

# Eigen Based Traffic Sign Recognition Which Aids In Achieving Intelligent Speed Adaptation

Hasan Fleyeh and Erfan Davami

**Abstract.** Speed is one of the major factors by which the traffic safety is affected. If the speed limit traffic signs on the road are recognised and displayed to a driver, this will be a motivation to keep the vehicle's speed within the permitted range. The purpose of this paper is to investigate Eigen-based traffic sign recognition which can aid in the development of Intelligent Speed Adaptation. This system is based on invoking the PCA technique to detect the unknown speed limit traffic sign and computes its best effective Eigen vectors. The traffic sign is then recognized and classified by using the shortest Euclidean distance to the different speed limit traffic sign classes. The system was trained using 24 037 images which were collected in different light conditions. To check the robustness of this system, it was tested against 1429 images and it was found that the accuracy of recognition was 97.5% which indicates clearly the high robustness targeted by this system.

**Keywords.** Traffic signs, pattern recognition, machine vision, PCA, classification.

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## 1 Introduction

One of the major causes of accidents on roads is illegal or inappropriate speed. Speed represents one of the main factors by which traffic safety is affected as both the risk of fatal crashes and the severity of accidents increase. Speeding is a very well-known problem to road authorities around the world. These authorities are very strict with speed limits regulations in general and they try to force drivers in particular parts of the road, where danger is obvious, to maintain their speed within a certain range by installing speed limit cameras. Intelligent Speed Adaptation (ISA) is an in-vehicle technology which warns drivers, discourages them or even prevents the vehicle from exceeding the speed limit [1, 2].

Usually, a GPS which is connected to the location of speed limit traffic signs is used to specify the speed on the road and deliver it to the driver. However, speed limit traffic signs can also be detected and recognised by employing a vision based traffic sign recognition system which detects and recognises these traffic



Figure 1. Potential difficulties when dealing with signs, from upper left to bottom right: Faded, Challenging weather conditions, Bad lighting geometry, Damaged sign, Occluded sign, and Highlighted sign.

signs from the video stream and gives them to the drivers. Generally, the detection of speed limit traffic signs is achieved by combining their colour and shape information and the recognition and classification is usually carried out by a certain classifier.

Using traffic sign recognition is challenging as visibility is affected by weather conditions such as fog, rain, clouds and snow [3]. The colour information is sensitive to the variations in light conditions such as shadows, clouds, and the sun [3–5]. It can be affected by the illuminant colour (daylight), illumination geometry, and viewing geometry [6]. The presence of objects, such as buildings or vehicles, similar in colour and shape to the road signs in the scene under consideration can also affect recognition efficiency. Signs may be found disoriented, damaged or occluded. If the image is acquired from a moving car, then it often suffers from motion blur and car vibration. Figure 1 depicts a number of challenges for traffic sign recognition systems.

The main contribution of this paper is to introduce an approach which is effective for the case of speed limit recognition and gives high recognition rates. This paper investigates the Eigen-based traffic sign recognition as a technique by which the current speed limit is provided to the driver on ongoing basis. It is based on collecting the speed limit traffic sign's image by a camera, extracting the candidate traffic sign from the image according to its colour-shape specifications and invoking the Eigen-based system to recognise it.

The remainder of this paper is organised as follows. The relevant work is presented in Section 2. In Section 3 the proposed Eigen-based speed limit recognition system is described. Image analysis and recognition are described in Section 4. The experiments and results based on the proposed approach are given in Section 5 and in Section 6 the conclusions drawn from this work are presented.

## 2 Relevant Work

In recent years, research into traffic sign recognition has grown rapidly because of the real need for such systems not only for future vehicles but also for the current in-vehicle assistant systems. Performance indexes necessary for these systems include high recognition rates, real-time implementation, many traffic sign categories as recognition objects, robustness for variant environments, and feasibility under poor visibility conditions.

Torresen et al. [7] proposed an approach for detecting Norwegian speed limit signs. It consists of three major steps: Colour-based filtering, locating sign(s) in an image and detection of numbers on the sign. The system was applied on 198 images and the recognition rate was about 91%.

