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A Neural Network Based Traffic Flow Evaluation System for Highways

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Abstract. D 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.

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, various serious additional problems appear 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 vehicles in the lateral-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.

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 (Gupte *et al.,* 2002). 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, the results are sensitive to light changes.

(Zhiwei *et al.,* 2004) used an alternative method based on Gaussian distribution 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. (Rad and Jamzad, 2005) 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 (Zhang *et al.,* 2004; Chen *et al.,* 2004; Ji *et al.,* 2006). The pixel intensities could be modeled using the median model (Zhang *et al.,* 2004). (Chen *et al.,* 2004) calculated the frequency ratios of intensity values 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. (Ji *et al.,* 2006) proposed self-adaptive background and updating algorithms based on an optical flow. 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 (Schneiderman and Kanade, 2000; Zhao and Nevatia, 2003; Rajagopalan *et al.,* 1999). However, due to the absence of an accurate distribution for vehicle models, only approximate probability distributions are used. This leads to significant errors in detection and make the approach inapplicable for complicated scenes.

Other approaches use explicit and detailed models (Hinz, 2003; Ruskone *et al.,* 1996; Hoffman *et al.,* 2004). (Hinz, 2003) proposed the detection and counting of cars in aerial images. The technique needs a very large number of images for cars in different directions with respect to the camera, with different shapes and colors. The vehicle detection or recognition is implemented using a tree-like model hierarchy. This process needs a large memory and long processing time. (Ruskone *et al.,* 1996) used a hierarchical model 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. Vehicle detection could be implemented by finding various characteristic features in images of a monochrome camera (Hoffman, Dang and Stiller, 2004). 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.

Neural networks are used for vehicle detection (Mantri and Bullock, 1995; Ha, Lee and Kim, 2004). 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.

(Liu *et al.*, 2001) used fuzzy measures to detect vehicles. The detection depends on the light intensity value. 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.

(Flores, 2004) proposed the inter-frame difference method. 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 proposed to detect and count vehicles. In the first phase of the approach, the 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 caused 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.

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. Figure 1 summarizes these five basic steps.

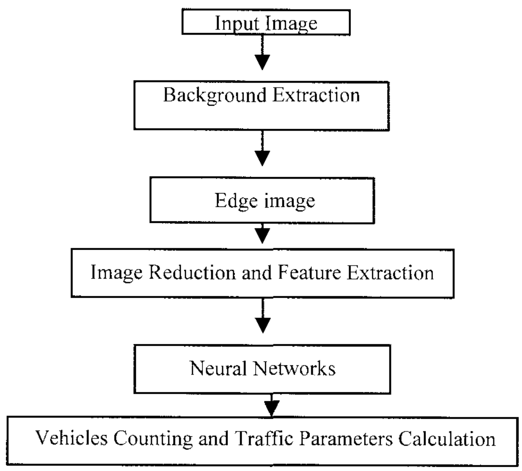


Fig. 1. Steps of traffic parameters calculation.

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 (Ha, Lee and Kim, 2004):

Step 1. 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 $D^{t,t-1} = |C^{t} - C^{t-1}|$.

Step 3. Specify the threshold level T using maximum entropy criterion (MEC).

Step 4. Convert the differences to binary.

Step 5. Calculate the Difference Product (DP) using the bitwise logical AND operation: $DP^{t} = DB^{t-1,t-2} \& DB^{t,t-1}$.

Step 6. Apply binary dilation (DLT) of $DP^{t}i,j$, where i and j represent row and column coordinates for each pixel.

Step 7. Apply closing and opening morphological operators.

Step 8. Calculate moving object region (MOR) by filtering the closed image.

Step 9. Fill the moving object region.

Step 10. 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. Figure 2 shows the flow chart for automatic background extraction.

