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Shape-Based Traffic Sign Recognition Using Biologically Motivated Features

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***Abstract*: This paper presents a shape-based biologically motivated research study to recognize the Iranian traffic signs. A biological model called HMAX is used as feature extractor to deal with traffic sign images, taken in real scenes. The extracted feature vectors are simply classified using a K-Nearest Neighbor classifier. Proposed model is implemented using a self collected dataset to evaluate its effectiveness. Three experiments have been implemented to evaluate performance of the proposed model, compared to some conventional models such as PCA, DCT and 2DPCA. The experiments have been done in cases in which the position, scale and the viewing-angle of objects in images are variable. The difference in recognition rate of the proposed model in comparison with other forging methods was impressive in all implementations. In each experiment the difference in performance of proposed model compared to conventional models was about 60% on the same database. The high model's recognition rate will increase system stability and reliability on real time application.**

Keywords: Traffic Sign Recognition, HMAX Model, Nearest Neighbor, Two Dimensional Principal Components Analysis.

I. Introduction

In a modern society, implementing an assistant traffic sign recognition system is a necessary requirement. This system can be employed as an important part in intelligent vehicles. Also, if a system is provided to recognize traffic signs, number of car crashes can be largely reduced. Therefore, car manufacturing companies are interested in embedding a robust system structure on their products to recognize traffic signs. Other advantages of applying traffic sign recognition systems are: sign maintenance, inventory in highways and cities, driver support systems and intelligent autonomous vehicles. Traffic sign recognition is a subdivision of pattern recognition problem. Each proposed algorithm to recognize traffic signs should be invariant in variable lighting condition, rotation, image transformations and scale of signs. So, the most important point to implement this kind of recognition system is developing an approach that is accurate for sign recognition with different transformation, resolutions and qualities. A lot of traffic sign recognition systems have been proposed since 1980s. Mainly, two major ways for sign recognition have been proposed in previously surveys which are based on image color and shape information. Color-based models claim that color is more important compared to other image characteristics for detection and classification tasks. Some scientists claim that using shape information is enough for recognition (because of lack of a standard color system in different nations and reflecting daylight by signs). So, they have focused on shape-based algorithms to encounter sign recognition problem. The shape-based models operate on images regardless their color information. Focus of this kind of sign recognizers is on image gray scales. Some of shape-based models are: Hough Transform, Similarity of binary images and Distance Transform Matching. Also, some machine vision programmers have concentrated on fusion methods of color based and shape-based algorithms. Chandiramani and Dhotre have proposed a color based methods for detection and recognition through color image segmentation using HSV color space on color images [2]. The image regions of interest are represented using HOG descriptors and are fed into trained Support Vector Machines (SVMs) in order to be classified. Their experiments results were satisfactory in sign detection and recognition. Wali et al. proposed a shape matching and color Segmentation based Traffic Sign detection and recognition System [3]. The experimental results revealed that, by comparing with the similar color segmentation based techniques, the proposed system has a higher accuracy of traffic sign detection rate with a lower computational time. Billah et al. have tried to find out the capability of adaptive neuro fuzzy inference system (ANFIS) for traffic sign recognition. They have used video and image processing for detecting circular shaped signs and used ANFIS for recognizing signs. Their proposed method works on circular signs and shows more than 98% accuracy [4]. Also, Soendoro et al. applied a combination method of Color based method and SVM to do the traffic sign recognition. Approximated circle, square or triangle images will be marked as traffic sign and processed in recognition step with linear c-SVM. SVM classification based on binary images led to 97% accuracy [5]. Recognition of traffic signs in digital images, based on color is faced with limitations such as:

- *Low performance of system with poor light condition*
- *The absence of system with rain and snow fall*
- *Reflect the light by signs which make color segmentation more difficult.*

Although shape based models have higher accuracy than color based models, but they also have weaknesses. Some of them are:

- *Low performance with damaged signs.*
- *Impact of distance between sign and camera on recognition*
- *The angle of viewer than sign in image.*