Wu and Tsai [8] presented an algorithm for detecting speed limit signs from video imaging to support real-time road inventory data collection operations. The algorithm consisted of color segmentation based on locally adaptive thresholding extraction of regions of interest using a depth-first-search algorithm, followed by speed limit sign detection and speed limit number extraction by means of optical character recognition and 2D correlation. The algorithm produced 3% false negatives and 0% false positives (97% recognition rate) out of 123 images containing speed limit signs.

Paulo and Correia [9] proposed a recognition algorithm which analyses the outer contours of pictograms. Matching of signs against the database is done using the curvature space scale representation. The algorithm was tested with a set of images using several types of cameras, from low resolution phone cameras, to 5 MPixel photo cameras. The recognition rate was 67.9% for danger signs, 69.1% for prohibition signs, 83.8% for obligation, and 75.3% for information signs.

Hoferlin and Zimmermann [10] presented a system for the recognition of circular traffic signs. The system introduces the application of local Scale Invariant Feature Transform (SIFT) features for content-based traffic sign detection along with widely applied shape-based approaches. To refine the localisation of the detected traffic sign candidates, a technique, called Contracting Curve Density (CCD) was employed. The recognition stage was based on SIFT and Speeded-Up

Robust Features (SURF) descriptions of the candidates executed by a neural network. The system performance was evaluated using 30 minutes video containing 133 traffic signs. The system could detect 97% of these traffic signs.

Ruta et al. [11] utilised a novel image representation and discriminative feature selection algorithms to detect and track traffic signs. The detector captures instances of equiangular polygons in the scene which is first appropriately filtered to extract the relevant colour information and establish the regions of interest. The tracker predicts the position and the scale of the detected sign candidate over time to reduce computation. The detection and recognition rates achieved by the system were 79.4% for red circles (RC), 97.3% for blue circles (BC), 84.8% for yellow triangles (YT), and 81.3% for blue squares (BS).

Escalera et al. [12] introduced a novel system for multi-class classification of traffic signs based on error correcting output codes (ECOC) which is based on an ensemble of binary classifiers that are trained on bi-partition of classes. The data consisted of 15,000 road frames collected under different conditions. Validation of the classification was achieved by different classifiers which were Gentle Adaboost with decision stumps and Radial Basis Function *SVM* with the parameter gamma. The detection rate was 98.2% for speed traffic signs, 97.9% for circular, and 99.8% for triangular traffic signs.

### 3 The Proposed System

The block diagram of the proposed speed limit recognition system is illustrated in Figure 2. Recognition of traffic signs is achieved by two different phases which are the training phase and the testing phase. In the training phase, the Eigen-based system, which is proposed by Fleyeh and Davami [13], is trained by a set of binary images in which the traffic signs are centred and normalised. This set is extracted from a larger database of raw images collected by a camera mounted on a moving vehicle. In the testing phase, the speed limit traffic signs are detected using their colour information and recognised by the Eigen-based system.

Images for training and testing were collected in different light conditions such as sunny, cloudy, rainy and snowy conditions. Speed limit traffic signs in this set of images are scale, translation, and rotation variant. This means that these images were collected from different distances between the vehicle and the traffic sign; thus, the sign can be located anywhere in the image, and it can be at any orientation. The next section describes the way in which a traffic sign is detected and recognised.

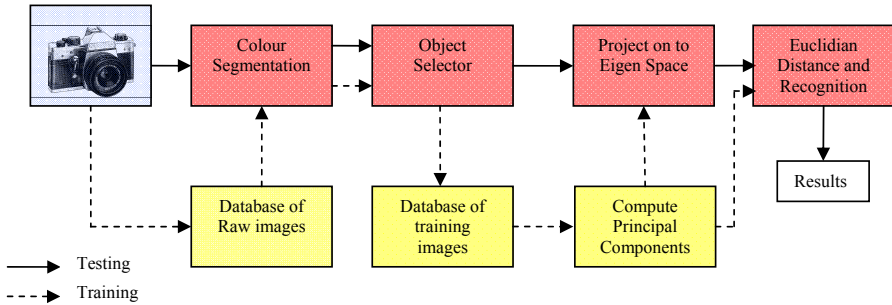


Figure 2. Block diagram of the proposed system.

