An ITS System for Determining Vehicular Waiting Time at Traffic Build-up Queues

M. M. Ata, M. El-Darieby, B. Abdulhai, E. Felemban, S. Basalamah, B. Zafar

Umm Al-Qura University, Makkah, Saudi Arabia

Summary
The increased need for mobility has led to transportation problems like congestion, accidents and pollution. However improving the reliability of delay estimates and real time dissemination of information remains a challenge .in this paper, an automated system for queue end monitoring has been proposed using image processing based Principal Component Analysis (PCA) technique as a powerful feature extraction methodology. Furthermore, the most salient features (PCs) which have been extracted from the PCA technique are directly fed to Artificial Neural Network (ANNs) based feed forward back propagation algorithm. The experimental results showed that the use of PCA as a feature extractor has accomplished the target with a processing time 19 sec and 5 epochs of training network only with a minimal percentage error of vehicle recognition depending on the new concept of road network implementation criteria that could be named as road side unit (RSU) which could be considered as a new contribution in the ITS field.
Key words:
Intelligent Transportation System (ITS), Road Side Unit (RSU), Feature Extraction, Principal Component Analysis (PCA), Digital Image Processing (DIP), and Artificial Neural Networks (ANNs).

1. Introduction

Seamless transportation is one of the pillars of our societal and economical sustainability. Intelligent Transportation Systems (ITS) offers potential solutions to growing congestion problems in major urban areas because of increasing mobility demands which has directly adverse effects on level of service, transportation costs, commerce, tourism, and the environment. Intelligent transportation system involves the use of IT and technology such as image processing and artificial neural networks for solving transportation problems.

. In this paper, we focus on ITS applications related to "traffic build-ups.", this helps mitigate issues of the, for example, environment, international trade and safety as follows:

- Reducing queue length at traffic signals cuts down significantly CO2 emissions inside cities as it means car engines would spend lesser time idling. The characterization of waiting time at these queues helps adjust the timing of traffic signals and is a basic component in Adaptive Signal Control.
- Reducing border crossing queuing delays have been identified as a major requirement for enhancing trade logistics. For example, it has been estimated that $40 million in operating costs are lost annually due to border crossing delays at the Blaine, WA border facility alone. With free flowing traffic, it would take just 7 minutes to cross the Niagara River Bridge, but in fact, the actual crossing time is 59 minutes.
- It has been suggested that the "delay per vehicle and length of queues" are two of the main of operational performance measures of work zones on highways and arterials.

We propose a cost-effective infrastructure-based system that detects accurately and dynamically vehicular waiting times at such queues. The system requires the deployment cost-effective road-side units (RSU). RSUs are used as vehicular sensors. We calculate the vehicular waiting time through coordinating the RSUs operations and exchange of information. Each RSU has a consumer-grade equipment of a camera and a wireless communications module (e.g. Wi-Fi module). The system relies on processing individual images (not videos) taken by the cameras of RSU. The RSU use artificial Neural Networks (ANNs) to identify vehicle, and RSU wireless communications (e.g. Wi-Fi module) to exchange information with other RSUs to enable the calculation of vehicular waiting times.

The proposed system has the following advantages; (i) a highly efficient and real-time system is achieved through in-network processing of real-time individual images as opposed to videos which affects directly on processing time and communication speed;(ii) cost effective as RSU are built using consumer-grade technologies and open source tools, (iii) highly reliable as there is no single point of failure (i.e., a centralized server) in the system. Data processing is performed at many RSUs. The failure of an RSU does not affect the operation of the system significantly.

The rest of this paper is organized as follow: Section II provides a review of the literature; Section III introduces the appropriate proposed system with respect to its composition and mechanism; Section IV provides the results of the PCA experiment based feature extraction,

Manuscript received May 5, 2012
Manuscript revised May 20, 2012

and Section V provides the final conclusions and future work of interest.