A system in which employed for traffic sign recognition, should act quickly and be robust to image transformations. By analyzing previously sign recognition methods and their strengths and weaknesses, it seems that work on shape based models could achieve more accurate results than color based one, because shape of signs is affected less than its color by external factors. Therefore, to overcome the most important problem of traffic sign recognition (i.e. poor rate of correct recognition), the discussion throughout this paper will be about implementing of a shape based biologically motivated approach and applying Hierarchical Model and X (HMAX) model to design an efficient traffic sign recognition system. The HMAX algorithm is a powerful tool to solve recognition problems in real scenes especially when recognition process is involved in image transformations such as: scale variations, rotations and different object's position in scene. This biological model was proposed by Poggio and Serre (1999) in Massachusetts Inistitute of Technology (MIT) [1]. The HMAX architecture is similar to human and primates visual system in different detection and recognition levels. The reason of using this model is trying to implement a system where acts like what happens in human's visual cortex, which is very accurate and rapid compared to computational models of recognition. The proposed biological model of this paper works on traffic sign images according to their shape in two phases. The first phase of operation is extracting important image features. The extracted features are in the form of patches (prototypes) which are selected randomly in size and position from all positive samples. The second phase is classifying acquired images.

The proposed model classifies input unknown images using a K-Nearest Neighbor (KNN) classifier. This classifier is simple and its implementation is very efficient in many cases of recognition. A feasibility and effectiveness investigation for the proposed model is conducted using an experimental traffic sign database which contains 200 images of 20 subjects. The rest of this paper is organized as followings: Section II presents our proposed model in detail. Section III discuss about the experimental results. Finally, in Section IV results are discussed, conclusions are drawn and future works are proposed.

II. Proposed Model

To design an accurate traffic sign recognition model, a simple but effective architecture is proposed. This model is composed of three main Layers: Input Layer, Perceptual Layer and Classification Layer, in which detailed description of this type of traffic sign recognition implementation will be presented in following subsections.

A. Input Layer

In this layer, traffic sign images are acquired, preprocessed (resized into 100 by 100 pixels) and passed to the next stages of model for feature extraction and classification.

B. Perceptual Layer

The main task of this layer is selection and extraction image features to convert them into a useful and applied feature vector. This stage called feature extraction. Mainly, feature extraction means extracting powerful features which carry useful information about image to use as input data for classification stage. This task is done in order to extract meaningful features of images to increase the speed of recognition system. Also, valueless information is discarded in this step. There are various methods for feature selection and extraction such as Principal Components Analysis (PCA) based algorithms [4], Linear Discriminant Analysis (LDA) [18] and Wavelet transform [19]. In this paper a biological framework for feature extraction called HMAX is used. This algorithm is inspired by processes of object detection and recognition in ventral stream of Human's Visual System (HVS). Recent surveys on ventral stream of visual cortex of human and primates led to different theories about dividing visual cortex into different levels in which information is encoded in that levels. Visual processing in ventral stream of cortex is hierarchical and feed-forward (See figure 1).

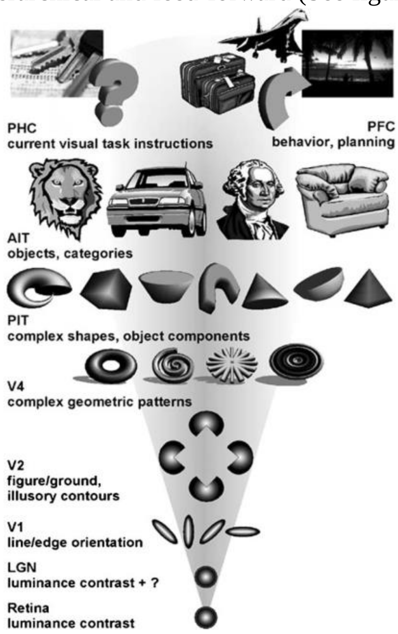

Figure 1. Hierarchical and feed-forward visual processing in ventral stream of cortex [21].