## 4 Image Analysis and Recognition

### a. Colour segmentation

Colour segmentation is carried out by an algorithm which is invariant to the effects of shadows and highlights [14]. RGB images under consideration are converted into HSV colour space. The HSV colour space is chosen because the Hue feature is invariant to shadows and highlights. The values of H, S, and V are normalised into  $[0,255]$ . This algorithm employs normalised H to represent the colour information while normalised S and V are invoked to specify and avoid the achromatic subspaces in HSV colour space [15]. When the H value of colour of the pixel in the input image is within the specified colour of the traffic sign, and this value is not in the achromatic area, then the corresponding pixel in the output image is set to white. Figure 3 depicts results of colour segmentation.

### b. Object Selector

Binary objects in the segmented image are extracted using the connected components labelling. All objects with red rims, yellow (Sweden) or white interiors (other countries), and appropriate dimensions are selected for further investigation. The process of extracting the object under consideration from the image is achieved by the steps depicted in Figure 3. The border of the candidate sign is specified (sub-image A) and its interior is filled with white pixels (sub-image B). An XOR operator is applied to these two sub-images, i.e. (sub-image C = sub-image A XOR sub-image B). The area in the original image which corresponds to sub-image C is extracted and converted into grey level (sub-image D). An automatic threshold value using Otsu method [16] is then applied (sub-image E) and the image is resized by pruning the black areas located outside the interior border

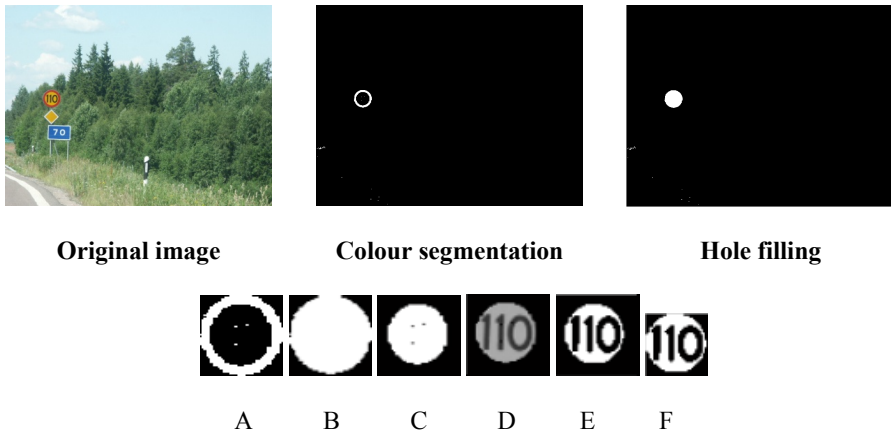


Figure 3. Steps to extract a candidate traffic signs from the image.

(sub-image F). All objects in the image are then extracted using connected components labelling and either saved for training or passed to the Eigen-based system for recognition.

### c. Training Database

The process of colour segmentation and shape analysis described in the previous subsections is completely automatic and it generates binary images of the traffic signs' interiors. The images in this stage are of different sizes. The Eigen-based system is responsible for normalising the images selected either for training or testing. Figure 4 shows part of the database of the pictograms used for recognition of the speed limit signs. The first column on the left hand side of this figure represents the non speed limit objects which are selected by the object selector unit because they fulfil the selection criteria but they are not speed limit traffic signs.

