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Intelligent Video-Based Monitoring of Freeway Traffic

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***Abstract*—**Freeways are originally designed to provide high mobility to road users. However, the increase in population and vehicle numbers has led to increasing congestions around the world. Daily recurrent congestion substantially reduces the freeway capacity when it is most needed. Building new highways and expanding the existing ones is an expensive solution and impractical in many situations. Intelligent and vision-based techniques can, however, be efficient tools in monitoring highways and increasing the capacity of the existing infrastructures. The crucial step for highway monitoring is vehicle detection. In this paper, we propose one of such techniques. The approach is based on artificial neural networks (ANN) for vehicles detection and counting. The detection process uses the freeway video images and starts by automatically extracting the image background from the successive video frames. Once the background is identified, subsequent frames are used to detect moving objects through image subtraction. The result is segmented using Sobel operator for edge detection. The ANN is, then, used in the detection and counting phase. Applying this technique to the busiest freeway in Riyadh (King Fahd Road) achieved higher than 98% detection accuracy despite the light intensity changes, the occlusion situations, and shadows.

***Keywords*—**Background Extraction, Neural Networks, Vehicle Detection, Freeway Traffic.

I. Introduction

FREEWAY traffic congestion has become a major problem worldwide. Freeways are designed to represent the arterial connections within and between major cities around the world, thereby providing rapid flow of traffic. Unfortunately, with the increasing congestion, the travel times increase drastically and freeways can no longer serve the purpose for which they were established. With such congestion, come various serious additional problems such as pollution and high rates of accidents. This leads to big losses in time, fuel, and billions of dollars annually. Building new highways is not always a practical solution for this problem. However, seeking alternative solutions that provide more efficient operation of existing freeways can reduce congestion. One of such alternatives is taking advantage of the rapid advances in the fields of computer vision and artificial intelligence to provide an advanced monitoring scheme for freeway traffic.

Vehicle detection is the main step in the freeway monitoring process. It has many applications in many fields such as military and civilian applications. It was implemented by installing loop detectors in the highway. However, loop detectors installation has many drawbacks. One of them is the disturbing of highway traffic. In addition, it cannot give detailed information regarding the traffic status such as queue length, number of vehicles in a given cross section, and the quality of service. Vision-based techniques, on the other hand, have many advantages. They are easy to install any time without interfering with the traffic. Cameras can be mounted on many alternative places such as buildings, poles, bridges, or towers. From these locations, vehicles could be counted, tracked, or classified. More importantly, different traffic parameters could be easily extracted.

In this paper, we propose an intelligent technique for vehicles detection. Starting from a stream of video frames of the highway traffic, and after few pre-processing steps, an artificial neural network counts the number of cars in the cross-section. From the Neural network results, essential traffic parameters can be extracted and an overall evaluation of the traffic flow can be made.

This paper presents the related work in the next section. In section three, the proposed method for vehicle detection is presented in detail. The application of the monitoring technique to real data is given in section four and the conclusions are drawn in section five.

II. Related Work

Vehicle detection is the fundamental phase of highway monitoring. Some of the commonly used approaches for vehicle detection are background subtraction, optical flow techniques, probabilistic methods, neural networks, and fuzzy measure techniques. In the background subtraction techniques, the difference between the current image and the background image is calculated [1]. The resulting image is filtered to extract moving vehicles. Remaining blobs are representing the moving vehicles. However, any noise could be regarded as moving vehicles which leads to error in detection. In addition, results are sensitive to light changes.

In [2], an alternative method based on Gaussian distribution is used to model every pixel of the background. However, this does not solve the problem of sensitivity to light changes. Moreover, this approach tends to require a large number of video frames to generate the background image. Reference [3]

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proposed a background differencing technique. The technique performs simple subtraction between successive frames. Then, it applies a series of morphological operations including closing and opening to filter out noise and to separate foreground objects from the background. In the detection process, the approach uses a Laplacian filter which produces objects boundaries. Although this technique improves the detection accuracy on the average, it is sensitive to intensity changes and occlusion situations.

Optical flow techniques are used to generate the background from the successive images through following changes in pixels intensity [4]-[6]. In [4], the pixel intensities are modeled using the median model. In [5], the frequency ratios of intensity values are calculated to distinguish moving pixels from stationary ones. The background is modeled from the biggest and frequented intensity values in successive images. This is similar to the median model but it offers improvements in time consumption and memory needed. In [6] self-adaptive background and updating algorithms based on an optical flow are presented. Although optical flow techniques give high detection rates, they need much longer computation time and larger memory allocation.

