification process is given in Figure 3. For hypotheses verification, three steps are available such as (i) feature extraction, (ii) training using OANN and (iii) verification process.

Figure 3 The proposed hypotheses verification process



3.3 Feature extraction

It is an important level in hypotheses verification stage. In this paper, we utilise the Histogram Orientation Gradients (HOG) descriptors for feature vector generation. In vision-based target object detection fields HOG is a well-known feature. Assume a data set *D* which has n number of traffic vehicle images. In this stage, we calculate the feature vector for all the images present in the data set. These feature vectors are further used for the training process. The step by step HOG feature vector extraction process is explained below;

Step 1: Examine the size of the image I as 64 × 64 which is present in the traffic vehicle data set "*D*". At first, the image is separated into small area ("cells") and combining many cells forming a block.

Step 2: Then, from every cell collect a histogram of gradient orientations.

Step 3: After that, we integrate and order the histogram in identical blocks.

Step 4: Then, we obtain a histogram of the block in step (3).

Step 5: Then, consider the next block and repeat the steps (3) and (4).

Step 6: Finally, we combine these block histograms into one vector.

The slopes of vehicle pictures are for the most part scattered in even and vertical bearings. This is recognisable in light of the fact that the vehicle's windows, wheels, and shapes contribute on a very basic level to the inclinations. So, we independently calculate the features and lastly, we join the vertical and horizontal features. The final feature vector is given in equation (3).

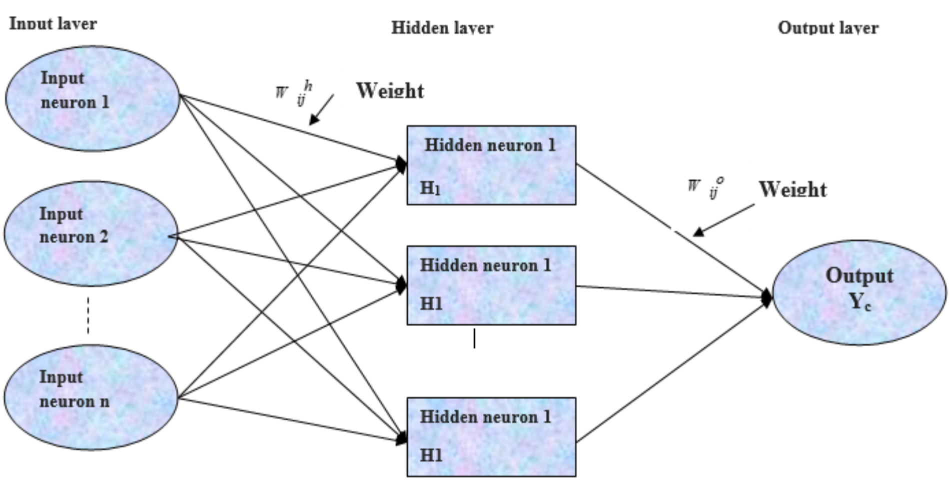
$$Feature\ vector = \begin{pmatrix} vector\ 1 \\ vector\ 2 \end{pmatrix} \tag{3}$$

Where Vector 1 and Vector 2 speak to the horizontal and vertical HOG includes separately, and last vector is Vector. This final vector is used for further processing.

3.4 Training using OANN

After the HoG feature vector generation, extracted features are given to the OANN classifier which is used to train the combined feature vectors. In this paper, we utilise two parts of the database for experimentation. The initial one is the GTI vehicle database, which is utilised to prepare the classifier and the second one is genuine traffic scenes which are utilised for speculation age and testing the classifier. The training phase at first, the extracted features are likely to the artificial neural network. Based on the number of features, the classifier identified given object is vehicle or non-vehicle. In this paper, we utilise ANN classifier for training feature vector. The traditional artificial neural networks are modified by means of grasshopper optimisation Algorithm is called OANN. To optimise the value of weight of the neural network, Grasshopper optimisation Algorithm (Saremi et al., 2017) is obtained. The main objective of OANN is categorising the input features into vehicles or non-vehicles. In Figure 4, the overall structure of artificial neural network has been shown.