### d. Eigen-based Analysis for Images

Principal Component Analysis (PCA), which is already well known as orthogonal linear transformations, was invented by Karl Pearson in 1901 [17]. It is a method which aims to reduce the volume of information to be handled and transforms a number of possibly correlated variables (redundant information) into a smaller number of uncorrelated variables (principal components). It transforms

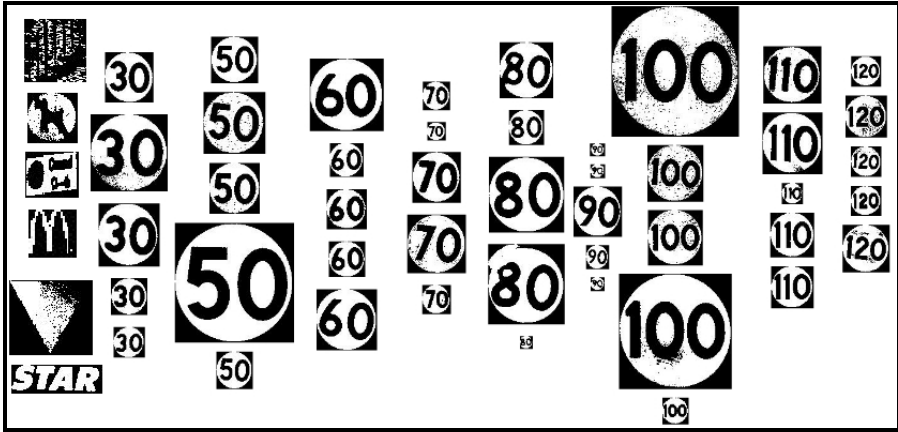


Figure 4. The Training Database.

the data into a new coordinate system based on its variance [18]. Eigen-based systems, which are based on PCA, are used to solve computer vision problems such as face recognition. Eigenfaces which are PCA based are developed by Sirovich and Kirby [19] and are used by Turk and Pentland [20] for face recognition.

In traffic sign recognition, Eigen-based analysis plays a central role to reduce the redundant information in the image and generate the fundamental components which describe the traffic sign. It can be invoked in two ways. The first is to detect the traffic sign among many candidates extracted from the images or videos under consideration. The second is to determine the similarity of a candidate with a certain number of classes of traffic signs.

These two capabilities are of great interest as far as the detection and recognition of new traffic signs in the scene are concerned. In the current work, the Eigen-based analysis is invoked to determine whether a certain candidate is a speed limit traffic sign by comparing the characteristic vector of this candidate with the principal components. Furthermore, classification can be achieved when the candidate's vector is close enough to a certain class of speed limit traffic signs. The method is used for traffic sign recognition and described in the following subsections.

### Training of Eigen-based System Using PCA

Let  $\mathbf{I}_i \in \mathbb{R}^{N \times N}$ ,  $i = 1, 2, \dots, M$  be a reference traffic sign image of size  $N \times N$  pixel which should be normalised and centred, where  $M$  represents the number of reference traffic sign images used to build the PCA model.

1. Convert the reference traffic sign image from  $N \times N$  representation into a column vector  $N^2 \times 1$  which is represented by  $\Gamma_i \in \mathbb{R}^{N^2 \times 1}$ .

2. Calculate the mean image  $\Psi$  from the  $M$  reference images

$$\Psi = \frac{1}{M} \sum_{i=1}^M \Gamma_i. \quad (1)$$

3. Compose the vectors  $\Phi_i$  as the difference between the column vector image and the mean image

$$\Phi_i = \Gamma_i - \Psi. \quad (2)$$

4. Compose the matrix  $\mathbf{A}$  which is given by

$$\mathbf{A} = [\Phi_1 \quad \dots \quad \Phi_M] = \begin{bmatrix} \Phi_{1,1} & \Phi_{2,1} & \dots & \Phi_{M,1} \\ \Phi_{1,2} & \Phi_{2,2} & \dots & \Phi_{M,2} \\ \vdots & \vdots & \ddots & \vdots \\ \Phi_{1,N^2} & \Phi_{2,N^2} & \dots & \Phi_{M,N^2} \end{bmatrix}. \quad (3)$$