2. Literature Review

a. Queue-End Monitoring

Previously proposed systems involve many technologies such as Video Image processing (VIP), Wireless Sensor Networks (WSN) as a road sensors. For example: Advanced Warning System (AWS) which was designed as an automated system to improve tunnel safety, reduce the potential for both primary and secondary collisions, and to reduce incident response times producing an incident management system[1,2].

The system has some key objectives; (i) Provide means of automated real-time advance notice to motorists entering the tunnel of queues or lane blockages that may be beyond their sight depending on video frames,(ii) Provide means of automatic dissemination of information on overall system events preferably via automatic email, and(iii) Provide means of remote Ministry LAN access to monitor and manually override when required [3].

b. Feature Extraction

Generalized feature extraction relies on a collection of feature extractors that function independently of domain and application. The feature vector, which is comprised of the set of all features used to describe the image, is a reduced dimensional representation of that image. This effect, means that the set of all features that could be used to describe a given image (large and in fact infinite infinitesimal changes in some parameter are allowed to separate different features) is limited to those actually stated in the feature vector.

One main purpose of dimensionality reduction is to meet engineering constraints in software and hardware complexity, the computing cost, and the desirability of compressing pattern information. In addition, recognition is often more accurate when the image is simplified through representation by important features or properties only.

3. PROPOSED SYSTEM

In this section we describe our system and practical aspects of its deployments. Then we describe the algorithms we used for image processing which will be followed by a description of how vehicular waiting time is calculated. Figure 1 shows the main components of a deployment of the proposed system. The system is composed of RSU deployed on the side of roads in areas around border crossing, checkpoints or highway work zones.

RSUs can be programmed to operate as data sensors. WMN are typically deployed in a quasi-stationary manner where some mesh access points are stationary. An RSU is a stationary access points that can be deployed on, for example, light posts.

Each RSU is configured to run the OpenWRT (http://www.openwrt.org) Linux distribution for embedded devices. OpenWRT is a Linux distribution that provides a Software Development Kit (SDK) that is used to compile custom code into a package to be installed on different RSUs. For the purposes of detecting waiting time, we interface cameras to RSU through USB ports.

We extended the camera software required to drive hardware modules. With this setup, each RSU, and its attached camera, is controlled to take snapshots of vehicles on the road.

RSU can communicate amongst them using Wi-Fi to forward data to and receive data from the Internet through the gateway. This augments RSU with spatial and contextual characteristics of surrounding environments. This wireless infrastructure enables routing of information in a multi-hop manner.

RSU exchange data packets over, possibly, mobile multi-hop. We use Optimized Link State Routing (OLSR) as a proactive routing protocol that maintains an up-to-date routing table. AP’s exchange OLSR HELLO messages periodically to build and maintain this table. This dynamic method of building the table enables AP to self-configure themselves to establish a WMN. HELLO messages advertise the one-hop interfaces of each AP. The periodic exchange of HELLO messages also enables the WMN to recover from a failed link or node. The system architecture does not require all RSU’s to be connected to the Internet.

In general, a special type of RSU, called gateway, allows integration with other network types (e.g., Internet). The gateway receives/ forwards the information using TCP/IP on the Internet where packets are rerouted to reach the Server. RSU and gateways self-configure themselves to identify their roles.

For example in figure 2, the three vehicles, red, green, blue constitute a platoon. The vehicular platoon drives until the end of a vehicular queue waiting at a check or border crossing point or backlogged after an incident (for example).RSU1 thought its installed camera captures image scenes for a vehicular platoon then router uses the images to start building an ANNs and start training it.

The resulting trained ANN structure information is forwarded to RSU2. RSU 2, through its Camera, captures image scene for the vehicle until the platoon of vehicles is detected and recognized using the trained ANNs. This information is also forwarded to the RSUs downstream and the process is repeated for higher accuracy and acculative time calculations. Figure 3 describe the main components of each RSU unit.

