Communications on Applied Electronics (CAE) - ISSN : 2394 - 4714
Foundation of Computer Science FCS, New York, USA
Volume 3 - No. 1, October 2015 - www.caeaccess.org

Real Time Traffic Sign Detection and Recognition using Adaptive Neuro Fuzzy Inference System

Mustain Billah*
Department of Information And Communication Technology
Mawlana Bhashani Science And Technology University
Tangail,Bangladesh

Sajjad Waheed
Department of Information And Communication Technology
Mawlana Bhashani Science And Technology University
Tangail,Bangladesh

Kawsar Ahmed
Department of Information And Communication Technology
Mawlana Bhashani Science And Technology University
Tangail,Bangladesh

Abu Hanifa
Department of Information And Communication Technology
Mawlana Bhashani Science And Technology University
Santosh,Tangail,Bangladesh

ABSTRACT

Traffic sign recognition is a major part of an automated intelligent driving vehicle or driver assistance systems.Perfect recognition of traffic sign helps an intelligent driving system giving valuable information about road signs,warnings, prohibitions thus increasing driving speed, security and decreasing risk of accident. Many techniques have been used for recognising traffic signs such as backpropagation neural network,support vector machines,convolutional neural network etc on different shaped signs. Fuzzy inference system has not been used in deep for this purpose. In this paper, we have tried to find out the capability of adaptive neuro fuzzy inference system(ANFIS) for traffic sign recognition. We have used video and image processing for detecting circular shaped signs and used ANFIS for recognizing detected signs.

General Terms

Computer Science, Image Processing

Keywords

Image processing, ANFIS, Traffic sign recognition, Intelligent driving, sign detection

1. INTRODUCTION

Intelligent Transport Systems [11] are an application of artificial intelligent.It saves our time, money, lives and opens the doors of using other technologies such as mobile data services, smart sensor, geographical position technologies. Road and traffic sign recognition is an important field of intelligent transport systems[4]. Traffic signs plays an essential role in driving as it gives important informations about the situation of traffic in the road, potential dangers and others instructions[7].

Fleyeh, Hasan, and Mark Dougherty[7] presents an overview of the road and traffic sign detection and recognition. It describes the characteristics of the road signs, the requirements and difficulties behind road signs detection and recognition, how to deal with outdoor images, and the different techniques used in the image segmentation based on the colour analysis, shape analysis. Traffic signs are of many types[5]. Some of them indicates speed limit, some indicates types of road,some specifies types of permitted vehicles.

Road sign recognition is a modern field.The first paper on this topic was published in 1984 showing various computer vision methods for object detection in outdoor scenes[10].As times have passed,new organizations and companies have been involved in finding and applying different techniques and methods for this purpose[20, 9, 12].

Fang, Chiung-Yao presents an automatic road sign detection and recognition system that is based on a computational model of human visual recognition processing[6]. Lorsakul, Auranuch, and Jackrit Suthakorn presents a study to recognize traffic sign patterns using Neural Networks technique[14].In paper[18], a low-power real-time traffic sign recognition system that is robust under various illumination conditions is proposed. S. Lu shows the application of multilayer neural network in traffic sign recognition[15]. Maldonado-Bascn, Saturnino et al. in their article[16] presented an automatic road-sign detection and recognition system based on support vector machines (SVMs) as one of the main advantages of the SVM over other networks is that its training is performed through the solution of a linearly constrained convex quadratic programming problem[14, 21].

Fig. 1. Different types of road signs

Traffic sign identification system has actually two part[7, 23]: detection and recognition. In the detection part various image processing techniques are used for preprocessing the captured image from the video[2]. Images are enhanced, filtered, segmented according to some properties[8].This process outputs an image containing the actual sign image only.

In the recognition stage, various features extracted[17] from different sign images to characterize them according to the extracted features are used as the input data of any recognition tools or techniques such as support vector machine[16], artificial neural network[14, 19, 22, 1]. Different labels are assingned to each input dataset. These labels indicate different signs.

In this paper, we have used the same procedure except that we have used ANFIS[13] as the recognition technique. For our experiment, we have taken only the circular shaped objects as input image[3]. We know ANFIS has better prediction and detection capability than other techniques.But as there is no work on traffic detection using ANFIS[10, 12] we have used it as a test experiment to cheque ANFIS performance and usability for traffic sign recognition.In our experiment, ANFIS has gained its expected performance.

The paper is organised as follows: Section 2 contains a brief description of theory of ANFIS.Section 3 describes the proposed model.It has some sub sections describing each parts of the model. In the section 4, results are analyzed.