5. Calculate the covariance matrix,  $\mathbf{C} \in \mathbb{R}^{N^2 \times N^2}$  which is given by

$$\mathbf{C} = \mathbf{A}\mathbf{A}^T = \frac{1}{M} \sum_{n=1}^M \Phi_n \Phi_n^T. \quad (4)$$

6. Calculating the associated Eigenvalues and Eigenvectors of the matrix  $\mathbf{C}$ . Computing the Eigenvectors of the  $\mathbf{C}$  matrix is not computationally feasible because of its size. Instead, the new matrix  $\mathbf{L} \in \mathbb{R}^{M \times M}$  such that  $\mathbf{L} = \mathbf{A}^T \mathbf{A}$ , where  $L_{mn} = \Phi_m^T \Phi_n$ , is used to find the Eigenvectors  $\mathbf{v}_i$  of  $\mathbf{L}$ . As the training set of traffic sign images is relatively small ( $M \ll N^2$ ), the associated Eigenvalues and Eigenvectors of  $\mathbf{L}$  can be computed from equation (5)

$$\mathbf{A}^T \mathbf{A} \cdot \mathbf{V} = \lambda \mathbf{I} \cdot \mathbf{V}, \quad (5)$$

where  $\mathbf{V} \in \mathbb{R}^{M \times M}$  is the matrix of the Eigenvectors of  $\mathbf{L}$ .

The Eigenvectors of  $\mathbf{C}$  is related to the Eigenvectors  $\mathbf{L}$  by the following equation

$$\mathbf{u}_l = \sum_{n=1}^M \mathbf{v}_{ln} \Phi_n \quad \text{for } l = 1, \dots, M, \quad (6)$$

where  $\mathbf{u}_l$  is  $l$ -th Eigenvector of  $\mathbf{C}$  and  $\mathbf{v}_l$  is the  $l$ -th eigenvector of  $\mathbf{L}$ . The Eigenvectors of  $\mathbf{C}$  are now calculated from equation (7).

$$\mathbf{U} = \mathbf{A} \cdot \mathbf{V}. \quad (7)$$

7. *Selecting the principle Eigenvalues.* The most significant Eigenvalues  $M'$  are selected from the set calculated in the former point such that  $\lambda_1 > \lambda_2 > \dots > \lambda_{M'}$ . The transformation matrix  $\mathbf{U} \in \mathbb{R}^{N^2 \times M'}$  is given by

$$\mathbf{U} = [ \mathbf{u}_1 \quad \mathbf{u}_2 \quad \dots \quad \mathbf{u}_{M'} ], \quad (8)$$

where  $[ \mathbf{u}_1 \quad \mathbf{u}_2 \quad \dots \quad \mathbf{u}_{M'} ]$  are the Eigenvectors corresponding to the Eigenvalues  $\lambda_1 > \lambda_2 > \dots > \lambda_{M'}$ .

8. Each traffic sign in the training set is now represented by a set of weights  $\omega_i$  represents the contribution of each Eigenvector in  $\mathbf{\Gamma}_i$  generated by a linear combination of the  $M'$  best Eigenvectors

$$\mathbf{\Omega}_i = [ \omega_{i,1} \quad \omega_{i,2} \quad \dots \quad \omega_{i,M'} ]^T \quad \text{for } i = 1, 2, \dots, M \quad (9)$$

and  $\omega_i = \mathbf{u}_i^T \mathbf{\Phi}_i$ .

### Classification of an Unknown Traffic Sign

The process of classifying an unknown new traffic sign  $\mathbf{\Gamma}$  to one of the traffic sign classes is achieved by the following steps:

1. *Normalise the unknown traffic sign image*

$$\mathbf{\Phi} = \mathbf{\Gamma} - \mathbf{\Psi}.$$

2. *Project onto the Eigen space.* By using the matrix  $\mathbf{U}_k$ , the new captured image is projected on the Eigen space. This is achieved as follows:

$$\mathbf{\Omega} = \mathbf{U}_k^T \mathbf{\Phi} = [ \omega_1 \quad \omega_2 \quad \dots \quad \omega_{M'} ]^T,$$

where  $\omega_k = \mathbf{u}_k^T (\mathbf{\Gamma} - \mathbf{\Psi})$

3. *Determine the class of the traffic sign.* The class of the unknown traffic sign is determined by finding the traffic sign class  $k$  which minimises the Euclidian distance

$$\varepsilon_k = \sqrt{\|(\mathbf{\Omega} - \mathbf{\Omega}_k)\|^2}, \quad (10)$$

where  $\mathbf{\Omega}_k$  is a vector which describes the  $k$ -th traffic sign class.