A number of approaches mainly based on probabilistic and statistical methods have been proposed [7]-[9]. However, due to the absence of an accurate distribution for vehicle models, only approximate probability distributions are used. This leads to high detection errors and make the approach inapplicable for complicated scenes.

Other approaches use explicit and detailed models [10]-[12]. In [10] the detection and counting of cars in aerial images is proposed. The technique needs a very large number of images for cars in different direction with respect to the camera, for different car shapes and colors, and for cars in different orientations. The vehicle detection or recognition is implemented using a tree-like model hierarchy. This process needs a large memory and long processing time. In [11] also, a hierarchical model is used to identify and cluster the image pixels in order to decide whether pixels have a strong probability to belong to a vehicle shape or not. In this case, an extensive computation is needed to detect vehicles without a significant improvement in correct detection rates. In [12] vehicle detection is implemented by finding various characteristic features in images of a monochrome camera. The detection process uses shadow and symmetry features of vehicles to generate vehicle hypothesis. This is beneficial for driver assistance but it is not applicable for vehicles counting especially in typically complicated scenes.

In [13], and [14] neural networks are used for vehicle detection. Although these techniques apparently give good results with high detection rates, the approach used does not seem to be easy to generalize to different scenarios and various scene complexities.

In [15] fuzzy measures are used to detect vehicles. The detection depends on the light intensity. When the light intensity value of a pixel falls in a certain interval, the fuzzy measures are used to decide whether this pixel belongs to a vehicle or to the background. This approach is highly sensitive to light changes in the environment and to the proper choice of the light intensity decision interval.

In [16] the inter-frame difference method is proposed. In this approach, vehicle detection is implemented by processing three successive frames and passing them through a number of logical operations. Vehicle detection using this method is low and it is highly sensitive to both the speed of vehicles and the speed of camera.

In this paper, a neural-network-based approach is used to detect and count vehicles. In the first phase of the approach, background is automatically extracted from the successive images. Using the identified background and the current image, a Sobel operator is used to obtain an edge image of the moving vehicles. The dimension of the edge image is then reduced and features are extracted to be processed by the neural network for vehicles counting. Image reduction is achieved through the use of Principle Component Analysis (PCA) or Wavelet transform. The work attempts to offer some contributions in three aspects. The first is solving the typical detection problems caused by non-vehicle regions such as active shadows. The second is solving the problems cause by partial or full occlusions resulting from overlapping vehicle images. Finally, the third aspect is providing a complete system that could be applicable for real time applications by making it simple to design and easy to implement.

III. Vehicles Detection and Counting Approach

The approach comprises five major steps. In the first step, the image background is extracted. Once the background is identified, only an update will be needed. In the second step, an edge image of moving objects is obtained using the identified background image and current frames. The obtained edge images are of the same resolution as the original images. Therefore, a size reduction is performed, in step three, to minimize the data and to allow faster processing in the subsequent steps. During this step essential features are extracted using a number of alternative approaches such as Principle Component Analysis (PCA) or Wavelet transforms. In step four, a radial basis neural network is used to count vehicles based on the features extracted in the previous step. The last step is simply using the counts obtained from the neural network to extract the essential traffic parameters. Fig. 1 summarizes these five basic steps.

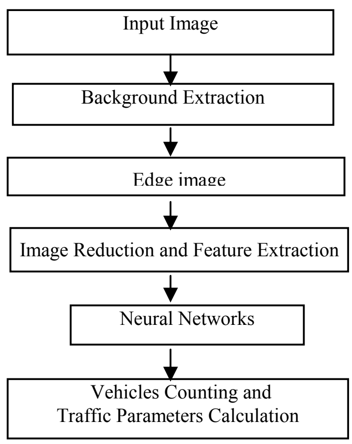


Fig. 1 Steps of vehicles detection and traffic parameters calculation

A. Automatic Background Extraction and Update

The image background represents unmoving (or stable) parts in the image. A number of successive images can be used to extract the background automatically. Automatic background extraction starts by processing the first three successive frames (images) as in the following steps [14]:

Step1. Use the first three successive frames C^{t-2}, C^{t-1}, and C^{t} to calculate $D^{t-1,t-2} = |C^{t-1} - C^{t-2}|$, and $D^{t,t-1} = |C^{t} - C^{t-1}|$.
Step3. Specify the gray threshold level T using maximum entropy criterion (MEC) [14].
Step4. Convert the differences to binary.
Step5. Calculate the Difference Product (DP) using the bitwise logical AND operation:
$DP^{t} = DB^{t-1,t-2} \,\&\, DB^{t,t-1}$.
Step6. Apply binary dilation (DLT) of $DP^{t}i,j$.
Step7. Apply closing and opening morphological operators.
Step8. Calculate moving object region (MOR) by filtering the closed image.
Step9. Fill the moving object region.
Step10. Estimate the initial background B(kk).
B(kk) = $MOR(kk)|C^{t}$, where the symbol '|' is the bitwise logical OR operator.

This procedure is iterated until all background pixels are extracted. Fig. 2 shows the flow chart for automatic background extraction.

Sunlight changes along the day. The background, therefore, must be updated accordingly (e.g., every 30 minutes) to capture these changes. The background update is performed using the following equation [14]:

$$B^{t+1} = \begin{cases} kB^{t}_{i,j} + (1-k)C^{t+1}_{i,j}, & if \quad D^{t+1}(i,j) < T \\ B^{t}_{i,j}, & otherwise \end{cases} \qquad (1)$$

$$0 \le k \le 1$$

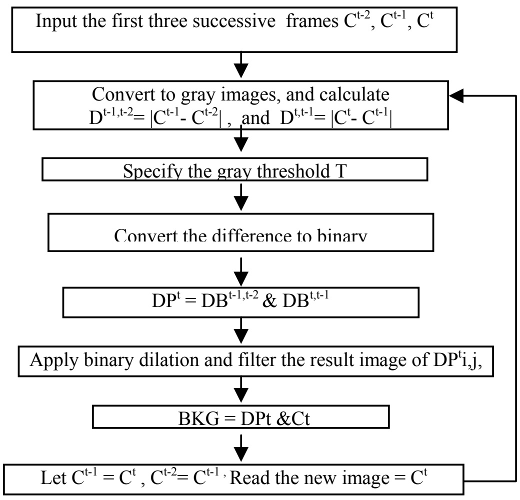


Fig. 2 Automatic background extraction flow chart

The value of *k* is chosen as 0.1 to speed up the update while preventing the background from corrupting the foreground objects.

B. Edge Calculation

Edge detection is the most common approach used to identify discontinuities in images. These discontinuities are the places in the image where the intensity changes rapidly. The Sobel operator is an efficient technique for edge detection. Fig. 3 shows the Sobel operator masks used [17]. These masks specify whether the image edge is sensitive to horizontal or vertical edges or both.

-1	-2	-1
0	0	0
1	2	1

-1	0	1
-2	0	2
-1	0	1

Fig. 3 Vertical and horizontal masks for Sobel edge detector

C. Image Reductions

The original image consists of a typically high number of pixels. Image size needs to be reduced while capturing the essential features. Such task can be achieved using a number of available techniques such as Wavelet or PCA.

Wavelet methods provide powerful tools for analyzing, compressing, and reconstructing signals and images. The major advantage of Wavelet transform is its capability of providing the time and frequency information simultaneously; hence, giving a time-frequency representation of the image [18]. A wavelet transform based on two-level decomposition produces seven sub-bands as shown in Fig. 4.

<table>
<tr><td>A2</td><td>H2</td><td rowspan="2">H1</td></tr>
<tr><td>V2</td><td>D2</td></tr>
<tr><td colspan="2">V1</td><td>D1</td></tr>
</table>

Fig. 4 Wavelet representation of an image

This type of two-dimensional wavelet transform leads to a decomposition of an image to detail and approximation coefficients. These coefficients consist of four components: the approximation component and the details component in three orientations (horizontal, vertical, and diagonal). Wavelets are the foundation for representing images in various degrees of resolution. The second level approximation component (A2) has the main features of the original image with reduced dimensions. A2 could be used in the subsequent process without loss of significant information. PCA is also a useful statistical technique that has found application in fields such as object recognition and image compression. It is a common technique for finding patterns in data of high dimension. The main objective of PCA is to reduce the dimensionality of the data set and to identify the new meaningful underlying variables [19]. It is a way of identifying patterns in data, and expressing the data in such a way to highlight their similarities and differences. PCA depends on eigenvalues and eigenvectors calculations. Once the eigenvectors are found, they can be sorted from the most to the least significant. The eigenvector with the highest eigenvalue is the principal component of the data set. The components with less significance could be ignored. The reduction could be achieved by ignoring components having values less than a specified percentage (e.g., 95%) of the highest one. To obtain the new data set, the original data set is simply multiplied by the transpose of the reduced eigenvector. The result is, then, a reduced data with the main features of the original set.