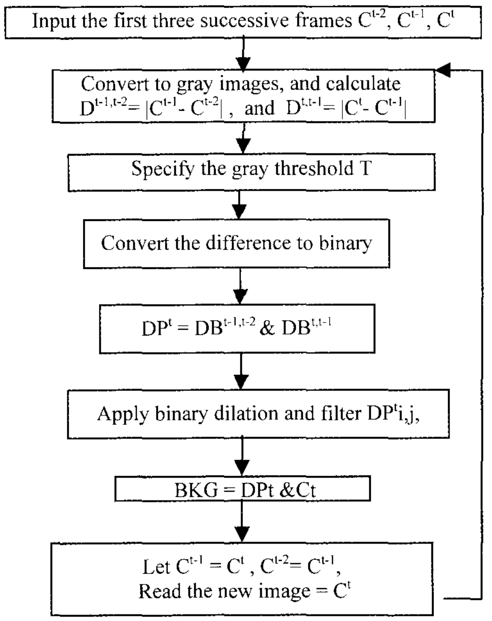


Fig. 2. Automatic background extraction flow chart.

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 (Ha, Lee and Kim, 2004):

$$B^{t+1} = \begin{cases} mB^t_{i,j} + (1-m)C^{t+1}_{i,j}, & if \quad D^{t+1}(i,j) < T \\ B^t_{i,j}, & otherwise \end{cases} \qquad (1)$$
$$0 \le m \le 1$$

The value of m 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. Figure 3 shows the Sobel operator masks used (Gonzalez, Woods and Eddins, 2004). 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 (Rao and Bopardikar, 1998). A wavelet transform based on two-level decomposition produces seven sub-bands as shown in Fig. 4.

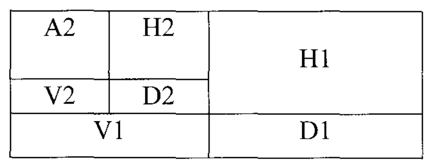


Fig. 4. Wavelet representation of an image.

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: approximation component and 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 the 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 the 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 (Smith, 2005). 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 eigenvectors are found, they can be sorted from the most to the least significant. 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 set 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 (Suleiman and Khalifa, 2006). 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. 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 (Hayken, 1994). It consists of three entirely different layers (input, hidden and output layers). The input layer broadcasts data to the hidden layer through a non-linear 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 (Al-Ghadeer, 2004). 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 calculated according to Table 1.

Table 1. Traffic flow conditions based on Density (May, 1990)

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

The density is defined as the number of vehicles per kilometer per lane. To calculate the density, the distance headway must be calculated. 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. The distance headway includes the length of the lead vehicle and the gap between the lead and the following vehicle as shown in the following equation (May, 1990):

$$d_{n+1}(t) = L_n + g_{n+1}(t) = \frac{L_S}{(N_V / N_L)} \qquad (3)$$

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 calculated from the following equation (May, 1990):

$$k = \frac{1}{\bar{d}} \qquad (4)$$

where k = density (vehicles per lane-km)

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

Results

A digital camera was used to record videos of King Fahad Road in Riyadh City. The scenes were recorded for frontal and lateral views. To record the frontal views for moving vehicles, the camera was mounted on the bridges over the highway. For the lateral views, the camera was mounted on towers in the vicinity. More than 80 hours of King Fahad Road 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:

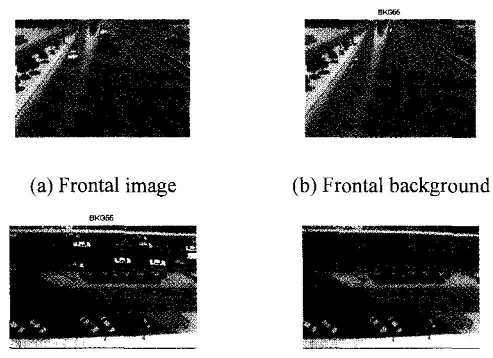
- A Pentium-IV 700 MHz PC with 512 MB SDRAM.
- A digital video camera: Sony DCR-HC36 (in webcam mode).
- Matlab 7.0 as a software development tool.