## 5 Implementation of the Eigen-Based System

The Eigen-based system accepts images from either the training database or the object selector. In the training phase, a normalisation process was employed in order to create scale and translation invariant training images. Translation invariance was achieved by extracting the candidate object regardless of its position in the image, while scale invariance was achieved by normalising candidate objects to a certain size. Bilinear interpolation was employed to achieve size normalisation. The algorithm discards any object which has an area less than 100 pixels. As a result of size normalisation, highly distorted objects caused by perspective projection can be recovered. Figure 5 depicts a highly distorted traffic sign which was recovered by size normalisation. Rotation invariance is achieved by invoking images with rotated signs in the training phase. Table 1 shows part of the training set which includes a number of normalised and centred objects which represent the result of the normalisation process and a number of rotated signs to ensure the rotation invariance.

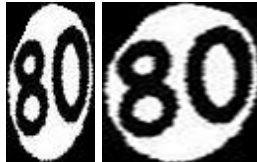


Figure 5. The influence of perspective projection can be diminished by size normalization.

The average image was calculated followed by the Eigen values. The first 98 Eigen values and Eigen vectors were selected ( $M' = 98$ ) and used to calculate the covariance matrix. Figure 6 shows the average image and the first 20 Eigen signs derived from the training set of the speed limit pictograms.

In the testing phase, candidate traffic signs were extracted using the colour segmentation and object selector and then forwarded to the Eigen-based system. This system normalised the object under consideration and classified it to one of the classes under consideration depending on the Euclidian distance between this object's Eigenvector and that of the different classes.

## 6 Results and Analysis

The proposed system was tested under different light and weather conditions such as sunny, cloudy, foggy, snow and rain fall. It showed high robustness as shown









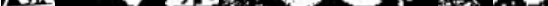
| Traffic Sign       | Abbreviation | Images   |
|--------------------|--------------|--|
| Speed limit<br>30  | SL30         |    |
| Speed limit<br>50  | SL50         |    |
| Speed limit<br>60  | SL60         |    |
| Speed limit<br>70  | SL70         |    |
| Speed limit<br>80  | SL80         |    |
| Speed limit<br>90  | SL90         |    |
| Speed limit<br>100 | SL100        |   |
| Speed limit<br>110 | SL110        |  |
| Other<br>Objects   | SL0          |  |

Table 1. Part of the image database of the speed limit pictograms.

later in this section. Figure 7 depicts a number of speed limit traffic signs examples which were correctly recognised and classified.

For training of the Eigen-based system, 24037 images were employed, while 1429 images were used in the testing phase. In order to evaluate the performance of the proposed approach,  $K$ -fold cross validation process with  $K = 10$  was employed. In this validation process, all candidates (positive and negative classes) extracted from the images by the object selector were forwarded to the Eigen-based system for classification. The number of true positives, true negatives, false

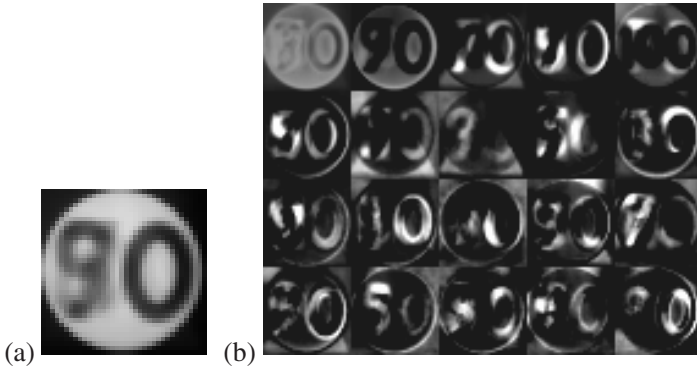


Figure 6. (a) The average image, (b) The first 20 Eigen speed limit traffic signs.