In this processes, receptive fields of Simple neurons (S units) combine their inputs with a bell-shaped tuning function to increase selectivity, and Complex neurons (C units) pull their inputs with maximum operation, and this is resulted in increasing of invariance to scale and other transformations.

In proposed model, meaningful feature vectors of from all images of database are extracted using HMAX model. HMAX feature extraction is invariant in various object's scales, position, rotation and image condition (lighting, camera characteristics and resolution). Therefore, basic aims of this model are building invariance for variety in scale, position, viewpoint and other image transformations. Figure 2 indicates a schmetic illustration of HMAX model. The basic version of this model consists of four computational layers try to simulate hierarchical and feed-forward mechanism of ventral stream of human and primates visual cortex. These layers are S1, C1, S2 and C2 respectively (simple S cells alternate complex C cells). The inputs of S units are combined with a bell-shaped function to increase selectivity. This process is implemented using Gabor functions with different sizes and orientations. C units pool their inputs through a maximum (MAX) operation, and it causes enhancement in invariance. These layers are derived from experiments on monkey IT cortex [8].

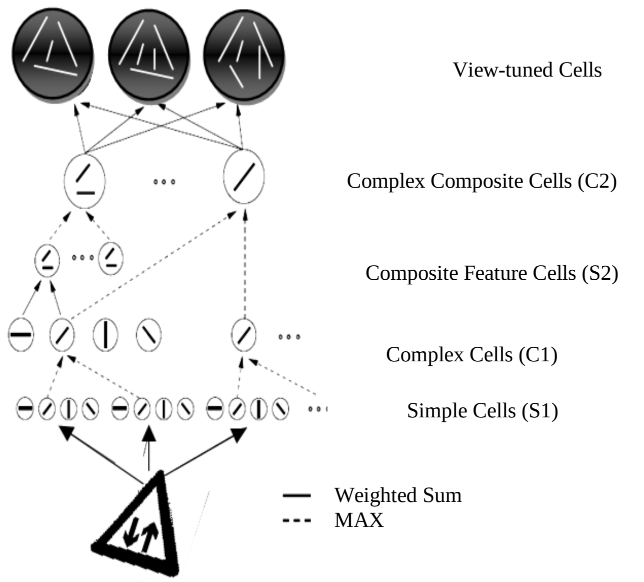

Figure 2. Schematic illustration of HMAX model. Adapted and redrawn from [8].

Biologically motivated feature extraction, describes a method which gives illumination and view invariant C2 features from all images of dataset [13]. Finally, derived feature vectors from HMAX, passed to a simple classifier to assign proper classes. The sketch of proposed model is shown in figure 3. A detailed description of all layers of this model will be presented in following subsections.

1) S1 Units

*S*1 units take the form of Gabor functions, which have been shown to provide a good model of cortical simple cell receptive fields [16]. Gabor functions are described by following equation:

$$F(x,y)=\exp\left(-\frac{(x_0^{\;2}+\gamma^2 y_0^{\;2})}{2\sigma^2}\right)\times\cos\left(\frac{2\pi}{\lambda}x_0\right) \tag{1}$$

$$x_0 = x\cos\theta + y\sin\theta\ , \qquad y_0 = -x\sin\theta + y\cos\theta \tag{2}$$

All filter parameters, *i.e.* the aspect ratio, $\gamma=0.3$, the orientation θ, the effective width σ, the wavelength λ as well as the filter sizes s were adjusted so that tuning properties of corresponding S1 units match to the bulk of V1 parafoveal simple cells [1]. Parameter Setting is done using biological experiments on monkey to obtain the best tuning properties. In this experiment, sizes of Gabor filters of S1 units are 7? to 17? 7 pixels in steps of 2 pixels. To keep the number of units tractable, we considered 4 orientations (0? 45? 90癒nd135? . In overall, we have 24 different *S*1 receptive field types (6 scales ×4 orientations).