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 later 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

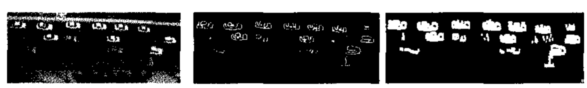
Figure 6 shows edges that are detected of the moving vehicles. Sobel operator is applied here to detect horizontal and vertical edges. The edges of the dark vehicles are not detected completely as in the case of white ones, but still there are some pixels to represent these vehicles. After the edges are detected, they are filled and filtered 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 substantial 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.

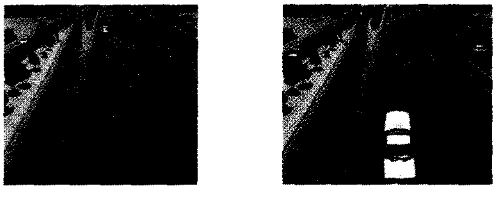
D. Neural network results

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. An iterative process is used to find the value of spread that results in minimum training error. Based on simulation, a spread value of $\sigma = 80$ is found to be adapted.

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 2 are not high because the vehicles sizes change as they get closer to the camera as shown in Fig. 7. Therefore, it can be concluded that the frontal view may not be a good choice for vehicle detection.

Table 2. 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	64	21.1	15.6
XY- Proj	49.5	58	24.77	29.4



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

Fig. 7. Vehicle size changing with respect to its distance from camera.

For the lateral view scenario, 513 images were used (342 for training and 171 for testing). Table 3 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 in the highest. Figure 8 shows a comparison between the actual count and the neural network output for lateral section images and Fig. 9 shows a zoomed sample of these results. From these figures, it can be concluded that the neural network is capable of achieving a curate results. It is worth mentioning here that the neural networks result is compared to the actual vehicle counts obtained manually by a human operator from the real image frames.

Table 3. 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- Proj	98.6	98.5	95.3	93.6

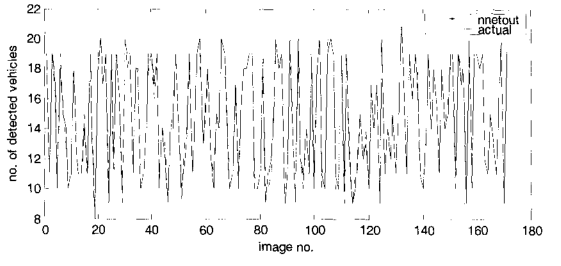


Fig. 8. Actual and neural network outputs.

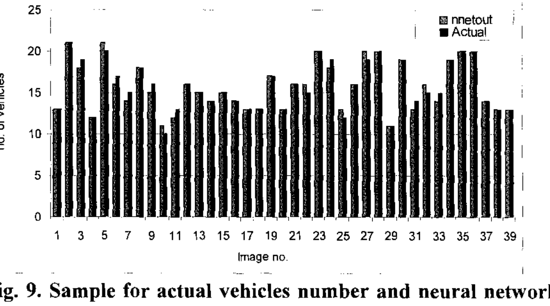


Fig. 9. Sample for actual vehicles number and neural network output.

The reduction in data dimension is expected to lead to a reduction in computation. Table 4 shows the average processing time required for each alternative approach.

Table 4. Average processing times

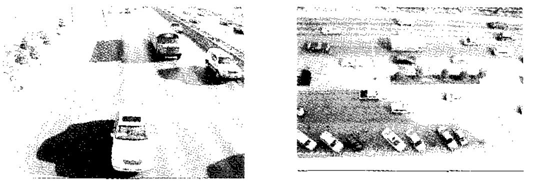
	Raw data	Wavelets	PCA	Wavelets + PCA
Training time (seconds)	24	6	5	5
Testing time (seconds)	4	2	1.9	1.8

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. 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 Eq. (4). Once the number of vehicles is counted and the lateral section length is known (55 m in this case), the density is calculated. Resorting to the previously given Table 1, other important traffic parameters could be determined and the highway monitoring can be achieved easily. Table 5 gives the neural network results for five different levels of service. From this table, it could be concluded that the results are accurate. In some cases where the detected vehicles differ from the actual one, the output level of service is still the same and unchanged. This shows the efficiency of using this approach.