Figure 7. Correctly classified speed limit traffic signs.

| Traffic Sign class | P class | TP  | FN | N class | TN  | FP | TPR   | FPR   | Acc.  |
|--------------------|---------|-----|----|---------|-----|----|-------|-------|-------|
| SL30               | 101     | 100 | 1  | 249     | 248 | 1  | 0,990 | 0,004 | 0,994 |
| SL50               | 101     | 95  | 6  | 92      | 92  | 0  | 0,940 | 0     | 0,969 |
| SL60               | 107     | 102 | 5  | 73      | 73  | 0  | 0,953 | 0     | 0,972 |
| SL70               | 100     | 96  | 4  | 61      | 61  | 0  | 0,960 | 0     | 0,975 |
| SL80               | 110     | 105 | 5  | 48      | 48  | 0  | 0,954 | 0     | 0,968 |
| SL90               | 101     | 95  | 6  | 10      | 10  | 0  | 0,940 | 0     | 0,946 |
| SL100              | 101     | 101 | 0  | 43      | 43  | 0  | 1     | 0     | 1     |
| SL110              | 101     | 94  | 7  | 31      | 31  | 0  | 0,931 | 0     | 0,947 |
|                    | 822     | 788 | 34 | 607     | 606 | 1  | 0,959 | 0,001 | 0,975 |

Table 2. Analysis of error rates. P class: Traffic sign, N class: Non-traffic sign, TP: True Positive, FN: False negative, TN: True Negative, FP: False Positive, TPR: True Positive Rate, FPR: False Positive Rate, Acc: Accuracy.

positives and false negatives for each speed limit class were computed. Table 2 illustrates the results computed for each class.

The average accuracy of classification drawn for speed limit traffic signs is 97.5%. The results indicate that high recognition rates were achievable by the proposed approach. Further analysis indicates that for all speed limit classes, the number of traffic signs which were misclassified as another class is zero. This is due to the fact that the object selector is very well tuned to filter out all undesired objects. In addition, the training of Eigen-based system is good enough to make the distinction among classes very clear.

False positives represent the case where a non-traffic sign object is recognised as a traffic sign. This is a very dangerous situation when the driver gets incorrect information about the speed from the system. If the vehicle runs at speed 50 km/h, for instance, and the system indicates a speed of 90 km/h, then this will lead to a fatal situation. Fortunately, the system generated just one false positive among 607 non-traffic sign objects (negative class). This corresponds to 0.16%, which is a very low false positive error rate. On the other hand, false negatives occur when a speed limit traffic sign is not detected and recognized. Although this error is higher than false positives but it is less harmful. The reason is that the changing of speed is always indicated by placing two speed limit signs on both sides of the road. Missing one speed limit sign leaves room to recognise the other. Figure 8 shows such a situation in which the traffic signs are both recognized.

Table 3 indicates that 46% of the misclassification is caused by the occluded signs, compared with 46% by the lighting geometry, 4% by the aging effect of the

