Speed Sign Recognition using Independent Component Analysis

Ayman M Mansour, Jafar Abukhait, Imad Zyout
Electrical & Computer Engineering, Tafila Technical University
P. O. Box 179, Tafila 66110, Jordan

***Abstract*— This paper proposes a system for speed limit signs recognition in the United States. The proposed system is based on Independent Component Analysis (ICA). Our proposed system can be used in driver assistant system (DAS) or autonomous vehicles. The proposed system consists of four stages: 1) color segmentation to remove non-speed sign objects from the scene; 2) speed sign shape detection and recognition using geometric means; 3) Representation of speed sign images using Independent Component Analysis (ICA) ; 4) feature extraction and classification of speed sign images. The proposed system is invariant to scale, rotation, and partial occlusion. Independent Component Analysis (ICA) has been used in this paper to capture the inherent properties of the speed signs in order to be recognized. This was done by creating an independent component bank (or can be called as basis function bank) from a training set of speed signs. Feature vectors are generated from IC's bank which is used for recognizing speed signs in the testing stage. Our experimental results show a significant recognition accuracy rate of rectangular speed signs.**

***Keywords*— Speed Sign Recognition, Independent Component Analysis, Feature Extraction, Classification, Independent Components (IC's) bank.**

I. INTRODUCTION

Transportation agencies nowadays try to improve roadway network to guarantee driver safety and mobility. Mobility is measured by travel reliability and travel time, while safety is measured by number of traffic crashes. Driver assistant systems (DAS) have been suggested to increase driver safety [1].

Road signs play a key role to regulate traffic and warn drivers over roadways. Driver assistant systems (DAS) can benefit from these signs using computer vision techniques in building automated road sign detection and recognition. While road sign detection is used to detect possible sign objects and removing non-road sign object from the scene, road sign recognition (RSR) is used to categorize the detected object to one of road sign classes.

In general, road sign recognition (RSR) has two stages: detection and classification where recognition accuracy depends on both stages. Speed sign recognition is considered a road sign recognition problem with less constraints regarding shape and signs content. Regarding road sign detection, three main methods are being used in the literature: color-based, shape-based, and integrated methods that use both color and shape information simultaneously. Color-based methods use sign's color information to remove non-road sign objects from the scene. While color thresholding in RGB is being used to segment road sign images ([2], [3], [4]), other researchers use Hue Saturation Intensity (HSI) space in the segmentation process ([5], [6]).

Different shape-based methods have been deployed to detect road signs objects including speed sign ones. In [2], SVM was deployed to recognize sign shapes using four vectors of border to bounding box distances as shape features while in [7, 8], distance to border (DtB) vector was used as the shape feature. Principal component analysis (PCA) and k-nearest neighbor (KNN) classifier were used to detect the sign in [4]. Boosted detector cascade was trained with dissociated dipoles to detect ROI while Hough transform and radial symmetry were used to recognize triangular or circular shape road signs [9]. Haar-like features were used in [10] while Genetic algorithm used in [5] to detect road sign shape. In [13], fast radial symmetry was used to detect circular speed signs from a gray-scale image without using color information. In [14], a self-organizing map (SOM) has been used on Gabor wavelet convoluted images to distinguish road signs from non-road sign objects.

Regarding recognition, different techniques were suggested to improve classification accuracy and processing time. Artificial Neural Network (ANN) was used by several researchers to classify different road sign sets to their categories ([5], [6], [15], [16], [17]). Cross correlation was also used as a template matching criteria between sign templates and road sign images to identify road sign objects ([4], [8], [18], [19]).

Statistical, structural, or spectral features along with different classifiers were used in road sign recognition. Histogram was used as an image descriptor in [20] while Principal Component Analysis (PCA) was used in [4]. Zernike moment [21], Scale-invariant feature transform (SIFT) [22], and color distance transform (CDT) ([23], [24]) were also deployed as image descriptors. Support vector machine (SVM) ([2], [21]), K-nearest neighbor (KNN) [4, 20, 22], Forest Error-Correcting Output Code (F-ECOC) [9], and Bayesian generative modeling [25] were used as classifiers in the road sign recognition process.

