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# A Back Propagation Neural Network and Genetic Algorithm for Vehicle Detection

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**Abstract**

Robust and vehicle detection from video is still challenging one. In this paper, a novel method for different type of vehicle detection using Back Propagation Neural Network (BPNN) was presented. In the method, constrain the vehicle detection method for different classes, such as different type of vehicles. After the frame separation from the video, we utilized the adaptive thresholding and Gaussian Mixture model for background subtraction and for vehicle detection. Several type of vehicle detection is difficult one, because every type of vehicle has different size and area, so feature extraction is needed. Then, target vehicle with larger size and larger area have to be reduced using feature selection method using Genetic algorithm. Finally different type of vehicle is detected using BPNN.

**Keywords:** Genetic Algorithm, Back Propagation neural network, Vehicle detection

## I. INTRODUCTION

Vehicle detection is an important problem in much application such as parking system, self-guided vehicle, driver assistance system, vehicle count and vehicle speed. With rapid increasing in traffic volume, vehicle detection is an important demand for traffic monitoring [1-10]. Vehicle detection is detected by sensors. There are two types of sensor to observe the vehicle detection, that are active sensor and passive sensor. One of the most common approaches is active sensor such as lidar, millimeter wave radars, and lasers [11]. Even though active sensors have some drawback such as expenditure of cost is high, scanning speed and spatial resolution is low. One of the main difficult is interference, when large number of vehicle driven in same direction simultaneously. On other hand of sensor is passive sensor and it is inexpensive, the main advantage of this type of sensor is effectively detect, when car turn on curves and move from one road to another road.

Detection and classification of vehicle in a video is an important area of research and it has numerous applications. Application such as counting number of cars in a busy traffic hour, counting the entering or leaving vehicle from parking area and also some of the fraud activities in an toll collections. Video based vehicle detection is based on motion estimation method, Gaussian scale mixture model [12, 13], background subtraction method [14, 15] and optical flow estimation method [16]. Background subtraction is one of the popular methods in video based vehicle detection. Some of the few vehicle detection method use graph cuts [17], object based segmentation [18], sensor fusion [19] for detecting the moving vehicle from the frame of the video.Various methods are available for classification of vehicle after the vehicle is detection from the moving vehicle. Feature based algorithm is one of the traditional method to classify the vehicle [20], other methods such as linear and nonlinear classifier [21, 22], neural network [23].

In this paper, new classification and detection methods are proposed for moving vehicle from the video. Four steps are implemented in this paper, first adaptive thresholding is proposed for noise removal and background subtraction. Gaussian Mixture model is implemented for vehicle detection. Genetic algorithm is used for feature selection and detected vehicle is classified by Back Propagation Neural Network.

## II. BACKGROUND SUBTRACTION

It is necessary to obtain the difference between the current frame and the background model.

$$D_t(x,y) = |I_t(x,y) - BM_{t-1}(x,y)|$$

In the above equation, $BM_{t-1}(x,y)$ is the intensity of the pixel $(x,y)$ of the background model at time t and $I_t(x,y)$ is the intensity of pixel $(x,y)$ in the current frame at time t.

The difference $D_t(x,y)$ s then compared to an adaptive threshold $Th_{ad}$ for foreground background pixel classification, the computation for $Th_{ad}$ is described in [11]. $Th_{ad}$is obtained iteratively using the histogram of the difference frame $D_t(x,y)$) to account for frame-to-frame changes in the background [11]. The pixel is classified in two ways

$$D_t(x,y) < Th_{ad}, \text{then it as a background pixel}$$
$$D_t(x,y) \geq Th_{ad}, \text{then it is a foreground pixel}$$

## III. VEHICLE DETECTION

In this paper, vehicle detection is based on the Gaussian Mixture Model (GMM).

Generally GMM is formulated by below equation:

$$P(X_t) = \sum_{i=1}^{K} \omega_{i,t}\eta(X_t; \mu_{i,t}, \Sigma_{i,t})$$

Here

$$\sum_{i=1}^{K} \omega_{i,t} = 1$$

The mean of such a mixture equals

$$\mu_t = \sum_{i=1}^{K} \omega_{i,t}\mu_{i,t}$$

The above is used to indicate the weighted sum of means of the component density. K represents the number of distribution; each frame index time is indicated by t, weight and mean of the Gaussian mixture model at given time is represented by $\omega \text{ and } \mu$.