Figure 1: Main components of deployment

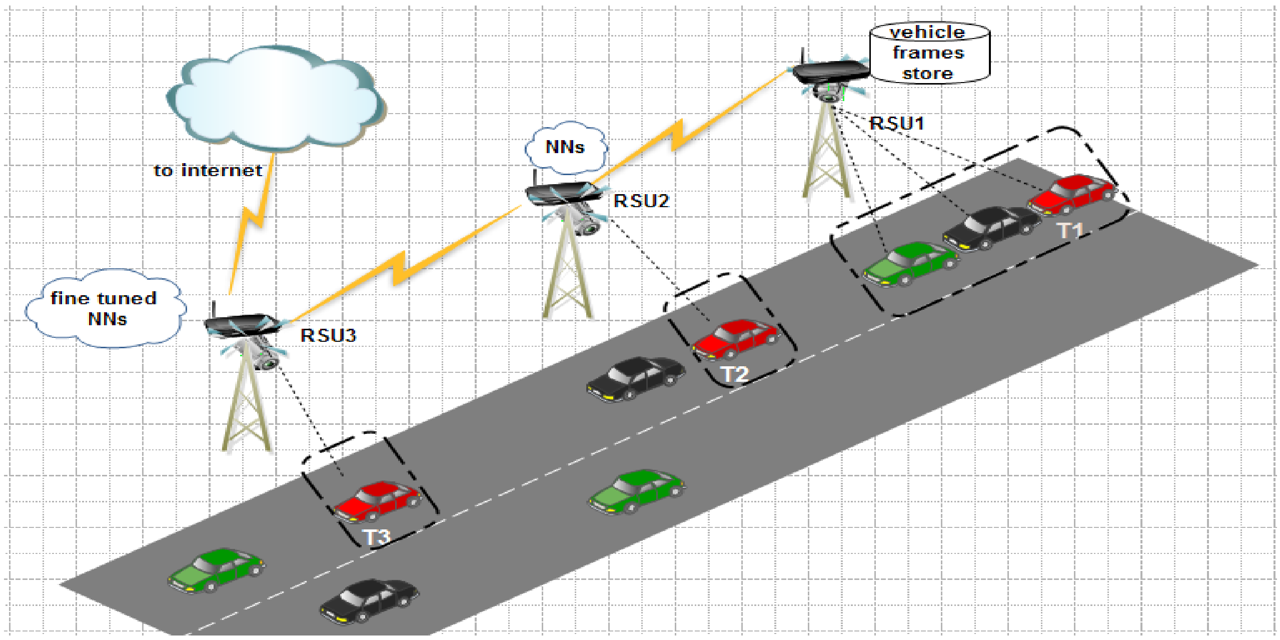

Figure2: system deployment

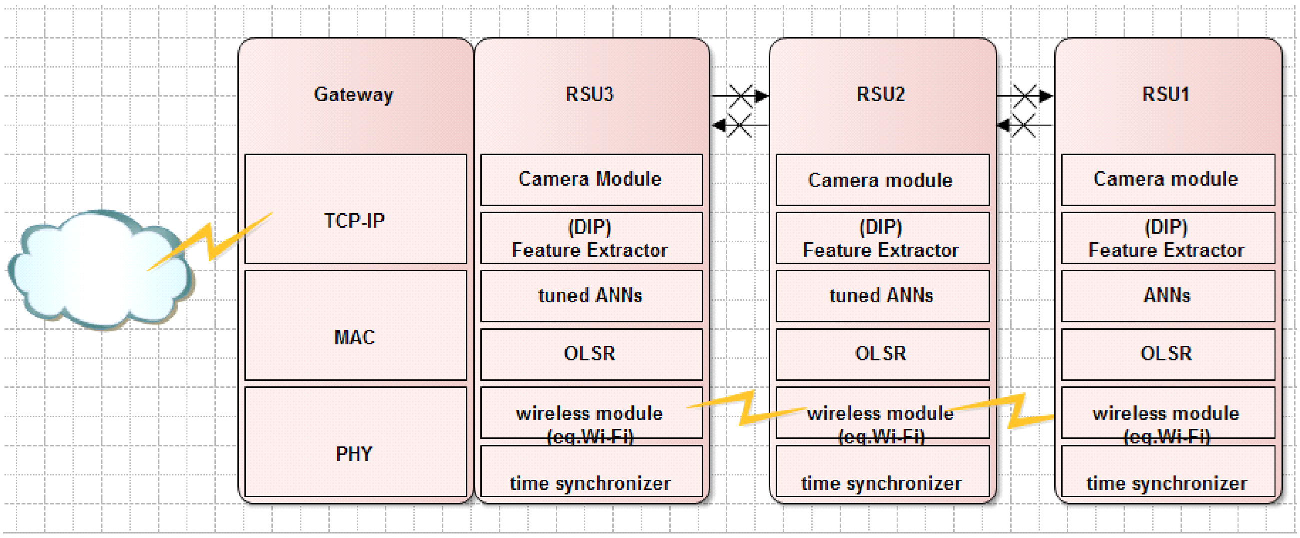

Figure3:RSU construction

a. DIP module based feature extraction

In the proposed system, we use principal component analysis (PCA) based feature extractor. PCA is a second order statistical method that transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called PCs. PCA is generally used to reduce the dimensionality of a dataset while retaining as much information as possible.

Instead of using all the PCs of the covariance matrix, the data can be represented in terms of only a few basis vectors [4, 5]. PCA is considered an effective and powerful statistical feature extractor to extract the most salient features. Figure 4 describes the main four steps for extracting PCs from each vehicle image.

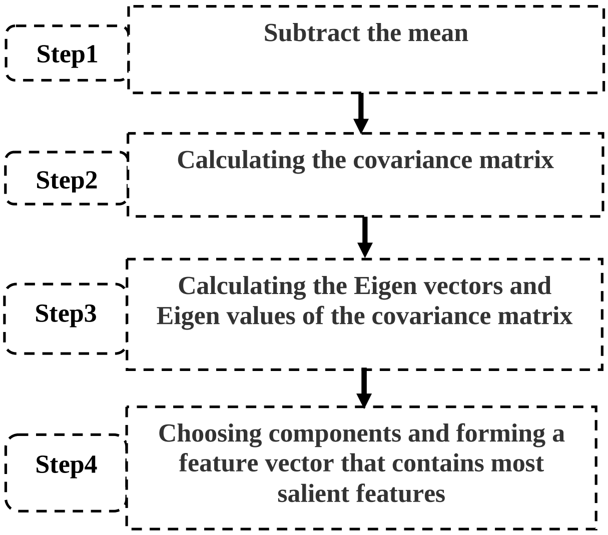

Figure 4: basic steps for PCA algorithm

PCA algorithm have been applied for each vehicle image x1, x2, x3, x4, x5,and x6 (assuming queue of 6 vehicles) to transform theses vectors into a new vector form of Y according to Equation (1):

$$Y = A(X - m_X) \quad (1)$$

where vector m_X is the vector of mean values of the vehicle image matrix and defined by the relation defined in Equation (2):

$$m_X = E\{X\} = \frac{1}{N}\sum_{n=1}^{N} X_k \quad (2)$$

and the matrix A is determined by the covariance matrix Cx according to Equation(3). Rows in the matrix A are formed from the Eigen vectors of Cx ordered according to corresponding Eigen values in descending order.

$$C_X = E\{(X - m_X)(X - m_X)^T\}$$

$$= \frac{1}{N}\sum_{n=1}^{N} X_k {X_k}^T - m_X {m_X}^T \quad (3)$$

As the vector x of input variables is n dimensional the size of C_X is n×n. The elements $C_x(i,i)$ lying in C_x main diagonal are the variances of x vector as follow according to Equation (4):

$$C_X(i,i) = E\{(X_i - m_i)^2\} \quad (4)$$

Also, the other values $C_X(i,j)$ determine the covariance between input variables xi, xj as follow:

$$E\{(X_i - m_i)(X_j - m_j)\} \quad (5)$$

b. Time Calculation through Camera Coordination

The following steps describe how vehicular waiting time is calculated:

1. RSU1 through its installed camera captures image scenes for vehicles then uses the images to start training and building an ANN.
2. RSU1 registers the time (TRSU1) and location when vehicle crosses RSU module as the exact location of the RSU is fixed and known a piriori, and the relative location of the vehicle with respect to the RSU module can be calculated.
3. A feed-forward back propagation neural network has been utilized and built with a differentiable transfer function which uses from 2 to 3 scenes for each vehicle.
4. Each NNs use PCA as a feature extractor to extract most salient features for the training process.
5. The resulting trained ANN structure and timing information is forwarded to RSU2 via the RSU Wi-Fi interface and through its locally maintained routing tables via OLSR. We assume RSU's are synced in time.
6. RSU 2, through its Camera, captures image scene for vehicle. The trained ANN is used to recognize vehicles.
7. The images taken are used to fine-tune the training of the ANN.
8. The RSU registers the time of vehicle crossing by RSU. The fine-tuned ANN and registered time are forwarded to RSU3 via the RSU Wi-Fi interface.
9. As the vehicle is identified, the RSU registers the time of vehicle crossing by RSU 2 by the relation (waiting time=TRSU2-TRSU1).
10. The fine-tuned ANN and registered time are forwarded to RSU3 via the RSU Wi-Fi interface.

Figure 5 show How the RSU sends the NNs in case of activation.

11. The process is repeated for RSUs as shown in Figure 6. Simple timing calculations can provide information on waiting times for a vehicle as well as their average speeds. Averaging timing and speed information on a number of vehicles results in increasing the accuracy of this information.
12. Finally, accurate vehicular waiting time information is forwarded via the gateway and the Internet to Traffic Management Center headquarters.

4. Experiment Results

We ran simulation experiments to study the performance of the proposed ANN-based PCA system. The objective of the experiments is measuring four performance indices have been measured and tested. These are:

(i) Neural network performance,
(ii) Regression performance,
(iii) Percentage of vehicle recognition error, and
(iv) Processing time

All these performance indices could provide a good view for the hardware implementation.

The performance of all tested ANNs-based PCA was evaluated through Table.1 which illustrates the results. For the PCA based feature extractor, the best validation performance has been achieved at epoch 5 and regression is approximately equal to 1 with acceptable processing time equal (19 sec).

Table 2 shows the vehicle recognition errors for the vehicles we tested. Due to orthogonally property of the Eigen vectors which extracted from PCA algorithm, the neural network is fed by very effective features that cause minimal error of vehicle recognition. Figure 7 show mean squared error achieved versus the number of epochs for the training, testing and validation samples.

The figure also shows that the best validation performance achieved is 4.1553e-005. Figure 8 show the regression (R) which represent an approach to modeling the relationship between target value (T) of (train, validation, and test) samples and appropriate output (Y) .The use of PCA satisfying best fit of date which reflects that the sum of the squares of the distances between the line and the data points are minimal so (R=1).

all cases of the regression as represented by linear straight line equation(Y=T) reflects the higher accuracy and minimal error of extracted features using PCA. The results illustrate how PCA achieves its target results within acceptable processing time and number of salient features needed.

5. Conclusion and future work

In this paper we proposed a novel system for the prediction of vehicular waiting times at different traffic locations and conditions including traffic signals, border crossings, and work zones. We described the main components of the system and many real life deployment concepts of the system. We also described image processing algorithm used to determine such waiting times. We used Wi-Fi based wireless communication to coordinate and share information between different parts of the system.

We used Artificial Neural Networks to recognize vehicles and PCA-based algorithm to extract features of images. Performance results indicate that the use of Principal Component Analysis (PCA) as a feature extraction provides our system with the most salient features producing a minimal error of vehicle recognition within fairly acceptable processing time. This results in providing advanced automatic waiting time prediction system depending on images not video frames which decrease processing time needed and complexity of the neural networks and communication overhead between system modules.

In the future work of interest, we will produce new experiments using other feature extractors such as (Empirical Mode Decomposition (EMD)-Independent Component Analysis (ICA)-transformed domain feature extraction (Fast Fourier Transform (FFT)-wavelet transform-Discrete Cosine Transform (DCT)) and other recognition methodology such as 2-D correlation, Fuzzy logic, and Genetic Algorithms.