2. THEORY OF ANFIS

ANFIS derives its name from adaptive neuro-fuzzy inference system.It works similarly to that of neural networks. Using a given input/output data set, ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a backpropagation algorithm alone or in combination with a least squares type of method. This adjustment allows the fuzzy systems to learn from the data they are modeling. Assume that the fuzzy inference system has two inputs x and y and one output z. A first-order Sugeno fuzzy model has rules as the following:

Rule1:
If x is A1 and y is B1, then f1 = p1x + q1y + r1

Rule2:
If x is A2 and y is B2, then f2 = p2x + q2y + r2

Here,

$$output = \frac{w1.f1 + w2.f2}{w1 + w2} \tag{1}$$

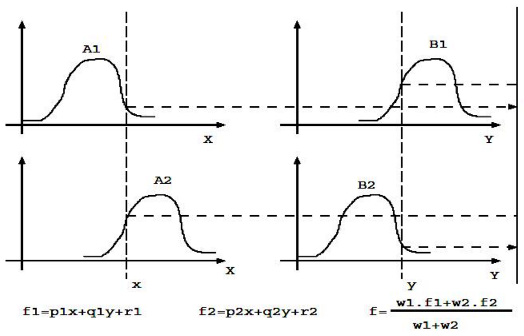

Fig. 2. Sugeno model

Layer 1 - I
$O_{1,i}$ is the output of the ith node of the layer 1. Every node i in this layer is an adaptive node with a node function.

$$O_{1,i} = Ai(x)\text{for}i = 1, 2, or \tag{2}$$

$$O_{1,i} = Bi - 2(x)\text{for}i = 3, 4 \tag{3}$$

x (or y) is the input node i and Ai (or Bi-2) is a linguistic label associated with this node. Therefore $O_{1,i}$ is the membership grade of a fuzzy set A1 ,A2, B1, B2).

Layer 2
Every node in this layer is a fixed node labeled "Prod". The output is the product of all the incoming signals.

$$O_{2,i} = wi = Ai(x).Bi(y) \quad \text{for} \quad i = 1, 2, .. \tag{4}$$

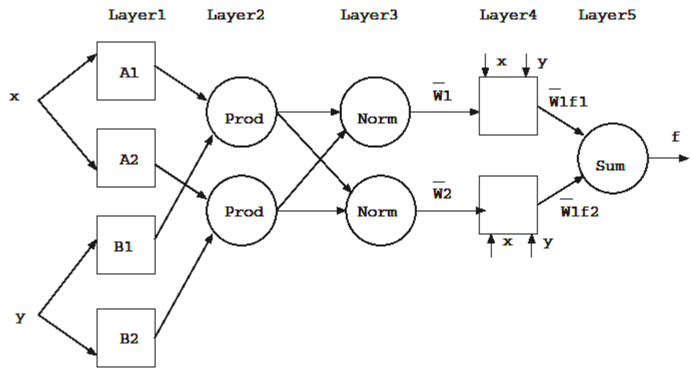

Fig. 3. Anfis architechture with two input variable

Each node represents the fire strength of the rule Any other T-norm operator that perform the AND operator can be used.

Layer 3
Every node in this layer is a fixed node labeled Norm.The ith node calculates the ratio of the ith rulets firing strenght to the sum of all rulets firing strengths.

$$O_{3,i} = wi = \frac{wi}{w1 + w2} \quad \text{for} \quad i = 1, 2, ... \tag{5}$$

Outputs are called normalized firing strengths.

Layer 4
Every node i in this layer is an adaptive node with a node function:

$$O_{3,i} = \bar{wi}.fi = \bar{wi}(px + qi.y + r) \quad \text{for} \quad i = 1, 2, ... \tag{6}$$

wi is the normalized firing strenght from layer 3. {pi, qi, ri} is the parameter set of this node. These are referred to as consequent parameters.

Layer 5
The single node in this layer is a fixed node labeled sum, which computes the overall output as the summation of all incoming signals:

$$O_{5,\,i} = \sum \bar{wi}.fi = \frac{\sum \bar{wi}.fi}{\sum \bar{wi}} fi \quad \text{for} \quad i = 1, 2, ... \tag{7}$$

Infact, ANFIS is the combination of both ANN fuzzy logic. ANN algorithms are also used for anfis training, learning.

3. OUR PROPOSED MODEL

As stated earlier, our proposed system has mainly two stage. The detection stage (image preprocessing) and the recognition stage (ANFIS). Fig4 in following page shows a flow diagram of our model.