Pixel based background subtraction involved in this paper, if the pixel belongs to background or some foreground object

For this pixel decision, Bayesian decision is taken followed by below equation:

$$R = \frac{P(BG|\vec{x}^{\omega})}{P(FG|\vec{x}^{\omega})}$$

In the above equation BG represents the Pixel of background at given time, pixel is represented by $\vec{x}$. In the same way FG represents the Pixel of foreground at given time, pixel is indicated by $\vec{x}$.

In generally vehicle detection, foreground object location is difficult to seen, so in this paper set the Pixel of background object is equal to Pixel of foreground object and assume uniform distribution for the foreground object appearance.

If the pixel belongs to background then the respective pixel is given by followed equation.

$$P\left(\vec{x}^{(t)}|BG\right) > c_{thr}$$

Background subtraction is obtained; if the respective pixel is greater than the given threshold value is given by $c_{thr}$

The GMM is a mixture of k Gaussian distributions that point the change of state of the corresponding pixels from one frame to another. The algorithm developed applies Gaussian mixtures to each frame and transforms images once colorful into binary images. For the corresponding pixels that undergo no state changes, the value 1 (black) is attributed and for pixels that undergo drastic changes in state, the value 0 (white) is attributed. Thus, it is possible generating the locations of all moving objects in the video.

## IV. FEATURE EXTRACTION

Feature extraction is one of the important functions in image processing. In this paper, we have to find out the different type of vehicles, so we need to obtain the shape and size of their individual vehicle, through this shape features, detect the vehicle. Several features are obtained in this vehicle detection.

**Area:** To find out the total number of pixels in an vehicle.

**Centroid:** It is center of the mass of the vehicle region. It have two coordinate, first coordinate is horizontal coordinate of the center of the vehicle, and the second coordinate is the vertical coordinate of the center of the vehicle**.**

**Perimeter:** perimeter is obtained by finding the boundary of the labeled component, and calculates the distance between the adjoining pair of pixels around the border of the region.

**Solidity:** Solidity is defined as the area of the region divided by the area of the convex hull of the region.

**Major Axis length:** It is find out by the distance from ach focus to any point.

$$\boldsymbol{Major\ Axis\ Length = a + b}$$

**Minor Axis length:** It is derived from the below equation

$$\boldsymbol{Minor\ axis = \sqrt{(a+b)^2 - f^2}}$$

Where f is the distance between foci, $a, b$ are the distances from each focus to any point in an image.

**Eccentricity:** The eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length.

**Equivalent Diameter:** It is calculated by following equation

$$\boldsymbol{Equivalent\ Diameter = \sqrt{4 * Area/pi}}$$

Then finally find out the mean for detected vehicle, mean value of RGB region and mean difference of RGB regions

## V. FEATURE SELECTION BASED ON GENETIC ALGORITHM

Genetic algorithm is one of the recognition methods for optimization and global search problems. GA algorithm is proposed in 1970 [24] by john Holland, they combined three process namely natural selection, mutation and crossover, population is developed with target problem.

In GA populations are formulated as abstract representations (called chromosomes) of candidate solutions (called individuals or phenotypes) to an optimization problem. This algorithm maintain a population for each individual for each iteration

$$Pop(g) = \{x_1(g), \dots, x_M(g)\},$$

In above equation, potential solution is indicated by each individual for the problem. Based on individual adaption and genetic operation such as crossover and mutation, obtained a new population using selection process and it is one of the iterative process. Fitness is calculated for every individual of population for each generation. Generating and reproducing new individual by crossing and muting, with best adaptation measure. Tentative new population is generated for genetic process by selected individual from repeated selection process. After selecting this population, transformation process is undergoing. After the selection process, crossover process is started, it creates two new individual namely offspring, this offspring is created by the combination of two randomly selected individual of the population. High crossover probability is required for good genetic algorithm performance and this operator is randomly applied with a specific probability $p_c$. Mutation is a unitary transformation which creates, with certain probability, $p_m$, a new individual by a small change in a single individual. Low mutation probability is required for good mutation performance.