2) C1 Units

These units are more complicated and have larger receptive fields than S1 units. C1 units have response to edges or bars anywhere into their receptive fields. They pool outputs of S1 units using a MAX operation, which is the response r of a complex unit corresponds to response of the strongest of its m afferents $(x_1, x_2, \ldots, x_m)$ from previous $S1$ layer such that:

$$r = \max_{j=1\ldots m} x_j \tag{3}$$

Table 1 indicates S1 and C1 Parameters, tuned in HMAX model used these implementations.

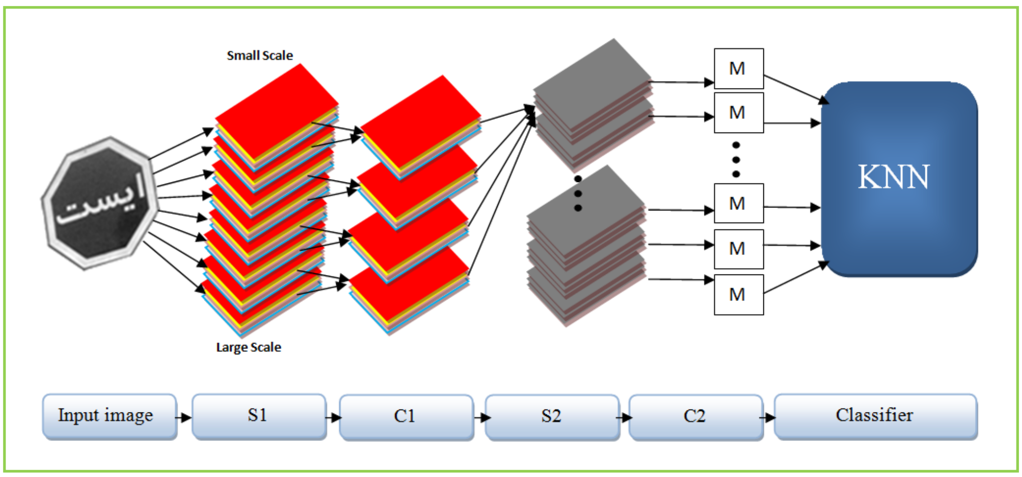

Figure 3. The sketch of proposed model. Adapted and redrawn from [15].

Table 1. S1 and C1 Parameters

C1 Layer			S1 Layer		
S1 Bands	**Ns×Ns Mask Size**	**ΔS Overlapping**	**S1 filter Size**	**σ of Gabor**	**λ of Gabor**
1	**8×8**	**4**	**7×7** **9×9**	**2.8** **3.6**	**3.5** **4.6**
2	**10×10**	**5**	**11×11** **13×13**	**4.5** **5.4**	**5.6** **6.8**
3	**12×12**	**6**	**15×15** **17×17**	**6.3** **7.3**	**7.9** **9.1**

3) S2 Units

In this layer, units pool their inputs from C1 layer using spatial neighborhood for each orientation. The behavior of S2 units is as Radial Basis Function (RBF) units [13]. The response of each S2 unit depends on Euclidean distance between a new input and prototypes that before stored such that:

$$r = \exp(-\beta \| X - P_i \|^2) \qquad (4)$$

Where, β is the sharpness value of tuning, P_i is the sorted prototype and X is new input image.

4) C2 Units

After extracting S2 units by HMAX, C2 units are extracted as shift and scale invariant units by taking a global maximum over all scales and positions for S2 units. HMAX model in S2 layer measures the rate of matching between a stored prototype and an input image to find the best matching and discards the rest (See Eq. 4).
The result is N × C2 feature vector that N corresponds to number of prototypes extracted during learning stage (in all implementations of this paper N=50) which is described in following subsection.

C. The Learning Stage

In this stage, 50 prototypes are selected by a simple sampling. Prototypes are chosen randomly in various sizes and positions from a target set of positive traffic sign images. Prototypes are extracted from C1 layer outputs in four orientations. In this experiment, patches of 6 different sizes are extracted (n= 7, 9, 11, 13, 15, 17). In overall, there are 50 prototypes, 6 scales and 4 orientations to compute.