Figure 4 Overall Structure of ANN classifier



Let us consider vector $\{S_1, S_2, ..., S_a\}$ represents the value of input nodes, vector $\{H_1, H_2, ..., H_b\}$ represents the value of hidden nodes and $\{Y_1, Y_2, ..., Y_c\}$ represents the value of output nodes. stands for weight associated, where *i* is the input layer node and *j* is the secret layer node, W^{o}_{jk} stand for weight connecting *j* and *k* as an output node. The training process is explained below;

Step 1: At first, we develop the neural network with the input data as the input units *S*, Hidden units H and an output unit Y .

Step 2: Then, we given the feature vector to input nodes $\{S_1, S_2, ..., S_a\}$ and fix weight for every neuron's present in the ANN structure except the input layer that has neurons.

Step 3: After that, in each node *i*, we multiply the input layer value S_i by comparing the weight value between the input layer and the hidden layer w^{h}_{ij} . Here, we obtain the hidden neuron input value H_j. According to equation (4), we calculate the H_j.

$$H_j = \sum_{i=1}^{a} S_i * w^{h}_{ij} \tag{4}$$

The tansig activation function is used to process the H_j using equation (5).

$$F(x) = \frac{1}{1+e^{-x}} \tag{5}$$

$$F\left(H_j\right) = \frac{1}{1+e^{-\left(H_j\right)}} \tag{6}$$

Step 4: After the hidden layer calculation, we have to calculate the output value given input data.

Now, in every *j* node, the hidden layer has a value H_j as the output is multiplied between input with the weighted value of the hidden layer and an output layer w^{o}_{jk} we obtain the output Y_k.

$$_k = \sum_{j=1}^{b} w^{o}_{jk} F\left(H_j\right) \tag{7}$$

$$F\left(Y_k\right) = \frac{1}{1+e^{-(Y_k)}} \tag{8}$$

Step 5: After the output layer calculation, the error of the output node has to be calculated. Then, the error of the output node is calculated using equation (9).

$$E = \frac{1}{2} \sum_{k=1}^{c} \left(T_k - Y_k\right)^2 \tag{9}$$

Where T_k represents the target value and Y_k represent the output value. To minimise the output error value, in this paper, we optimally find the weight value. If the error value is less; we obtain the maximum classification accuracy.

Step 6: Weight optimisation using GOA

The is to minimise the error value of the neural network; we optimally calculate the weight value using GOA. Weight optimisation is explained below;

Solution encoding: The weights in the neural network are encoded as a list of real numbers. In this structure, two weights are available such as hidden neuron weight W_{ij}^h and output neuron weight W_{jk}^o. The initial solution (weights) representation is given in Figure 5.

Figure 5 Initial solution format

W_{11}	W_{12}	....	W_{1n}	W_{21}	W_{22}	....	W_{2n}

Dimension of the hidden neuron weight W_{ij}^h **Dimension of the output neuron weight** W_{jk}^o

Fitness calculation: Then we calculate the objective function or fitness function to each solution using the error function given in equation (10).

$$E = \frac{1}{2}\sum_{k=1}^{c}\left(T_k - Y_k\right)^2 \tag{10}$$

where T_k represents the target value and Y_k represent the predicted output.

Updation using grasshopper optimisation: The solution based on the grasshopper optimisation algorithm, is updated after calculating the fitness value.

$$X_i = S_i + G_i + A_i \tag{11}$$

i.e., X_i represents i-th grasshopper position; social interaction is represented as S_i gravity force on the i-th grasshopper is represented as G_i and the wind advection represents A.

$$S_i = \sum_{\substack{j=1 \\ j\neq i}}^{N} s\left(d_{ij}\right)\hat{d}_{ij} \tag{12}$$

$$d_{ij} = \left|X_j - X_i\right| \tag{13}$$

$$\hat{d}_{ij} = \frac{X_j - X_i}{d_{ij}} \tag{14}$$

Distance between the i-th and the j-th grasshopper is represented as d_{ij} and s represents the strength of the social force. The gravity force (G_i) is calculated using equation (15).