**Algorithm for Genetic algorithm:**

Step 1: Initialization
Step 2: generation counter g=0
Step 3: Assign Population size i.e.,
$for\ i - 1\ to\ M\ do$
Step 4: Set individual $x_i$ to random values
Step 5: Fitness function $F_i \leftarrow f(x_i)$
Step 6: end for
Step 7: $Pop \leftarrow \{x_1, x_2, \ldots, x_M\}$
Step 8: $F \leftarrow \{F_1, F_2, \ldots, F_M\}$
Step 9: Main loop is started from this step
Step 10: while (not termination condition) do
Step 11: Genetic operator is started from this Step.
Step 12: $Pop \leftarrow Selection(Pop, F)$
Step 13: $Pop \leftarrow$
$Crossover(Pop, probability\ of\ crossover\ p_c)$
Step 14:
$Pop \leftarrow Mutation(Pop, \quad probability\ of\ nutation\ p_m)$
Step 15:
Evaluation loop is started from this step
Step 16: $for\ i - 1\ to\ M\ do$
Step 17: $F_i \leftarrow f(x_i)$
Step 18: end for
Step 19: $F \leftarrow \{F_1, F_2, \ldots, F_M\}$
Step 20: $g \leftarrow g + 1$
Step 21: end while

## VI. CLASSIFICATION BASED ON BACK PROPAGATION NEURAL NETWORK

The Back-Propagation algorithm as applied to multi-layer neural networks back propagates the errors of the output layer throughout the network to derive errors for all of the neurons in the hidden layers [24, 25].

BPNN network as shown in fig.1, consists of three layer feed-forward neural network. Pattern vectors are the input to the BPNN network. The input vector is applied to the first layer neuron after from the first layer it sends to the second layer neuron through sigmoid.

Randomly apply the initial values to the weight for training the BPNN network. With the given train parameter, trained the network by back-Prop. Desired response pattern is shall to be given for each individual training pattern. The desired response pattern is compared with the actual response pattern for the given input pattern, and the difference, the error pattern or error vector, is back-propagated throughout to compute the instantaneous gradient of the magnitude square of the error vector with respect to the weights. Weight of the network is changed and it tis proportional to the negative of the instantaneous gradient. Up to next input training pattern, repeating this process.

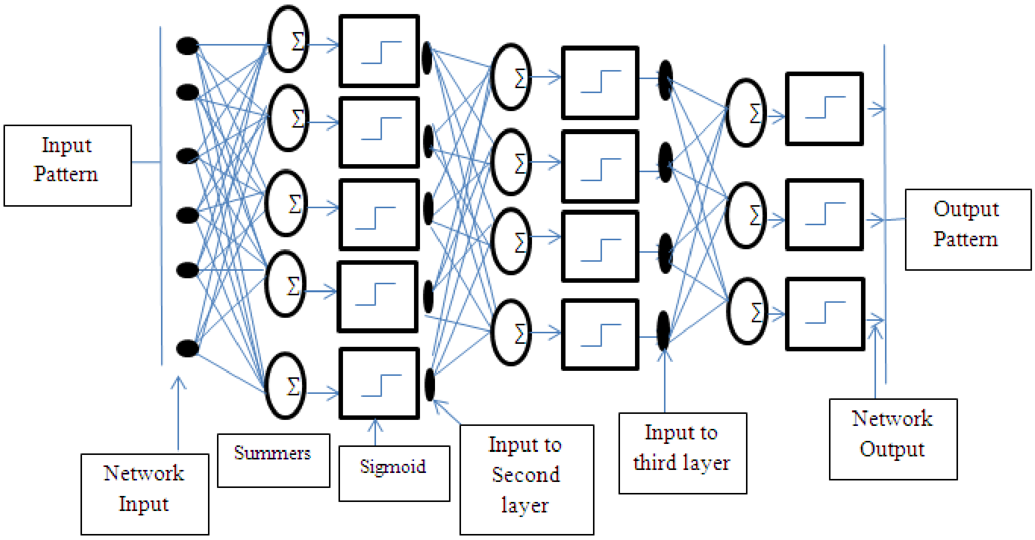


**Figure 1: Back Propagation Neural Network**

Error vectors are low, when the networks are trained with the given training parameters. The weights are stabilized and are essentially unchanging; at this situation new input patterns are applied to the network. Through first and second layer new input patterns are obtained then they mapped nonlinearly to the third layer neuron.