After the dimension of the image is reduced, we need an efficient tool to transform the image information from two-dimensional to one-dimensional so that it could be fed to the neural network. One efficient alternative is the projection profile of the image, which is a compact representation of the spatial pixel content distribution [20]. A horizontal projection profile is defined as the vector of pixels intensity summations over each row. Likewise, a vertical projection is defined as the vector of pixels intensity summations over each column. These projections are called X and Y projections, respectively.

D. Vehicle Counting using Neural Networks

Once the horizontal and vertical projections are calculated, the neural networks could be used. Projected images will be used as inputs to the network. We need to design ANN depending on the vector of known inputs with their outputs, so a supervised neural network needs to be designed. The design of a supervised neural network could be achieved in different ways. Back propagation and radial basis function (RBF) paradigms are two different methods to implement supervised algorithms [21]. The Back-propagation technique is regarded as an application of an optimization method known in statistics as stochastic approximation, while radial basis function (RBF) is used as a curve fitting (approximation) in high-dimensional space . Learning in RBF is equivalent to finding a surface in a multidimensional space that provides and measures the best fit to the training data. Thus, RBF is used as a general technique to interpolate multidimensional data and it is better than the traditional strict interpolation methods [21]. It consists of three entirely different layers (input, hidden and output layers). The input layer broadcasts data to the hidden layer through a nonlinear transformation, whereas the transformation from the hidden layer to the output layer is a linear one. The transfer function for the RBF is given by:

$$f(n) = e^{-n/\sigma} \tag{2}$$

The variable σ controls the width of the RBF and it is called the spread parameter [22]. It is important that the spread parameter be large enough to enable the transfer functions to have overlapping regions of the input vector elements.

E. Freeway Density Extraction

The fundamental characteristics of freeway traffic are flow, speed, and density. The traffic density is a fundamental macroscopic parameter that could be used in assessing the traffic performance. It is used as a primary control variable in the freeway control systems. The traffic density is defined as the number of vehicles existing in a given length of the highway. As the density is calculated, the level of service, and the flow conditions could be evaluated according to Table I.

The density is defined as the number of vehicles per km per lane. To calculate the density, the distance headway must be computed. Headway could be defined as the distance from a selected point on the lead vehicle to the same point on the next vehicle. Usually, the front edges or bumpers are selected since they are more often detected in automatic detection systems.

TABLE I
TRAFFIC FLOW CONDITIONS BASED ON DENSITY [23]

Density (vehicles/lane . km)	Level of Service	Flow conditions	
0-19	A	Free –flow	Un-congested Flow conditions
19-32	B	Reasonable free-flow	
32-48	C	Stable operations	
48-67	D	Borders on unstable operation	
67-107	E	Extremely unstable flow operation	Near-capacity flow
107-160	F	Forced or breakdown	Congested flow conditions
>160		Incident situation	

The distance headway includes the length of the lead vehicle and the gap between the lead and following vehicle is given in the following equation [23]:

$$\begin{aligned} d_{n+1}(t) &= L_n + g_{n+1}(t) \\ &= \frac{L_S}{(N_V / N_L)} \end{aligned} \tag{3}$$

Where $d_{n+1}(t)$ = distance headway of vehicle n+1 at time t
L_n = physical length of vehicle n
$g_{n+1}(t)$ = gap length between vehicle n and n+1 at time t
L_S = length of the lateral section (km)
N_V = number of vehicles in the lateral section
N_L = number of lanes in the lateral section

Once the headway distance is calculated, the traffic density could be determined from the following equation [23],

$$k = \frac{1}{\bar{d}} \tag{4}$$

Where k = density (vehicles per lane-km)
$\bar{d}$ = average distance headway (lane-km per vehicle)

IV. RESULTS

A digital camera was used to record videos of King Fahad highway in Riyadh city. The scenes were recorded for frontal and lateral views. To record frontal views for moving vehicles, the camera was mounted on the bridges over the highway. For lateral views, the camera was mounted on towers in the vicinity. More than 80 hours of King Fahad highway traffic were recorded during the daylight with different illuminations and sunlight directions. This helped in creating a large enough database for adequate analysis and testing.