3.1 Detection Stage

Actually it is the video and image processing stage.While going through a road, all the outside scenes are recorded by the ITS (Intelligent transport system).Whenever a scene containing traffic sign appears, it should be analyzed and it is our initial input.

3.1.1 Converting to binary. In this stage,we convert each image from grayscale to its binary form which contain 1 for white portion and 0 for black portion.

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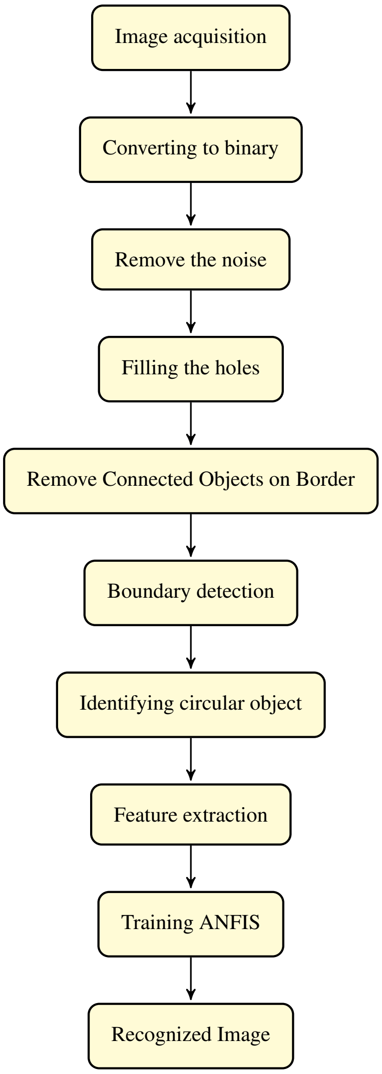

Fig. 4. Our proposed model for traffic sign recognition using ANFIS

Fig. 5. Captured image from video

3.1.2 Remove the noise. Using morphology functions, we have removed pixels which do not belong to the objects of interest.Obects under 30 pixel have been removed.

3.1.3 Filling the holes. Fill any holes, to estimate the area enclosed by each of the boundaries.

3.1.4 Remove Connected Objects on Border. Any objects that are connected to the border of the image have been removed in order to decrease the unwanted objects.

3.1.5 Again Remove the noise. As there are still some unwanted noises and smaller object it may create problem while finding circular section.So we have removed the objects under 2000 pixel.

3.1.6 Boundary detection. In boundary detection stage, we have concentrated only on the exterior boundaries ,not the inner contours.

3.1.7 Identifying circular object. Now it is time to estimate each object's area and perimeter and use these results to form a simple metric indicating the roundness of an object:

$$metric = 4 * pi * area/perimeter^2 \quad (8)$$

This metric is equal to one only for a circle and it is less than one for any other shape.We have used a threshold of 0.60 so that only the circular objects can be classified as round.These process returns the circular object with a bounding box.

3.1.8 Cropping the circular object. As we need only the circular object,it should be cropped from the whole image.Foe accomplishing this task we have used a simple "circle finding" algorithm.

circle finding algorithm:

1.Get the dimensions and number of color bands of the image.
2.Initialize parameters for the circle, such as it's location and radius.
3.Initialize an image to a logical image of the circle .
4. Mask the image with the circle.
5.Obtain the circular sign object.

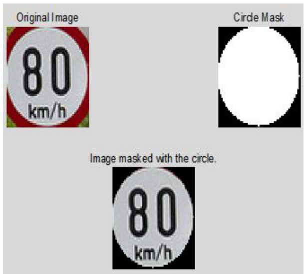

Fig. 6. Cropped circular object with blank background

3.1.9 Image Resize. Images are captured from different distances.To make their area equal, we have resized every circular image in a fixed size.Finally, these is the actual input image of our system.

3.2 Recognition Stage

In the rcognition stage, some important features are cextracted for each sign and these features are given as input dataset to ANFIS for training.

3.3 Feature Extraction

Now the main and critical point comes.It is feature extraction, the main part on which proposed systems accuracy depends. After getting the resized image, it is time to find out important features from the image. we can gain many information from an image but all of them do not influence the outcome of a system. we have found out many features but choosen only six of them, as large number of input to ANFIS makes the computer system complex to train the ANFIS creating large sets of rules.Choosen six features:

Total black pixel. As size of characters are different, so the number of black pixels(number of 0s) are also different.

$$Totalblackpixel = row * columnnnz(Image) \quad (9)$$

nnz is the number of nonzero elements.