$$G_i = -g\hat{e}_g \tag{15}$$

Gravitational constant g and $\hat{e}_g$ demonstrates the unity vector towards the centre of the earth. Wind advection A_i is determined using equation (16).

$$A_i = u\hat{e}_w \tag{16}$$

Constant drift is represented as u and unit vector in the direction of the wind as $\hat{e}_w$. The alternative values such as S, G and A in equation (17).

$$X_i = \sum_{\substack{j=1 \\ j\neq i}}^{N} s\left(\left|X_j - X_I\right|\right)\frac{X_j - X_i}{d_{ij}} - g\hat{e}_g + u\hat{e}_w \tag{17}$$

A number of grasshoppers are N and $s(r) = f\, e^{\frac{-r}{l}} - e^{-r}$. By equating (17), the solution can be updated.

Termination: The calculation ends its execution just if a most extreme number of cycles is accomplished and the nest which is holding the best wellness esteem is chosen and it is given as the best weight estimation of ANN model.

Step 7: The optimised load value is given to the neural network. Finally, the trained structure is stored.

3.5 Verification process

In the testing process, we verify that we detected an object which is obtained from the HG step is vehicle or not. The Hypotheses verification process is given in Figure 2. Here, at first, calculate the horizontal and vertical features of shadow-based detected the object using HOG descriptor. Then, we give the features to trained OANN classifier which is verified HG object is a vehicle or not.

4 Result and discussion

The experimental conclusion and its comprehensive analysis will be conferred in this portion. The results are analysed in terms of different metrics namely, accuracy, sensitivity, and specificity and for experimentation two sets of videos are utilised. The performance of the approach is tested under various approach and its results are distinguished from the actual procedure. The tests are led on Intel (R) Core i5 processor, 3.20 GHz, 4 GB RAM, and the working framework stage is Microsoft Windows 7 Professional. A mat lab version (7.12) is used in this current method.

4.1 Evaluation metrics

To examine the current method we need assorted evaluation cadenced principles are to be determined. From True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) cadenced principle are been created. There are three utilities such as sensitivity, specificity and accuracy are been examined in our cadenced principle. From the below equations, the performance of our cadenced principle is shown.

Sensitivity: The ratio of actual positives to the sensitivity measures are been recognised correctly. It identifies with the limit of the test to recognise positive outcomes.

$$Sensitivity = \frac{Number\ of\ true\ positives}{Number\ of\ true\ positives + Number\ of\ false\ negatives} \times 100 \tag{18}$$

Specificity: The ratio of negatives to the sensitivity measure is been recognised correctly. It identifies with the limit of the test to recognise negative outcomes.

$$Specificity = \frac{Number\ of\ true\ negatives}{Number\ of\ true\ negatives + Number\ of\ false\ positives} \times 100 \tag{19}$$

Accuracy: The following expression shows the accuracy of our system.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

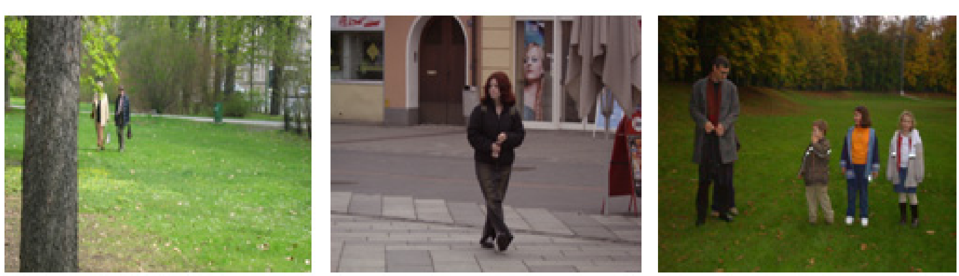
From our proposed system, the positives and negatives that are anticipated are done correctly by accuracy.