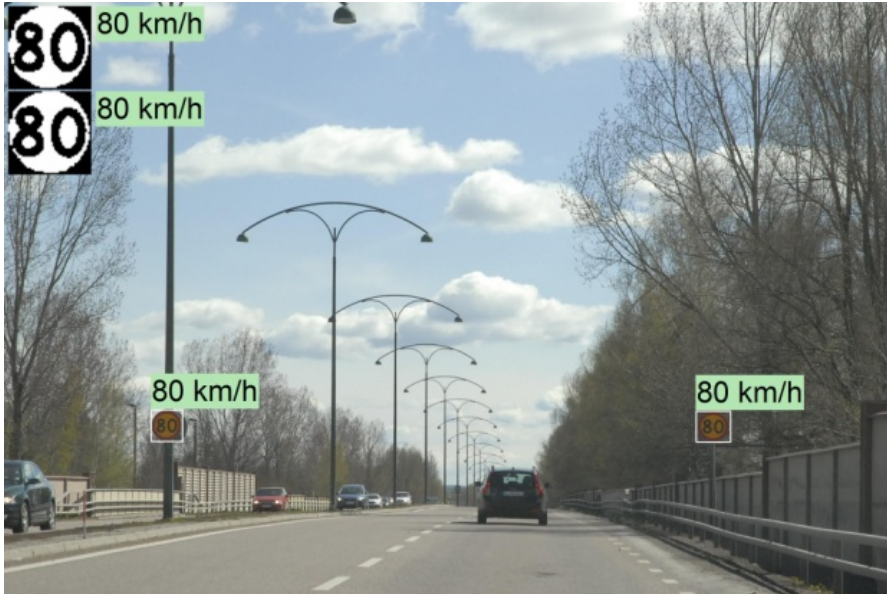


Figure 8. New speed region is always marked by two speed limit signs.

| Reason            | Error Percentage Rate % |
|-------------------|-------------------------|
| Blurred images    | 4%                      |
| Sign Aging        | 4%                      |
| Lighting Geometry | 46%                     |
| Occluded Signs    | 46%                     |

Table 3. Reasons for false negatives.

traffic signs, and 4% by the blurred images. Since the total error produced by the proposed algorithm is 2.5%, then the distribution of the error on the main reasons for error is given by 1.15% for the occluded signs, 1.15% for the lighting geometry, 0.1% for the effect of aging of traffic signs, and 0.1% for blurred images.

The algorithm was also tested by a set of images collected at specific distances from the traffic sign. The distances covered in this experiment were 10–120 m in a step of 10 m between one traffic sign and the next. The proposed approach showed high robustness and could recognise and classify all the traffic signs covered by the experiment as shown in Figure 9. The images included traffic signs located in



Figure 9. Classification of speed limit traffic sign on different distances. Top Left: 10 m distance, Bottom Right: 120 m distance. Images are taken in 10 m step.

different positions in the image and the size of these traffic signs changed by the distance. This illustrates the invariance of the proposed approach to the translation and scaling.

Benchmark test of the current approach achieved using Dell Latitude E6400 shows that the average classification time per candidate sign is given by 0.001 sec.

## 7 Conclusions and Future Work

In this paper, an Eigen-based Intelligent Speed Adaptation system which is based on using traffic sign recognition was presented. The proposed approach is invariant to perspective distortion and in-plane transformations, i.e. translation, scaling, and rotation, which is a property needed for this kind of work. It is invoked to

detect and recognise speed limit traffic signs according to their properties which are colour, shape and interior. The system works in two phases; the training and the testing. In the training phase speed limit traffic signs were colour segmented and candidate objects with certain specifications were automatically extracted and used to build a training database for the Eigen-based system. In the testing phase, candidate traffic signs were extracted from images in the same manner described in the training phase and forwarded to the Eigen-based system. Based on the Euclidian distance between the candidate's Eigen vector and that of the different speed limit classes, the candidate traffic sign was assigned to the class of the shortest Euclidian distance. The testing detailed in this paper produced a high recognition rate of speed limit traffic signs.

The proposed approach works better than most of the approaches presented in the state of the art except for the AdaBoost which is characterised by a high computational complexity. Thus, this approach has high performance due to the high recognition rate and low computational cost.

The current approach can be modified in the future to build a complete Eigen-based traffic sign detection and recognition system which can function for night driving. Such a system will be able to extract traffic sign images and classify them automatically using grey level images collected at night.

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### Author information

Hasan Fleyeh, Department of Computer Engineering, School of Technology and Business Studies, Dalarna University, Borlänge, Sweden.

E-mail: hf1@du.se

Erfan Davami, Department of Computer Engineering, School of Technology and Business Studies, Dalarna University, Borlänge, Sweden.

E-mail: v09erfda@du.se