The system used for implementing and evaluating the proposed algorithm comprises:

- A Pentium-IV 700MHz PC with 512MB SDRAM.
- A digital video camera: Sony DCR-HC36 (in webcam mode).
- Matlab 7.0 as a software development tool.

A. Background Extraction

To highlight the adequacy of the background extraction algorithm, Fig. 5 shows a sample result for this step of the approach. From the figure it is clear that the background is extracted equally well for lateral and frontal views. The accuracy of this step is particularly important as it directly affects the accuracy of the subsequent detection steps.

B. Edge Detection

Fig. 6 shows the edges that are detected of the moving vehicles. The edges of the dark vehicles are not detected completely as in the case of white ones, but still there are some pixels to represent these vehicles. After the edges are detected, they are dilated and filled to get more significant pixels as shown in Fig. 6(c).


(a) Frontal image (b) Frontal background


(c) Lateral image (d) Lateral background

Fig. 5 Highway images and the corresponding extracted backgrounds

(a) Lateral image (b) Detected edges (c) Dilated edges

Fig. 6 Edge detection of moving vehicles after background subtraction

C. Image Reduction

Applying a two-level wavelet transform to the data, offered a subtanatial data reduction by about 90%. For an input image of size 110x320, the wavelet produces an image of size 38x91 (which is about 10% of the original size). In the case of PCA, data was reduced by about 95% when taking only the most significant 5% of the eigenvalues.

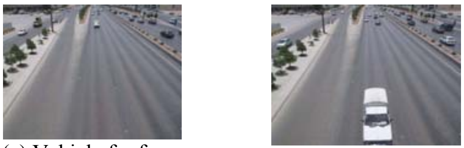
D. Neural Network Results

In preparation for the neural network application, projections of the reduced data are calculated using the summation of pixel intensities over the horizontal (X) and vertical (Y) axes. These projections reveal the nature of the given matrix. Actually, they convert the given matrix with resolution NxM to vectors consisting of N and M elements (for X projection and Y projection, respectively). These vectors represent the ANN input. If both projections are to be used (e.g., XY projection), the resulting vector will be of size N+M. The RBF network depends on the spread parameter which should be chosen prior to training. This parameter was optimized through an iterative process and was consequently chosen to have the value of $\sigma = 80$.

For the frontal view scenario, a total of 600 images were used. Out of these, 400 images were used for training and 200 for testing. The detection rates shown in Table II are not high because the vehicles sizes change as they get closer to the camera as shown in Fig. 7.

TABLE II
FRONTAL PERCENT DETECTION RESULTS USING 400 TESTING IMAGES

	No Reduction	Wavelet	PCA	Wavelet + PCA
X-Proj	31.2	32	35.8	28.44
Y-Proj	52.3	44	21.1	15.6
XY-Proj	49.5	48	24.77	20.4



(a) Vehicle far from camera (b) Vehicle closer to camera

Fig. 7 Vehicle size changing as it becomes closer to the camera

For the lateral view scenario, 513 images were used (342 for training and 171 for testing). Table III gives the detection rate results. The detection rates are high in this case (larger than 98% for XY-projection at no reduction and Wavelet cases). Wavelet detection is higher than that of PCA because the data reduction in the latter is higher. The detection in the case of using both Wavelet and PCA is the lowest as expected, because the data reduction is highest.

TABLE III
LATERAL PERCENT DETECTION RESULTS USING 513 IMAGES

	No Reduction	Wavelet	PCA	Wavelet + PCA
X- Proj	98.4	96.5	95.5	94.1
Y- Proj	83.	68	56.1	52.6
XY-	98.6	98.5	95.3	93.6

Fig. 8 shows comparison between the actual count and the neural network output for lateral section images and Fig. 9 shows a zoomed sample of these results.