In this work, an automated recognition system is proposed that has the ability to classify six categories of speed signs in the United States. These six categories are: Speed Limit 15, Speed Limit 25, Speed Limit 35, Speed Limit 45, Speed Limit 55, and others (which include all rectangular white signs other than the previous five speed signs) as shown in Fig.1.

Fig.1. The six sign categories tested by our proposed system.

In this paper we introduce the use of Independent component analysis (ICA) in speed sign recognition. Independent Component Analysis (ICA) is well-known method of finding latent structure in data. ICA is a statistical method that expresses a set of multi-dimensional observations as a combination of unknown variables. These underlying variables are called independent component and they are assumed to be statistically independent of each other [26]. ICA is the technique that recovers a set of independent signals from a set of measured signals. It is assumed that each measured signal is a linear combination of each of the independent signals [26]. What distinguishes ICA from other methods is that it looks for components that are both statistically independent, and non-gaussian [32].

Independent component analysis (ICA) may be used, for example, in blind source separation (BSS) [29] and identifying or equalizing instantaneous multiple-input multiple-output (I-MIMO) models. It has found applications e.g., in wireless communications, biomedical signal processing [30] and data mining problems ([26], [27], [28]).

The proposed approach was based on creating Independent Components (IC's) bank which can be called as basis functions of speed sign images. The resulted bank is used in both training and testing stages for feature extraction.

II. PROPOSED SYSTEM OVERVIEW

In this paper, we present an automated detection and recognition system of USA speed signs following four stages (see Fig.2.).

1. Speed sign color segmentation: this stage extract speed sign objects by converting sign images to achromatic ones and applying RGB color thresholding.
2. Geometric rectangular shape detection: this stage rejects non-speed sign objects and detects rectangular shapes using a set of cascaded geometric detectors.
3. Representation of speed sign images using Independent Component Analysis (ICA).
4. Feature extraction and classification of speed sign images.

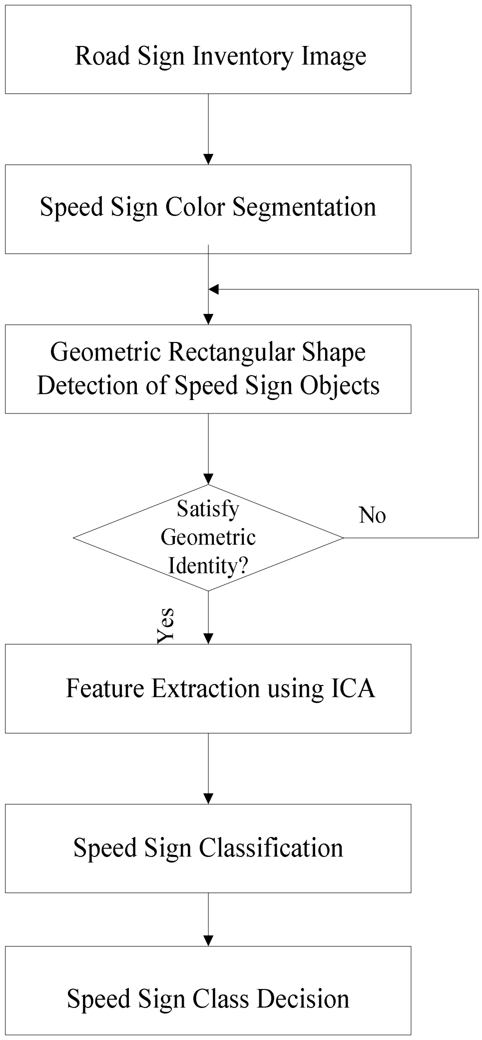

Fig.2. Flow diagram of the proposed system.

A. *Speed Sign Color Segmentation*

Speed sign inventory image would be segmented to extract white color objects resulting in a binary image. Each white object in the resulting binary image would be tested in the next stage to detect possible rectangular shape. A normalized RGB space was used initially in this stage to reduce RGB illumination changes and to ease the process of threshold values selection.

Since white color is very sensitive to illumination changes, we have used the chromatic/achromatic decomposition technique suggested in [11] to generate a gray image (achromatic image) with no color information. This chromatic/achromatic decomposition can be done by applying RGB differences and using specific thresholds to determine the closeness of these RGB components since gray images have equal or close RGB components. Another color thresholds would be applied on the gray image (Achromatic image) to segment the bright parts of this gray image which is most likely would be the white color (Fig.3).