**BPNN training algorithm:**

In back-propagation algorithm the steepest-descent minimization method is used. For adjustment of the weight and threshold coefficients it holds that:

$$w_{ij}^{(k+1)} = w_{ij}^{(k)} - \lambda \left( \frac{\partial E}{\partial w_{ij}} \right)^{(k)}$$

$$\vartheta_i^{(k+1)} = \vartheta_i^{(k)} - \lambda \left( \frac{\partial E}{\partial \vartheta_i} \right)$$

In the above equation, rate of learning is represented by $\lambda$. The key problem is calculation of the derivation $\frac{\partial E}{\partial w_{ij}}$ and $\frac{\partial E}{\partial \vartheta_i}$.

First step:

$$E - \frac{1}{2}(x_0 - \hat{x}_0)^2 - \frac{1}{2}\sum_k g_k^2$$

In the above equation, $g_k = x_k - \hat{x}_k$ for k belongs to output layer, $g_k = 0$ for k not belongs to output layer.

Second Step:

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial x_i}\frac{\partial x_i}{\partial w_{ij}} = \frac{\partial E}{\partial x_i}\frac{\partial f(\xi_i)}{\partial w_{ij}}$$

$$= \frac{\partial E}{\partial x_i}\frac{\partial f(\xi_i)}{\partial \xi_i}\frac{\partial \xi_i}{\partial w_{ij}}$$

$$= \frac{\partial E}{\partial x_i} f'(\xi_i)\frac{\partial(\xi_i)}{\partial w_{ij}}$$

$$= \frac{\partial E}{\partial x_i} f'(\xi_i)\frac{\partial\left(\sum_{j\in\Gamma_i^{-1}} w_{ij}x_j + \vartheta_i\right)}{\partial w_{ij}}$$

$$= \frac{\partial E}{\partial x_i} f'(\xi_i)x_j \tag{7}$$

$$\frac{\partial E}{\partial \vartheta_i} = \frac{\partial E}{\partial x_i}\frac{\partial x_i}{\partial \vartheta_{ij}} = \frac{\partial E}{\partial x_i} f'(\xi_i).l \tag{8}$$

From the above two equation, below relationship is formed

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial \vartheta_i}.x_j \tag{9}$$

Third step:

$$\frac{\partial E}{\partial x_i} = g_i \tag{10}$$

In the above equation, i belong to hidden layer

$$\frac{\partial E}{\partial x_i} = \sum_{l\in\Gamma_i}\frac{\partial E}{\partial x_i}\frac{\partial x_i}{\partial x_i} = \sum_{l\in\Gamma_i}\frac{\partial E}{\partial x_i}\frac{\partial f(\xi_i)}{\partial x_i}$$

$$= \sum_{l\in\Gamma_i}\frac{\partial E}{\partial x_i}\frac{\partial f(\xi_i)}{\partial x_i}\frac{\partial \xi_i}{\partial x_i} = \sum_{l\in\Gamma_i}\frac{\partial E}{\partial x_i} f'(\xi_i)w_{li}$$

$$= \sum_{l\in\Gamma_i}\frac{\partial E}{\partial \vartheta_i} w_{li} \tag{11}$$

Because

$$\frac{\partial E}{\partial x_i} f'(\xi_i) = \frac{\partial E}{\partial \vartheta_i} \tag{12}$$

Based on the above given approach the derivatives of the objective function for the output layer and then for the hidden layers can be recurrently calculated. This algorithm is called the back-propagation, because the output error propagates from the output layer through the hidden layers to the input layer.

## VII. RESULTS AND DISCUSSION

Experiments were mainly conducted on vehicle video sequence to track and detect the vehicles such as cars, bikes followed by four steps which was implemented in MATLAB. Video sequence is shown in fig.2. Initially adaptive thresholding is done to remove noise.