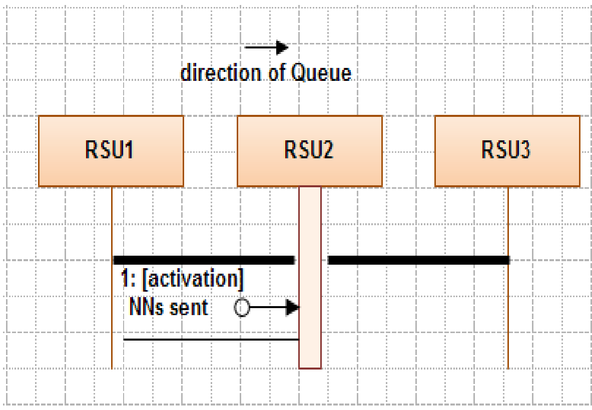

Figure5:performance if RSU2 is activated

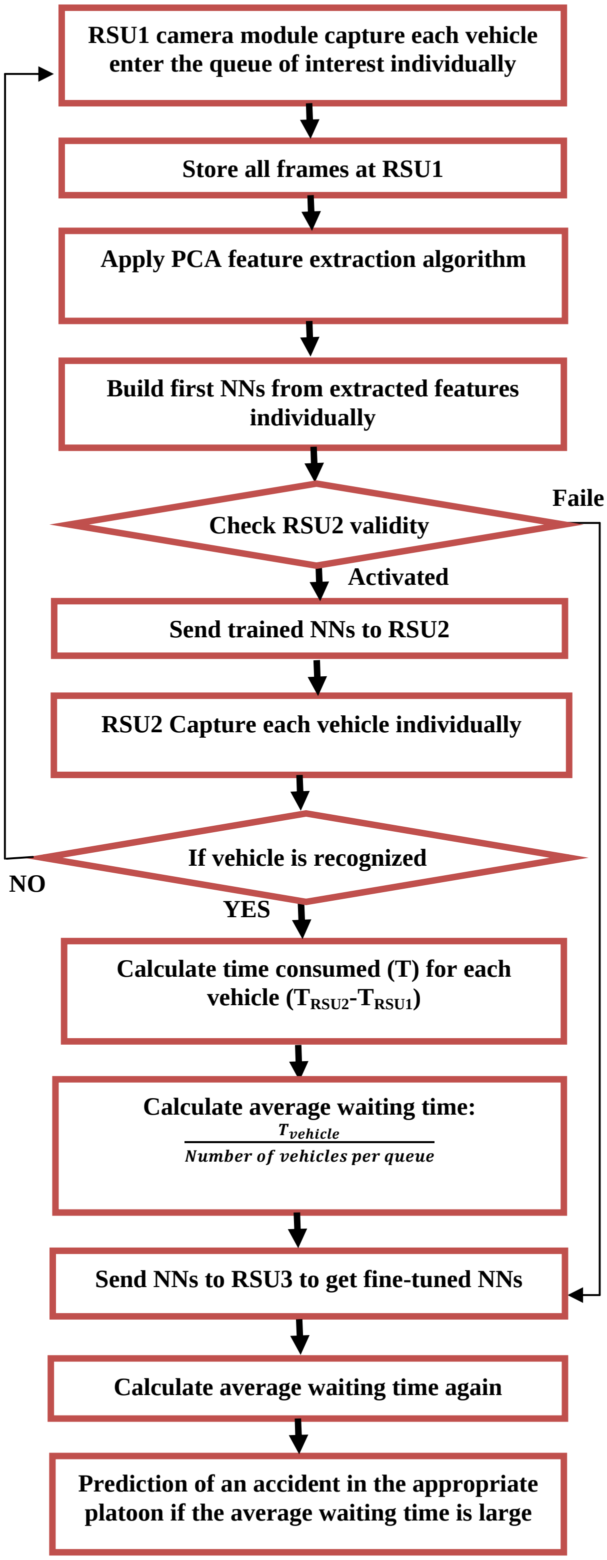

Figure6: Time calculation algorithm

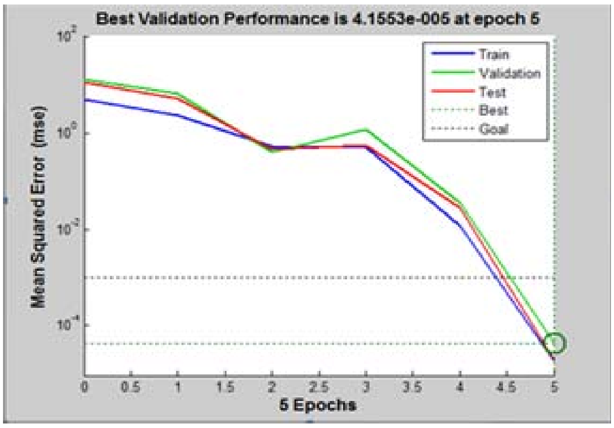

Figure7: network performance based PCA

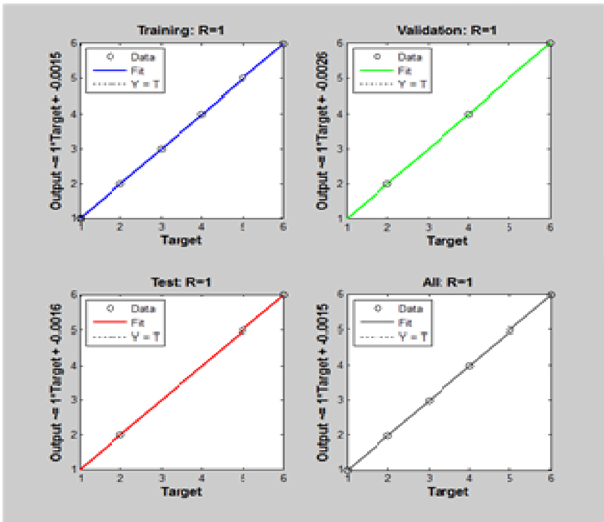

Figure8: network regression based PCA

Table.1 Network specifications

Network specifications	ANNs based PCA
Number of inputs	259
Number of hidden neurons	10
Number of iterations	5
Train ratio	70%
Validation ratio	15%
Test ratio	15%
Processing Time	19 sec

Table.2 vehicle recognition errors

Error=(Target-Output) ANNs based PCA	Car index
0.001592404373095	Car1
0.003301086460745	Car2
0.002602984550787	Car3
0.008249677368291	Car4
3.436377551171432e-04	Car5
0.006760424622620	Car6

Acknowledgments

The authors would like to thank the Center of Research Excellence in Hajj and Omrah (HajjCoRE), Umm Al-Qura University. Under Project number P1129, titled "UQU-Sense."

Reference

[1] R.Browne, M.Fox, S.Smith " Highway 404 HOV Tunnel Advance Warning System," the 2008 Annual Conference of the Transportation Association of CanadaToronto, Ontario, Technical Paper – TAC 2008 AGM.
[2] Wong, Kate (Delcan); Lee, Rex (Delcan); and Tai, Ken (MTO). Implementation of the Queue-end Warning System (QWS) along the Approaches to the Canada-U.S. Border. Proceedings of the 2003 ITS World Congress, Madrid, Spain.
[3] A.M.Khan " Prediction and Display of Delay at Road Border Crossings," The Open Transportation Journal, Vol. 4, pp. 9-22.2010.
[4] A tutorial on Principal Component Analysis, Lindsey Smith(2002):http://www.cs.otago.ac.nz/cosc453/student_tutorials/principal_components.pdf (last visit 1/4/2012).
[5] N. Lawrence," Probabilistic Non-linear Principal Component Analysis with Gaussian Process Latent Variable Models", Journal of Machine Learning Research Vol.6 pp.1783–1816, 2005.