B. *Geometric rectangular shape detection*

The purpose of this stage is to accept or discard speed sign objects forwarded from the previous stage and determine if the identified shape of the object is an acceptable rectangular speed sign. Two cascaded geometric detectors are used to check each object in the binary image forwarded from the previous stage:

1) Area: This implements the area of both speed sign background and foreground. This detector is used to discard all small and large objects from the segmented frame.
2) Solidity: This implements the ratio between number of ROI background pixels (ROI pixels excluding foreground pixels such as text or drawing messages within the sign) and the total number of ROI pixels [12].

$$SR = \frac{\sum ROI\ background\ pixels}{\sum total\ ROI\ \ pixels} \quad (1)$$

This detector is used to discard extremely solid and extremely non-solid objects and to accept objects with solidity ratio falls within specific range (Fig.3).

Eight different points of each acceptable object are calculated which implement object's vertices. These eight points are: Top-Left: T_l ; Top-Right: T_r ; Right-Top: R_t ; Right-Bottom: R_b ; Bottom-Right : B_r ; Bottom-Left: B_l ; Left-Bottom: L_b ; Left-Top: L_t [12]. The proportional positions of these eight points are also used to measure the dimensions of each object as shown in Fig.4. Dimensions of shape can be calculated by finding the Euclidean Distance (D) between two vertices as:

$$D(t,r) = \sqrt{(x_t - x_r)^2 + (y_t - y_r)^2} \quad (2)$$

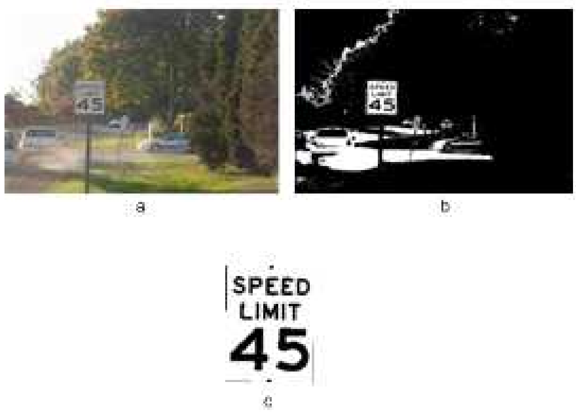

Fig.3. Shape recognition process of speed sign. a) original frame. b) segmented frame. c) detected speed sign.

The relative positions of these points are compared to search for a rectangular shape in addition to dimensions ratio which should satisfy preselected thresholds to discard non-symmetric objects obviously.

Each rectangular speed sign shape could have one of these two cases:

- Non-rotated rectangular speed sign which has to satisfy the following constraint:

$$T_l \approx L_t\ \&\ B_l \approx L_b\ \&\ (R_b \approx B_r\ \ or\ T_r \approx R_t) \quad (3)$$

- Rotated rectangular road sign which has to satisfy the following constraint:

$$B_r \approx B_l\ \&\ L_b \approx L_r\ \&\ (T_l \approx T_r\ \ or\ \ R_t \approx R_b) \quad (4)$$

where

$l_1 = D(B_r, L_b)$; $l_2 = D(R_t, B_r)$; $l_3 = D(T_l, R_t)$; $l_4 = D(L_b, T_l)$;

$l_5 = D(L_b, R_t)$; $l_6 = D(T_l, B_r)$

In any case, rectangular road sign shape should satisfy the following constraint:

- $l_5 \approx \sqrt{(l_1)^2 + (l_2)^2}\ \ or\ \ l_6 \approx \sqrt{(l_1)^2 + (l_4)^2}$ (5)