4.2 Data set description

Two types of data set such as GTI vehicle database and real-time traffic video in the proposed paper. The first GTI database was used for the train the classifier. The GTI vehicle database contains 3425 and 3900 of vehicle images and non-vehicle images respectively. The vehicle present n the data set has varied in color, shape, and size. For experimentation purpose, all the sizes of images are 64 × 64 in order. The database contains vehicles and non-vehicle images. The sample car images are present in Figure 6(a) and non-vehicle images present in Figure 6(b). The second database collected from the real traffic scene. Here, we utilise two videos. These videos are used for hypotheses generation and verification stage. The collected video contains much interference, such as traffic lines and trees. The collected first video contains 776 frames and the second video contains 90 frames. Some of the frames of 1st video are given in Figure 6(c) and 2nd video frames are presented in Figure 6(d).

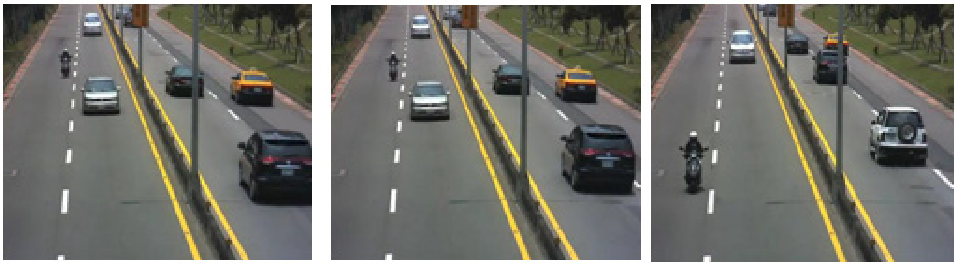
Figure 6 Experimental used images (a) GTI database care image (b) GTI database non-vehicle images (c) 1st video frames and (d) 2nd video frames

(a)



(b)

Figure 6 Experimental used images (a) GTI database care image (b) GTI database non-vehicle images (c) 1st video frames and (d) 2nd video frames (continued)



(c)

(d)

4.3 Experimental results

By using hypotheses generation (HG) and hypotheses verification (HV) a moving vehicle detection system has been developed. To detect the object using the hypotheses generation, the vehicle region should be darker as compared with the road side. From the following step, found out the vehicle and non-vehicle object also, because the non-vehicle objects also have the shadow. In the HV step, the non-vehicle hypotheses are been detected. The hypotheses generated objects are given in Figure 7.

Figure 7 Hypotheses generated objects

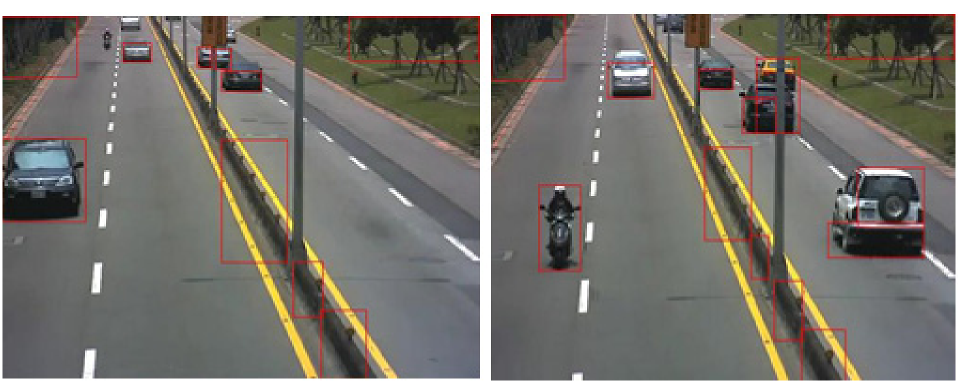


Figure 7 Hypotheses generated objects (continued)