D. The Classification Layer

To implement a simple and efficient classification stage, K-Nearest Neighbor (KNN) is employed as proposed model's classifier [17]. KNN is a method for classifying objects based on closest training examples in feature space. K-Nearest Neighbor algorithm is among the simplest of all machine learning algorithms.

Some advantages of KNN are:

- *invariant in noisy training data*
- *Effective if training data is large.*

And some disadvantages of KNN are:

- *Need to determine value of parameter K*
- *Computation cost is high (need to compute distance of each test instance to all training samples)*

KNN classifier requires:

- *An integer K*
- *A set of labeled examples (training data)*
- *A metric to measure "distance"*

Training process for this algorithm only consists of storing feature vectors and labels of training images. In classification process, an unlabelled test sample is simply assigned to the label of its K-Nearest Neighbors. Typically, the object is classified based on labels of its K-Nearest Neighbors by majority of votes. If K=1, object is simply classified in class of its nearest object (called Nearest Neighbor). When there are only two classes, K must be an odd integer (See figure 4)
In this examination, traffic sign images are propagated through the architecture illustrated in figure 3. C2 Standard Model Feature (SMF) vectors are passed to a KNN classifier (in this case K=1), to classify traffic sign images according their shapes. After we convert each image to a vector of fixed-length with real numbers, we used the most common distance function for KNN which is Euclidean distance. KNN classifier takes each extracted feature vector from test image, compares it to all of training set and assigns it the label of its nearest training image.

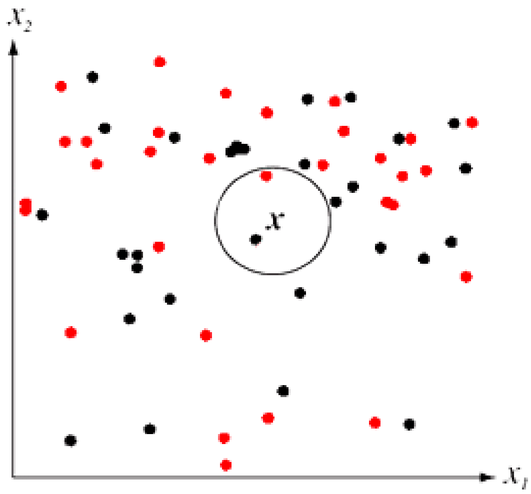

Figure 4. Classifying samples using KNN.

III. Experimental Results

To evaluate proposed model's efficiency and prove our claims, it is examined using an experimental traffic sign database. Utilized database has been collected by students of Shahid Rajaee Teacher Training University (SRTTU) of Tehran, in august 2010, using a low cost camera from Iranian traffic signs. This database contains 200 image samples of 20 subjects (organized into 20 sets in which 1 image -10 samples).

Traffic Sign images are varying across viewpoint, scale, illumination, rotation, depth and time, as shown in figure 5.

Figure 5. Some Samples of used traffic sign database.

To implement an accurate traffic sign recognition model and evaluate model's invariance to variations in sign's position, rotation and other transformations, some new samples are produced from original dataset images by changing the objects position, scale and rotation.
Then produced samples are resized to 100×100 pixels images. Some of images used as training and testing the model are shown in figure 6.

Figure 6. Samples of utilized experimental traffic sign dataset (SRTTU).

Also, some of randomly selected patches used for training the model which described in learning stage are shown in figure 7.

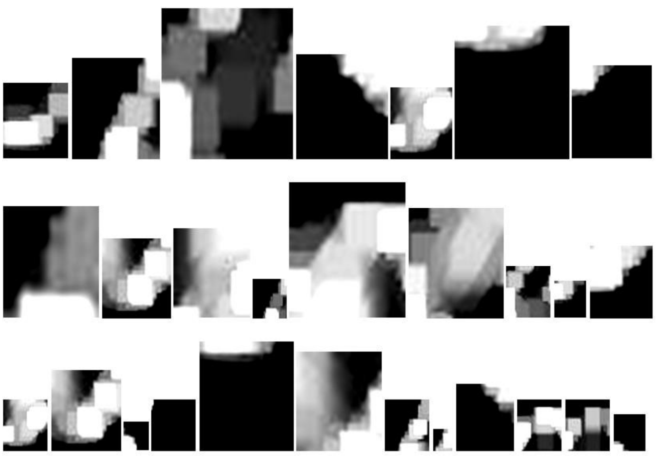

Figure 7. Samples of randomly selected prototypes used for training.