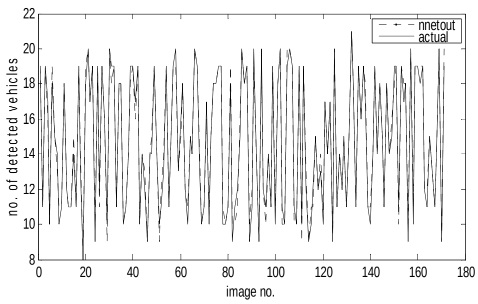


Fig. 8 Actual and neural network outputs

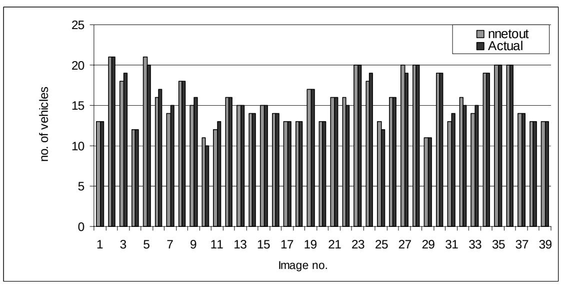


Fig. 9 Sample for actual vehicles number and neural network output

The reduction in data dimension is expected to lead to a reduction in computation. Table IV shows the average processing time required for each alternative approach.

TABLE IV
AVERAGE PROCESSING TIMES

	Raw Data	Wavelets	PCA	Wavelets + PCA
Training time(seconds)	24	6	5	5
Testing time(seconds)	4	2	1.9	1.8

E Discussion

In vehicle detection, there are typically two main factors that cause substantial errors in detection results. The first one is the active shadow of vehicles and the second one is the occlusion problem as shown in Fig. 10.

(a) Active shadow (b) Occlusion problem

Fig. 10 Typical difficulties that facing the vehicle detection issue

The edge pixels of a shadow are less significant than those of a vehicle so the edge detection phase contributes to solving this problem. Occlusion, on the other hand, means that two or more vehicles are running close to each other and may appear (to the vision system) as a single large vehicle. However, despite the existence of occlusion cases, and the presence of active shadows, the approach achieves high detection rates indicating its strong robustness to these typical detection problems.

F. Traffic Parameter Extraction

Traffic parameter extraction depends mainly on the density calculation as given in (4). Once the number of vehicles is counted and the lateral section length is known (55m in this case), the density is calculated. Resorting to the previously given Table I, other important traffic parameters could be determined and the highway monitoring can be achieved easily. Table V gives the neural network results for five different levels of service.

TABLE V
RESULTS FOR DIFFERENT LEVELS OF SERVICE

Case no.	No. of vehicles using		Density		Level of service	
	Actual	ANN	Actual	ANN	Actual	ANN
1	4	4	18	18	A	A
2	8	8	36	36	C	C
3	12	13	54	59	D	D
4	16	16	72	72	E	E
5	20	19	91	86	E	E

G. Comparison with Related Work

Comparison with the related work is essential for reevaluation of the procedure and the results. However, accurate comparison in this case is very difficult because the input traffic, lighting environment, operating system, and the position of the camera cannot be reproduced. In addition, a benchmark database is yet to be available. However, the comparison here is included to have a feel of the adequacy of the results and not necessary to compare the efficiency of an approach over another. Table VI gives this comparison.

TABLE VI
DETECTION RATES OF DIFFERENT APPROACHES

	View	Robust to shadows	Occlusion removal	Detection (%)
Gupte et al.[1]	Lateral			90
Rad and Jamzad [3]	Far frontal		√	96
Schneiderman et al.[[7]	Different views			83
Zhao et al.[[8]	Aerial			85
Rajagopalan et al. [9]	Frontal			73
Ha et al. [14]	Far frontal	√		96
This Work	Lateral	√	√	98

V. CONCLUSION

This paper presented a fast vision-based approach for vehicles detection and counting. The detection process uses the freeway video images and after the preprocessing stages neural networks are used in the detection and counting phase. Applying this technique to the busiest freeway in Riyadh (King Fahd Road) resulted in detection accuracy higher than 98% despite the light intensity changes, the occlusion situations, and shadows.

Frontal and lateral views of the highway are used for testing. While frontal views did not provide reasonable results, the detection results for lateral views are higher than 98%. The design of the neural network was straight-forward and overcame the main difficulties in vehicles detection process, namely the active shadows and the occlusion problems. In the traditional techniques a complete algorithm is designed to solve each problem separately. In addition, the ANN design is flexible and could be improved for future requirements.

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