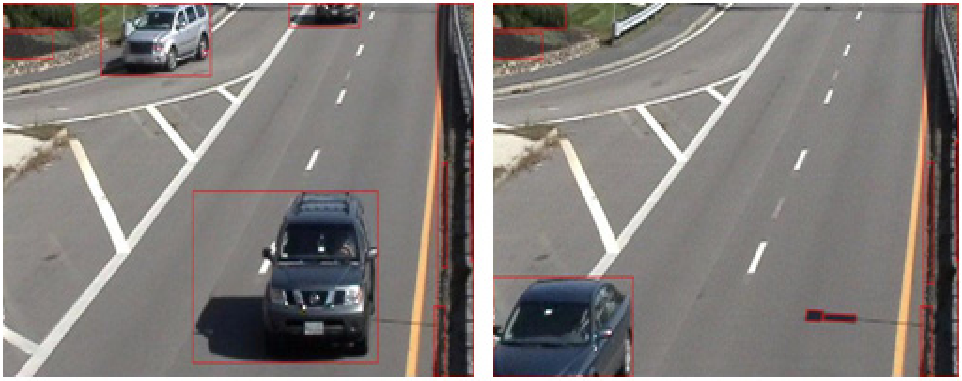
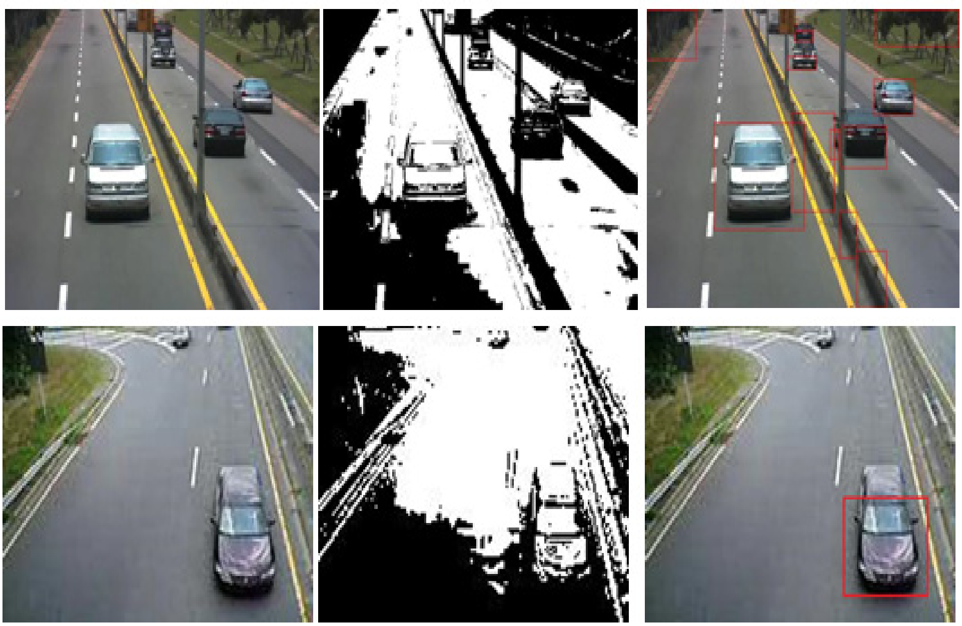


Figure 8 Hypotheses generation concludes; column (1) original image (2) linearisation result (3) vehicle hypotheses



(1) (2) (3)