These prototypes are selected from C2 maps at different positions and sizes from all positive training images.
To test the proposed model's invariance to variations in position, scale and rotation of signs in real scenes, and to compare it with mentioned conventional models, three experiments have been done with different sizes of training and testing sets. Our implementations have been done using 50% of dataset images to train and 50% of it to test. Also, we tried to make the problem harder by decreasing the bulk of training set. Handling a harder recognition problem could indicate the robustness of proposed model compared to other forgoing conventional models as following:

A) Recognition of traffic signs by changing the object's position

The first experiment is evaluating recognition rate of proposed model in cases in which position of object in pictures is changed.
By employing some image processing techniques, lots of new samples have generated from primarily image database, which are different in object's position in image. As mentioned in previous section, SRTTU database used in our experiments consists of 20 object classes and each class consists of 10 images in different angles and sizes.
To generate new samples, 25 samples are generated from any particular image of database. In overall, there is 5000 samples, in which used as training and testing samples. Generated samples from image 1 of the sign 1 in its own viewing angle are shown in figure 8.
In this experiment, 50 patches were taken from each input image. Image patches were selected randomly in different sizes and angles from different parts of image.

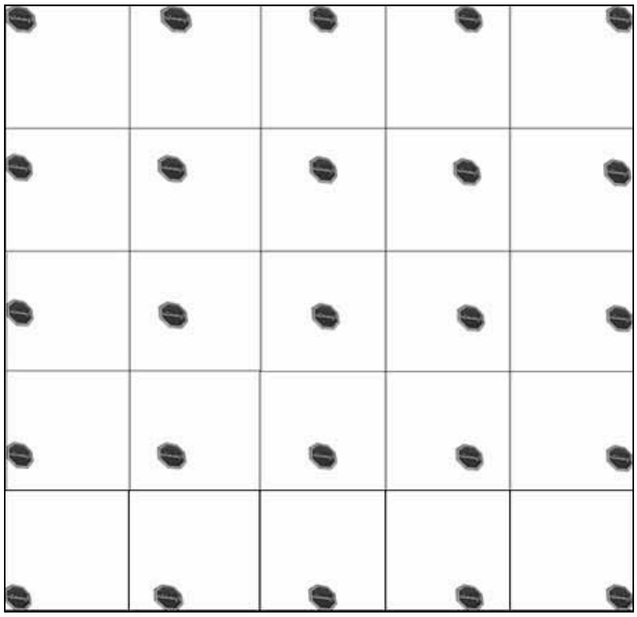

Figure 8. Generated samples from an individual sign image of dataset.

The results of recognition, by changing position of signs in images, using proposed model as well as implementation of some conventional models, for different number of training samples are listed in Table 2.

Table 2. The recognition accuracy of proposed model and some conventional models by changing position of signs in images.

#of Training Samples / *# of Test Samples*	2500 / 2500	2000 / 2500	1500 / 2500	1000 / 2500	500 / 2500
C2 SMFs+KNN	*61.5%*	*61%*	*60.5%*	*59%*	*51.5%*
PCA+KNN	6%	6%	5%	5%	5%
DCT+KNN	8%	7%	7%	5%	5%
2DPCA+KNN	9%	6%	6%	5%	5%

As seen in Table 2, traffic sign recognition accuracy, using proposed model (C2 SMFs+KNN), lead to satisfactory results, compared to conventional recognition procedures.