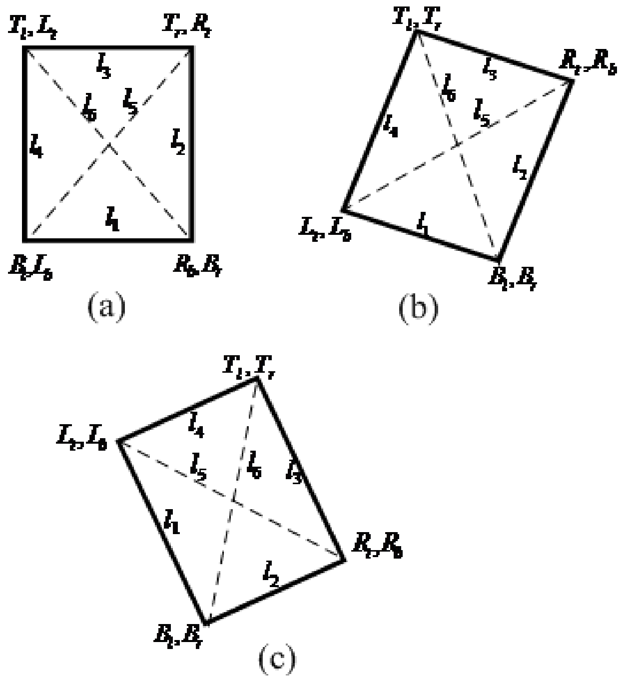

Fig.4. Showing speed sign shapes with the eight vertices and dimensions. a) non-rotated speed sign. b) rotated right speed sign. c) rotated left speed sign.

C. *Representation of Speed Sign Images using Independent Component Analysis (ICA)*

Normally in image analysis problems, the image is represented in different spaces to capture some of the characteristics of the image data. A classical technique is Principal Components Analysis (PCA) in which the components are not correlated. Principal Components Analysis (PCA) is a well known method for dimension reduction. PCA allows correlated data in a *n*-Dimension space to be modeled in a lower dimension space without losing a significant amount of information. Using the resulted reduced subspace, computations on the database become more efficient. One of the major problems of PCA is its limitation in capturing only the second-order statistics. Higher order statistics, which are important in image representations, are ignored in principal components. This limitation is solved using ICA.

Each image is assumed to be a linear combination of certain number of components that are statistically independent. In literature, many algorithms have been proposed by optimizing some criteria that are related to the independence ([26], [34]).

In this paper, the independent components bank is computed using a FastICA algorithm by Hyvainen ([27], [33]). The algorithm was derived based on negentropy; an first order approximation of mutual information. The FastICA algorithm has desirable number of properties when compared with existing methods for ICA. The convergence is cubic (or at least quadratic) compared with the ordinary ICA algorithms based on gradient descent methods, where the convergence is only linear. This leads to a very fast convergence. Having no step size parameters in FastICA makes that the algorithm is easy to use.

Using FastICA, the independent components can be estimated one by one, which is equivalent to do projection. This decreases the computational load of the method especially if some of independent components need to be estimated, not all of them. The FastICA is parallel, distributed, computationally simple, and requires little memory space. This fast ICA algorithm was empirically shown to be 10 to 100 times faster than other ICA algorithms

To calculate the Independent Components bank, first a given number of image windows of a specified size are extracted from the input speed sign images. The (m x m) image patches are represented as a column vector. We generate a large number of training vectors, ensuring that each training speed sign picture provides an equal amount of training vectors. The training images are normalized and made to have zero mean before doing the sampling in order to ensure that no speed sign image dominates the basis set.

These image windows are used as observations and the FastICA algorithm is applied on that set in order to derive the independent components bank ([27],[31]). PCA is finally used to get more dimension reduction by selecting only the eignvectors of the largest **L** eignvalues of the independent components bank matrix. The flowchart for finding the IC basis functions bank is shown in Fig.5.

In this paper, speed sign subset (60 speed sign images, 10 form each group; the groups are “sign 15”, “sign 25”, “sign 35”, “sign 45”, and others) were taken from our speed sign database. The images are all of size (50 x 50) pixels. The basic functions bank was called data dependent. So by changing any one of the 60 images new basis functions will be produced, and the user is hence required to provide images that contain the appropriate structure. The Independent Components are obtained by the proposed method shown in Fig.5. The resulted ICA basis bank is shown in Fig.6. The dimension was reduced by PCA, resulting in a total of 30 basis functions. The size of each basis function is (8x8). Note that independent components from different windows size are different.

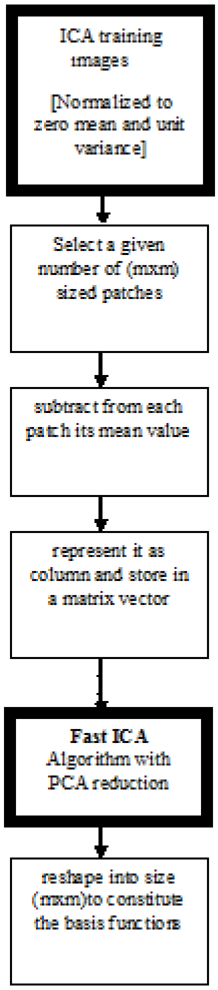

Fig.5. The Algorithm for generating IC basis functions.