Figure 9 Hypotheses verified object

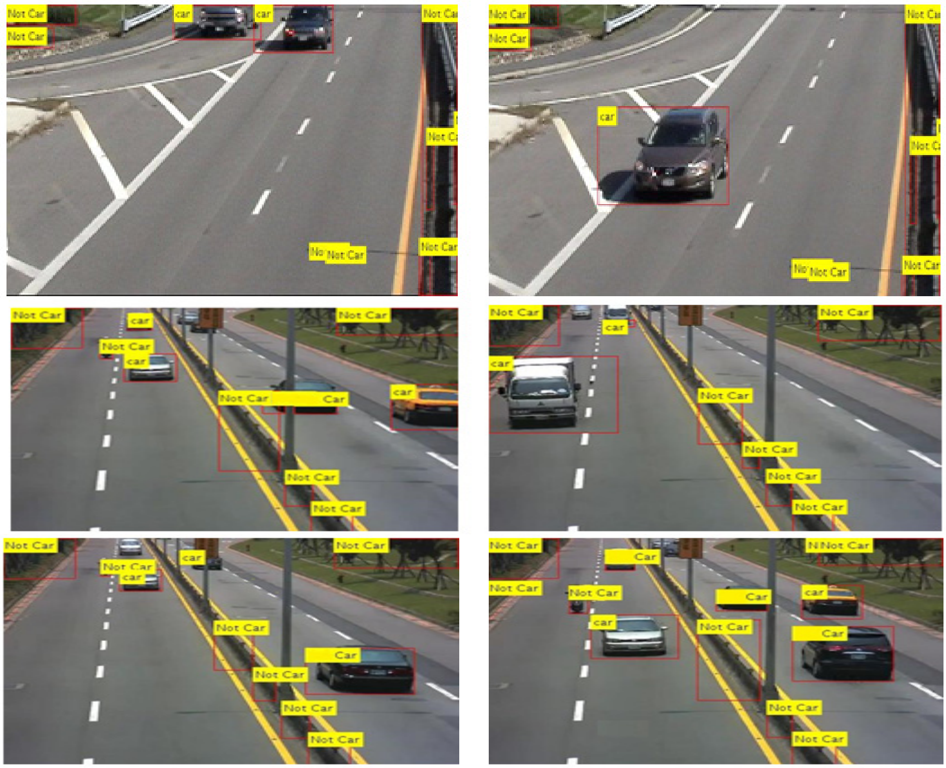
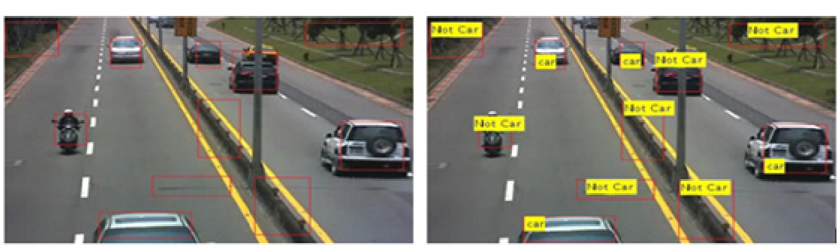


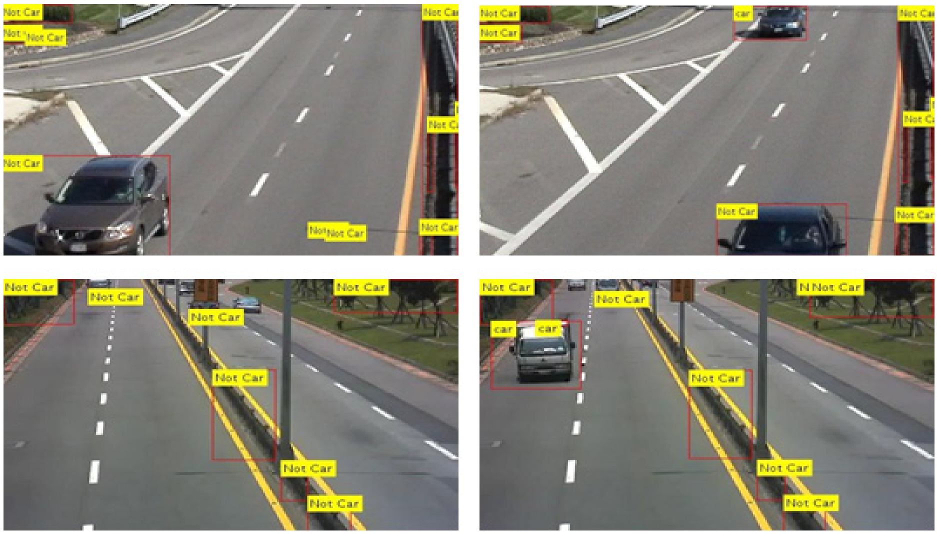
Figure 10 Vehicles obstruction accompanying detection (a) A cars linked; (b) two vehicles are evaluated as one, and (c) Owing the obstruction, two vehicles are confidential as non-vehicle

(a)



(b) (c)

Figure 11 Failure detection



In hypotheses generated stage, a large number of non-vehicle items and vehicle items are detected that are shown in Figures 7 and 8. Figure 9 shows the experimental results of hypotheses verification stage. Here, the selected hypotheses generated objects are checked whether these are vehicle or non-vehicle. In the verification stage, we utilise OANN. In the experimentation, sometimes the illumination affects the detection accuracy. In addition, in the analysis, when vehicles block with one another, shadows under vehicles may combine which can impact the recognition precision. Here, the joint vehicles are in some cases considered as one vehicle in the HG step and after that, the classifier will settle on the wrong choice and characterise this speculation into non-vehicles as appeared in Figure 10. In Figure 10(a) two cars are joined together, Figure 10(b) shows joined cars are considered as one object because the shadows are joined and Figure 10(c) shows the hypothesis is classified as non-vehicles. The classification is affected matrix is presented in Table 1.