(a) Active shadow (b) Occlusion problem

Fig. 10. Typical difficulties in vehicle detection.

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 6 gives this comparison. The results show that our approach is promising to solve shadow and occlusion problems. In addition, it gives high detection rate.

Table 5. Results for different levels of service

Case No.	No. of vehicles		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

Table 6. Detection rates of different approaches

	View	Method	Max. vehicles in scene	Robust to shadows	Occlusion removal	Maximum detection (%)
Gupte *et al.*, (2002)	Lateral	Background subtraction	4			90
Rad and Jamzad, (2005)	Far frontal	Background differencing – Laplacian filter	17		√	96
Schneiderman and Kanade, (2000)	Different views	Statistical- 3D model	4			83
Zhao and Nevatia, (2003)	Aerial	3 D modeling – Bayesian Network	50			85
Rajagopalan *et al.*, (1999)	Frontal	Higher order Statistics	9			73
Ha *et al.*, (2004)	Far frontal	Background subtraction- edge detection- binary seed filling	8	√		96
This work	Lateral	Neural Networks	22	√	√	98

Conclusions

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 in the order of 98% despite light intensity changes, occlusion situations, and shadows.

Frontal and lateral views of the highway are used for testing. While later views did not provide reasonable results, the detection results for the lateral views are in the order of 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, ANN design process is flexible and could be improved for future requirements.

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المراقبة التلفزيونية للطرق السريعة باستخدام الوسائل الذكية

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ملخص البحث. يمثل ازدحام الطرق أحد أهم المشاكل التي تؤرق دول العالم اليوم سواءً المتقدم منها أو النامي، وتستلزم إيجاد آلية فعالة للتغلب على مشكلة الازدحام المروري، وقد أثبتت الدراسات أن افتتاح طرق جديدة لا يمثل الحل لهذه المشكلة، بل إن الحل الناجع لهذه المشكلة يكمن في استخدام الطرق المتاحة بفعالية كبيرة باستخدام التكنولوجيا.

يعتبر حجر الأساس في حل هذه المشكلة هو تحديد عدد المركبات المتحركة في الصور الملتقطة للطرق، والذي بدوره يمثل أهمية كبيرة في عديد من التطبيقات العسكرية والمدنية. وفي هذا البحث قمنا بالتقاط مجموعة من المقاطع التلفزيونية لأحد أهم الطرق وأكثرها ازدحامًا في مدينة الرياض (طريق الملك فهد)، وتم تحليل هذه المقاطع ابتداءً بأول ثلاث صور ثم تستمر عملية تحديد النقاط (pixels) المتحركة في الصور المتتابعة واستبدالها بنقاط الخلفية الثابتة حتى نصل إلى استخلاص كامل الخلفية، ثم تطرح الخلفية من الصور وتوجد حواف (edges) الصورة الناتجة باستخدام ال(Sobel operator)، وتختزل أبعاد الصورة الناتجة ليتم تطبيق الشبكات العصبية الاصطناعية (ANN) بعد ذلك كوسيلة ذكية للكشف عن المركبات الموجودة في الطريق السريع وتحديد عددها، ولحل المشكلتين الرئيسيتين في الكشف عن عدد المركبات وهي الظل وحجب المركبات لبعضها عندما تظهر المركبتان المتجاورتان في الطريق كمركبة واحدة كبيرة.

بعمل مقارنة مع الدراسات المنشورة أثبتت النتائج فعالية هذه الطريقة للكشف عن عدد المركبات المتحركة بغض النظر عن الظروف الجوية المحيطة، وكان معدل الكشف عن المركبات المتحركة باستخدام هذه الطريقة أكثر من ٩٨٪.