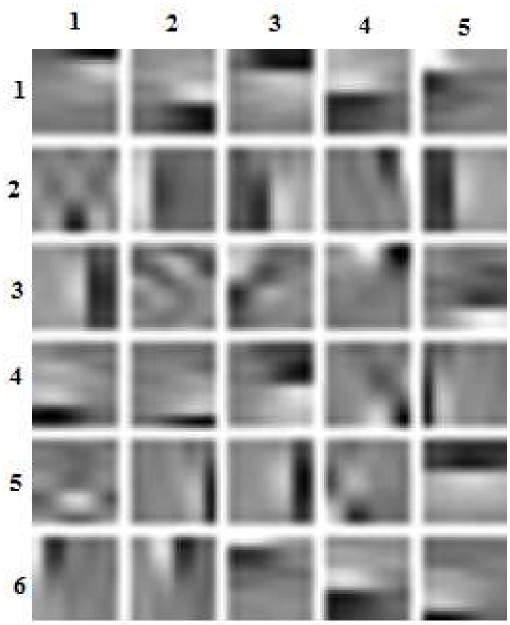

Fig.6. Example of (8 x 8) ICA basis functions for 60 road sign images.

D. Feature Extraction and Classification of Speed Sign Images

In the previous section the IC's Bank was generated. Now we will use the independent components in the bank to generate feature vectors for the traffic signs. The feature vectors are generated as shown in Fig.7.

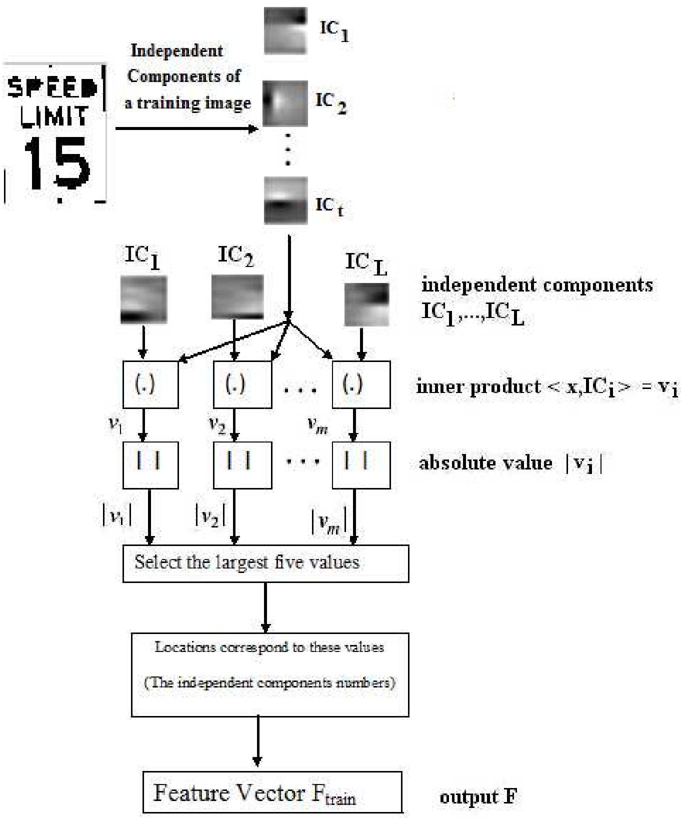

Fig.7. Feature Extraction Using ICA (proposed method).

First of all the independent components of an input speed sign training image is found using FastICA (lets called it "**x**'s"). Second the resulted independent components will be projected on the previously found IC's bank.

The inner product between the each independent component of the input image ($\mathbf{x}_i$'s) and the independent Components **(IC's)** banks, each with specific characteristics will be computed. The inner product shows the similarity between the IC's of the training images (x's) and the IC's of the bank.

If the bank consists of L independent components, the result from the inner product is L values for each x which is called $\mathbf{v}_i$ where i=1,…,L .