The results indicate that this model is invariant in moving the location of object in picture, while other famous models implemented on this database, give weak performances by objects changes in visual field and their recognition rate is as much of a chance which is not at all reliable. So, this model can suitably used in cases that a lot of moving objects occurs in visual field, to reach the desired results. As we know, object position in scene is very important in recognizing traffic signs, since car distance from the sign is changed each moment. In other words it can be said that object moves in real time captured image.

B) Recognition of traffic signs by changing object's orientations in pictures

The second experiment is evaluation of proposed model in recognizing objects with rotation of traffic sign images. First, proposed model is trained using entire original image database and then all pictures which are rotated +10 degrees, used as test samples. So, we have 200 training and 200 testing samples. Figure 9 indicates some images used for training and testing the model when a change in object viewing angle is happen.

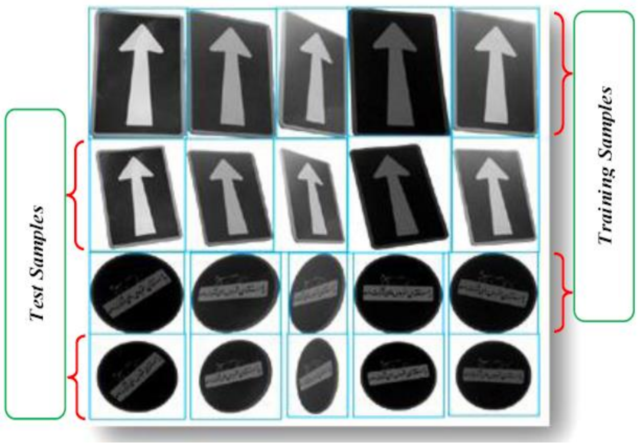

Figure 9. Some samples used as training and testing the model by changing images orientation.

In this examination, recognition accuracy of the model with 200 training and 200 testing samples was 96.5%. This rate of recognition compared to conventional models that implemented on the same database has significant advantage.

The recognition accuracy of suggested biological model and some conventional models such as PCA, The Discrete Cosine Transform (DCT) and Two-dimensional PCA (2DPCA) with different numbers of training samples on the same database, are shown in Table 3.

Table 3. The recognition accuracy of proposed model and some conventional models, with different numbers of training samples on the same database.

# of Training Samples / *# of Test Samples*	200 / 200	180 / 200	160 / 200	140 / 200	120 / 200
C2 SMFs+KNN	*96.5%*	*95%*	*94.5%*	*92.5%*	*88%*
PCA+KNN	32.5%	32%	30.5%	29.5%	29%
DCT+KNN	37%	36%	35%	34%	33%
2DPCA+KNN	38%	36%	35%	30%	29.5%

By analysis the content of this table, it can be concluded that, by rotating input images, the efficiency of proposed model has a significant advantage compared to results of mentioned conventional models.

C) Recognition of traffic signs by changing the scale of objects in the pictures

The last implemented experiment is evaluating the proposed model to recognize test samples with changes in scale of object in images.

To implement this part of evaluation, the proposed model is trained using entire original images database (The database consists of 20 classes and each class includes 10 traffic sign images in different angles and sizes), then all database images are resized as much as 20% smaller than original images, to be used as testing samples. So, we have 200 training and 200 testing samples to study models invariance to scaling.

Some images used as training and testing samples to evaluate the effectiveness of model, when test samples are resized 20% compared with the training images are shown in figure 10.

Figure 10. Some of training and testing sample used to investigate the proposed model's effectiveness when samples scales are changed.

In this experiment, recognition accuracy of proposed model for 200 training and 200 testing samples was about 92%. The recognition rate of proposed biological model and the efficiency of some other recognition models for different numbers of samples are shown in Table 4.

Table 4. The performance of proposed model compared to some conventional models, with different numbers of training samples on the same database, when the scales of images are changed.