**Figure 2: Video sequence**

**Figure 3: Background Subtraction using Gaussian Mixture model**

The background subtraction was done to detect the vehicles using Gaussian Mixture model and is shown in fig.3.


**Figure 4: Tracked vehicles**

Feature selection was done from detected moving object using Genetic Algorithm. Detected vehicle was classified by Back Propagation Neural Network as shown in fig.4.

**Table 1: Comparison Table with actual and detected vehicles**

| Vehicle name | Actual video | Vehicle detected using proposed method | Accuracy (%) |
| --- | --- | --- | --- |
| Car | 48 | 45 | 93.75 |
| Bikes | 2 | 2 | 100 |

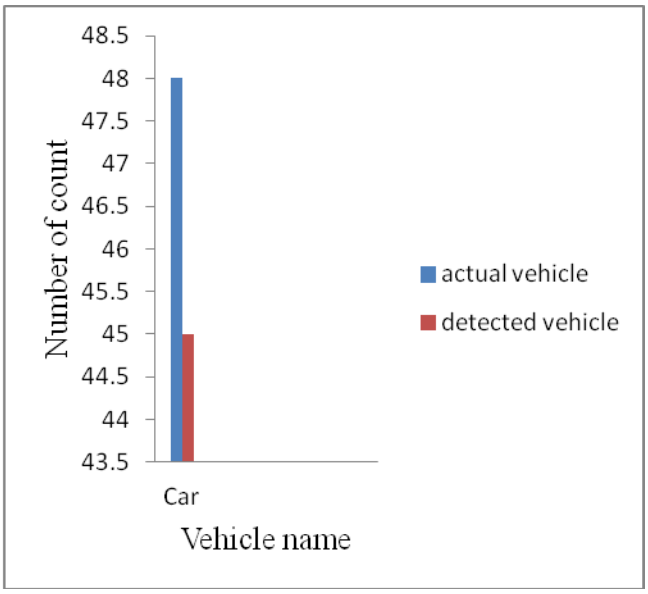


**Figure 5: Analysis between actual vehicle and detected vehicle for car**

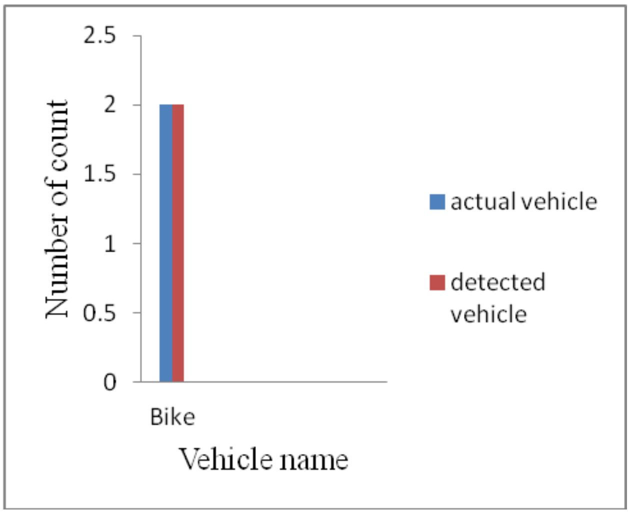


**Figure 6: Analysis between actual vehicle and detected vehicle for bike**

Table 1 shows the comparison between the actual vehicle and detected vehicle of car and bike from the video sequence. From the table 1 the accuracy measured is 94% for car and 100% for bike. Analysis for car and bike is shown in fig. 5 and fig. 6 respectively.

## VIII. CONCLUSION

This paper has focused to detect and track the vehicles in a video sequence in four steps. First step was to remove noise using adaptive thresholding and second step includes background subtraction by Gaussian Mixture model (GMM). Feature selection was done using Genetic Algorithm (GA) in third step. Finally, Back propagation neural network (BPNN) was proposed and executed in MATLAB to detect the vehicles. The analysis metric was done for actual vehicle and detected vehicle with the accuracy of 94% for car and 100% for bike. The future work can be extended to detect i) vehicles other than car and bike, ii) vehicles adjacent to trees and bridges.

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