$\mathbf{v}_i = <\mathbf{x}^T . \mathbf{IC}_i>$.

Each **v** corresponds to specific inherent properties. Thus, each independent component of the input image will have higher inner product values when it has been tuned to a certain independent component in the bank and vice versa. If **v** was the selected feature vector, it will have the size (Lx1) and this will lead to longer time in the recognition stage. It also requires more memory size.

After studying all the **v** values resulted from all the speed sign images, (around 138 speed sign images), we conclude the following: The location where the absolute largest five values occurred will be enough to distinguish between different speed signs. These locations correspond to the major independent components of a sign image of a certain category. We use the five location of the resulted absolute largest value in order to successfully distinguish between different speed sign images. These locations will be the feature vector **F** that is intrinsic to a speed sign group. In the learning stage, each feature vector of the training data $\mathbf{F}_{\mathbf{Train}}$ is assigned a class (1 for "speed 15", 2 for "speed 25", 3 for "35", 4 for speed "45" , 5 for "speed 55", 6 for " others").

In our case because the feature vector size is small **(5x1)**, so the nearest neighbor is used as classifier .To do the classification in our case the feature vector of a test speed sign image is found using the same independent component banks which was used before for training. The resulted feature vector is called $\mathbf{F}_{\mathbf{Test}}$. The $\mathbf{F}_{\mathbf{Test}}$ will be compared with training feature vectors $\mathbf{F}_{\mathbf{Train}}$'s and the one that gives the smallest squared Euclidean Distance will be the desired one and the other will be discarded. The Euclidean Distance describes the distance of the target test feature vector from a training feature vectors.

Euclidean Distance is the most common use of distance. In most cases when people said about distance, they will refer to Euclidean distance. Euclidean distance or simply 'distance' examines the root of square differences between coordinates of a pair of objects.

The squared Euclidean distance $= \| \mathbf{F}_{\mathbf{Test}} - \mathbf{F}_{\mathbf{Train\ k}} \|_2$

$$= \sum_{i=1}^{5} (\mathrm{F}_{\mathrm{Test}\ i} - \mathrm{F}_{\mathrm{Train}\ k\ i})^2 \qquad (6)$$

where $\| \mathbf{F}_{\mathbf{Test}} - \mathbf{F}_{\mathbf{Train\ k}} \|$ is the Euclidean distance between the test image feature vector and the trained feature vector, represent by the vector $\mathbf{F}_{\mathbf{Test}}$ and $\mathbf{F}_{\mathbf{Train\ k}}$ respectively. The size of $\mathbf{F}_{\mathbf{Test}}$ and $\mathbf{F}_{\mathbf{Train\ k}}$ is **(5x1).**

So, The vector $\mathbf{F}_{\mathbf{Test}}$ is classified to one of the training feature vectors $\mathbf{F}_{\mathbf{Train\ k}}$ if the Euclidean distance $\|\mathbf{F}_{\mathbf{Test}} - \mathbf{F}_{\mathbf{Train}}\|$ is minimum for k=j where j is the class the speed sign image belonged to.

The identity of the nearest training image **(j)** is assigned to the test image

$$j = \arg\min_{j\in[1,2,\ldots,k]} (dj) \qquad (7)$$

where dj (Euclidean Distance) describes the distance of the target test feature vector $\mathbf{F}_{\mathbf{Test}}$ from a training feature vector $\mathbf{F}_{\mathbf{Train\ j}}$.

III. Experimental Results

To verify the effectiveness of the proposed method, we present in this section the experimental results regarding speed signs recognition. In our experiments, we have worked on road sign frames captured using SAMSUNG ST65 camera in addition to images from VISAT™ mobile mapping system. Images were scaled to 864x648 pixels and 802x617 pixels by numeric fraction to overcome the impact of objects' distortion. The implementation was performed on MATLAB and the average processing time was 2.33 seconds per image frame on 2.67-GHz Pentium4.

The ICA classifier was trained on randomly selected portions of 8×8 sub-images of the speed sign images that are not included in the test images. The experiments were performed with input window size of (8×8) because through this size we have achieved the best classification accuracy as shown in Table 1.