#of Training Samples *# of Test Samples*	**200** **200**	**180** **200**	**160** **200**	**140** **200**	**120** **200**
C2 SMFs+KNN	***92%***	***88.5%***	***94.5%***	***87%***	***86%***
PCA+KNN	15.5%	15%	12.5%	11.5%	10%
DCT+KNN	17.5%	14%	14 %	13.5%	12.5 %
2DPCA+KNN	10%	9.5%	8%	8.5%	8.5%
2DPCA+KNN	10%	9.5%	8%	8.5%	8.5%

Proposed model's rate of recognition is a considerable outcome, compared to conventional models re-implementation results on the same database. When object size changes in the visual field (image screen), other famous models are not capable to lead to an acceptable result and they show high weaknesses in recognition. This is a significant point in cases in which camera and object are moved relative to each other, especially in recognizing traffic signs and road signs that we are dealing with an entirely moving camera, consideration to scale changes can lead to a remarkable improvement in performance of system.

As mentioned above, in this specific case (traffic sign recognition) and due to the position changes of object and observer (camera), sizes of objects in images are constantly changing. Therefore, using common computational models of object recognition, we are not able to gain appropriate performances. The proposed model is based on extracting shape-based features from traffic sign images using Standard Model Features (SMFs) and classifying test images using a simple classifier. In perceptual stage, 50 C2 feature vector are extracted from images of database. The resultant feature vectors are passed to a KNN classifier to determine the correct class for images. By employing the proposed model (C2 SMFs+KNN) on the experimental dataset with 50 training and 50 testing samples, correct recognition rate about **61.50**% is achieved when the position of signs was changed. Also, the recognition accuracy of the proposed model with 10 training and 10 testing samples, when test samples were rotated 10 degrees to left than training sample, was about **96.5%** and the recognition accuracy resulted from implementation of the proposed model with 10 training and 10 test samples when testing samples is 20% smaller than training samples, was about **92%**.

These rates of recognition are the average of 20 times run of our model on the database. As a comparison, we also give the experimental results of some conventional models such as PCA based models (PCA and 2DPCA) and DCT with KNN classifier with different numbers of training samples.

IV. Conclusion and Future works

We proposed an effective biological model to make applicable traffic sign recognition task. We implemented our experiments focusing on signs shape and geometrical characteristics regardless their color to design an accurate recognition model. The rate of recognition indicates that the proposed model is superior to other implemented models of sign recognition on the same dataset. Although this model is more accurate than others, it involves in a weakness in which its operation time is more than others if we implement our model using a traditional Central Processing Unit (CPU). Applying Gabor functions on images and also classifying samples using KNN is quite time consuming. To overcome the time problem and designing an accurate and fast recognition system based on the proposed model, authors suggest using a modern Graphical Processing Unit (GPU) instead CPU. GPUs are excellent processors for parallel processing operations especially when recognition systems deal with digits and digital matrices.

The key point of proposing this biological model is its invariance to image transformations such as changing the scale, view angle and position. PCA-based models and DCT involve in critical challenges when this variations occurs for objects in images. In overall, our experiments proved that the proposed model is not only feasible, but also it is more effective than other implementations of this experiment on the same database. We compared our model with (PCA, DCT and 2DPCA)+KNN models to demonstrate the superior performance, and experimental results supported our claims that rate of recognition using the proposed model is higher than other mentioned approaches in different external condition may affect the recognition system such as object's position, rotation and scale variations. Obviously, the biologically motivated traffic sign recognition model has noticeable recognition accuracy than other considered models.

The difference in recognition accuracy of the proposed model (HMAX+KNN) by changing object's position, view angle and scale than conventional models (PCA, DCT and 2DPCA)+KNN was about 51%, 50% and 75% respectively.

In this paper, a novel methodology for traffic sign recognition is presented and described, taking into consideration existing difficulties. The results are very satisfying and it has been shown that HMAX Standard Model Features (SMFs) are a good choice for representing the image, in this framework. Furthermore, KNN classifier is successfully developed, in order to classifying sign images.

Concerning some extensions of this work for the future, an improvement would be using an intelligent method for patch selecting into the procedure. Furthermore, it would be interesting to conduct experiments with different parameters for HMAX model and compare the resulting performances for classification layer. The overall competence of system is high, as it was proven to be invariant in situations in which position, rotation and scale of images are changed.

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