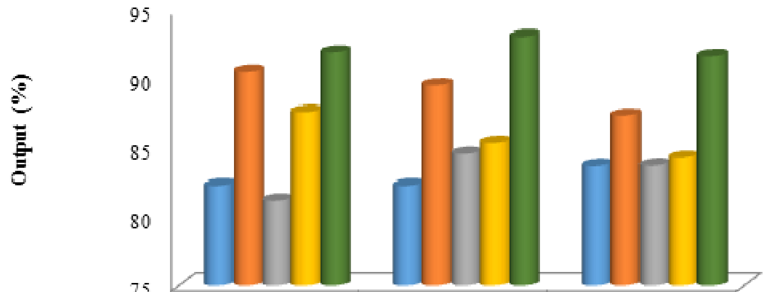
Table 1 Confusion matrix

	Vehicle	*Non-vehicle*	
Vehicle	1342 (TP) (93.06)	100 (FP) (6.93)	*Accuracy 91.93%*
Non-vehicle	1000 (FN) (91.66)	5001 (TN) (16.663)	

4.4 Comparative analysis

The projected work of moving vehicle detection system is accompanied to other methods in this paper. For comparative analysis, we utilise three scopes, i.e., Accuracy, Sensitivity, and Specificity. The related work result is given in Figure 12.

Figure 12 Performance of proposed vehicle detection using different measure



	Accuracy	Sensitivity	Specificity
Bo-Hao and Shin [16]	82.24	82.24	83.64
OCS-PNN[12]	90.5	89.5	87.35
SVM[28]	81.17	84.54	83.67
PCA[29]	87.6	85.34	84.26
OANN(Proposed)	91.93	93.06	91.66

To prove the effectiveness of the proposed methodology, we compare our method OANN-based moving vehicle detection with different four methods namely, Smitha and Rajkumar (2018), Chen and Huang (2015), SVM (Chen et al., 2009) and PCA (Peng et al., 2012). The PNN+CS-based moving object detection system was explained in my previous work which is given in Smitha and Rajkumar (2018). This method was a well-known method, but it cannot obtain the maximum accuracy. Moreover, Chen and Huang (2015) explained a moving object extraction. Here, they utilised PNN classifier under vehicle discovery. SVM-based moving vehicle detection system is explained in Chen et al. (2009). Here, the classification is done based on colour and types. Similarly, day light and night light-based vehicle detection are explained in Peng et al. (2012). The above Figure 12 displays that performance of the current vehicle detection system using different measures. When analysing Figure 9, the highest accuracy of 91.93% is obtained where by utilising OCS+PNN-based moving vehicle detection (Smitha and Rajkumar, 2018) the accuracy is 90.5 %, 82.24% for using Chen and Huang (2015), 81.17% for using SVM (Chen et al., 2009) and 87.6% for using PCA (Peng et al., 2012). This because in this paper, we optimally select the weight value using GOA. So, our method is attained better performance compared to other methods. Similarly, we obtain the maximum sensitivity of 93.06% and specificity of 91.66%. From the result section, our proposed moving vehicle detection system is better compared to other methods.

5 Outcome

A new way has been obtained in this paper that can detect the moving objects from real-time traffic video. The developed method has two stages such as Hypotheses Verification (HV) along with Hypotheses Generation (HG). Here, at first, hypotheses are generated from the real traffic video using the shadow-based method. A series of HOG features are derived in the HV step. Then, the generated features are given to the Optimal Artificial Neural Network (OANN), which was to identify the given object was a vehicle or not. The experimental result was carried out different methods and different measures. The proposed method obtains the highest accuracy of 91.93% that was compared with other methods. In future, we will develop vehicle detection and tracking with speed estimation for real-time videos.

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