TABLE I
CORRECT CLASSIFICATION RATE VERSUS WINDOW SIZE

Window size	Correct classification rate (%)
3x3	84.7%
5x5	87.4%
8x8	**90.9%**
12x12	85.6%

The size of the window should be a compromise between that it is large enough to contain sensible visual information and small enough to introduce generality in the data.

The algorithm was applied on 138 images. These images contain partially occluded, and geometrically distorted and rotated road signs, in addition to different scaled ones. Some of these images have no road signs and some have more than one road sign. Partial occlusion, rotation, and geometric distortion of 65 road signs were enforced by manual manipulation of sign images to compensate for the lack of enough number of raw images that satisfy these defects. Table 2 shows the results of the proposed system simulations. A recognition accuracy rate of (90.9%) was achieved with the ICA.

TABLE II
SUMMARY OF SPEED SIGN RECOGNITION RESULTS

Number of frames	138
Number of existed speed signs	111
Number of detected speed signs	101
Number of missed speed signs	10

The relative performance of Principal Components Analysis (PCA) and ICA are compared on the same database. PCA algorithm has a recognition efficiency of 70.3%. The proposed method gives better recognition accuracy on the used image database of 138 speed sign images.

IV. CONCLUSIONS

In this paper, we have proposed a recognition system of speed signs used in the U.S. The recognition system uses the set of cascaded detectors proposed in [12] for the detection of rectangular speed sign shapes and Independent Component Analysis (ICA) as a speed sign feature in the classification stage.

We have demonstrated that the ICA basis functions are able to capture the inherent properties of speed sign images. The proposed system indicates a high accuracy recognition rate in the experimental results. The other advantage of the proposed method is that the size of feature vectors is very small (5x1) and this yield to lower memory size and faster recognition.

The excellent classification error rate achieved in the experiments confirms that the uses of ICA basis functions are well-suited for speed sign recognition. So the proposed algorithm can be characterized as reliable.

We are working on improvements such as: 1) proposing another color segmentation technique that is more robust to variation in illumination; 2) improving the efficiency of detection of small scaled road sign objects by post-processing segmented frame; and 3) including the possibility of partial occlusion occurring on the left side of the road sign which can cover defects such as breakage of sign and graffiti.

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Dr. Ayman M Mansour received his Ph.D. degree in Electrical Engineering from Wayne State University in 2012. Dr. Mansour received his M.Sc degree in Electrical Engineering from University of Jordan, Jordan, in 2006 and his B.Sc degree in Electrical and Electronics Engineering from University of Sharjah, UAE, in 2004. He graduated top of his class in both Bachelor and Master. Currently, Dr. Mansour is an assistant professor in the Department of Electrical and computer Engineering, Tafila Technical University, Jordan. His areas of research include communication systems, multi-agent systems, fuzzy systems, data mining and intelligent systems. He conducted several researches in his area of interest. Dr. Mansour is a member of the Institute of Electrical and Electronic Engineers (IEEE), IEEE Honor Society (HKN), Tau Beta Pi Honor Society, Sigma Xi and Golden Key Honor Society.

Dr. Jafar Abukhait received his Ph.D. degree in Electrical and Computer Engineering from Western Michigan University, Michigan, USA, in 2012. Dr. Abukhait received his M.Sc degree in Computer Engineering/Embedded Systems from Yarmouk University, Jordan, in 2007 and his B.Sc degree in Computer Engineering from Yarmouk University, Jordan, in 2005. He graduated top of his class in Master. Dr. Abukhait is working now as an assistant professor in the Department of Electrical and Computer Engineering, Tafila Technical University, Jordan. His areas of research include Image Processing, Pattern Recognition, Artificial Intelligence, and Condition Assessment.

Dr. Imad Zyout is currently an Assistant Professor in Electrical Engineering Department at Tafila Technical University, Jordan. He earned his PhD in Electrical and Computer Engineering from Western Michigan University, Kalamazoo, USA, in 2010. He also received the BSc and MSc degrees in 1999 and 2005 from Jordan University of Science & Technology, Irbid, Jordan, all in electrical engineering. His research experience and interests are in wavelet-based image coding, morphological image processing, feature extraction, heuristic feature selection, and machine learning including the development of efficient algorithms for compression, segmentation, and pattern recognition and detection in mammography. He is a Member of the Institute of Electrical and Electronic Engineers (IEEE) and Jordan Engineers Association (JEA).