Entropy. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image.

$$entropy = entropy(Image) \tag{10}$$

GLCM. A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM). The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. GLCM contains four measures of an image.

Contrast. Returns a measure of the intensity contrast between a pixel and its neighbor over the whole image.

Correlation. Returns a measure of how correlated a pixel is to its neighbor over the whole image.

Energy. Returns the sum of squared elements in the GLCM.

Homogeneity. Returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

For example six feature values of discussed input is shown below:

Table 1. Results of ANFIS training for real time dataset

Features	Values
Total Black pixel	12950
Entropy	0.9835
Contrast	0.0450
Correlation	0.9078
Energy	0.4694
Homogeneity	0.9775

3.4 Training ANFIS

Our input dataset contains six input data for each sign. We have assigned an output label for each input dataset. For example, speed sign 60 is assigned 2, speed sign 15 is assigned 3. If a test image is given for recognition, its six features will be given as input to the ANFIS. If ANFIS produces a result 3, it will indicate that the test input was a 15 kilometer/hour speed sign.This is the overall concept of our ANFIS system. However, to gain the best inference system,we have tried a varites number of input membership functions. A sample is given below:

Table 2. Results of ANFIS training for real time dataset

MFs number	MFs name	Error
2 2 3 3	triangular	0.23710
3 3 3 3	trapezoidal	0.12710
2 2 3 3	triangular	0.10710
2 2 3 3	trapezoidal	0.14710

We have tried trapezoidal, gaussian, gbell and others MF but triangular MF gave the best result with 2 MF for Total black pixel input, 3 MF for Entropy input, 4 MF for Contrast, 2 MF for Crrelation, 3 MF for Energy, 4 MF for Homogeneity input variable. Structural view of our ANFIS model is given below:
Average error of our ANFIS is only 0.11894. A plot against our training data is shown below:

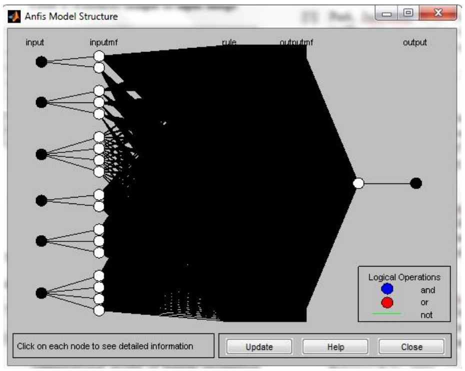

Fig. 7. Our trained ANFIS with 7 input

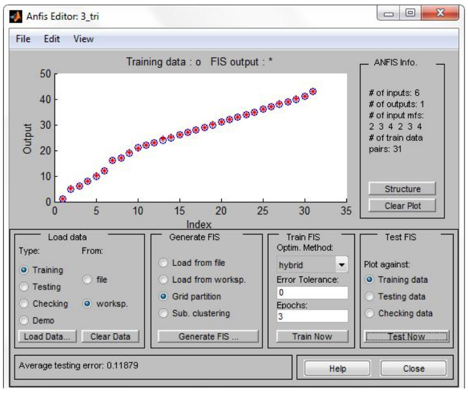

Fig. 8. Averaging error after training

4. RESULTS AND DISCUSSION

Different types of traffic signs were used to train ANFIS.We also kept a test dataset of signs for testing our ANFIS performance. We have told before that, each sign has its own output label which means a specific sign. For example, 1 means cross,5 means walking road,6 means go right,8 means going right is forbidden etc.After testing with the test dataset, we got fraction output value for some cases such as 5.34 instead of 5,or 6.204 instead of 6 etc. A sample of test dataset output is given below:

Table 3. ANFIS output vs actual output and meaning of sign

Anfis output	Actual output	Sign meaning
0.96792437	1	CROSS
5.034325163	5	Walking road
6.204921416	6	Go right
8.113596816	8	Going right forbidden
10.0158636	10	Bicycle road
12.03729536	12	No U turn

But our target is to recognize which sign it is.So we need round value.We used floor and ceiling function to gain round figure which corresponds to a specific sign.Thus our ANFIS system could recognize all the test sign perfectly. But recognising some sign is somewhat problamatic if input image contains much noise. However, we have gained satisfactory result which leads us to the use of ANFIS system for traffic sign recognition.

5. CONCLUSION

Traffic sign recognition is a complex task. It may not be easy all the time as image contains noise and complete noise removal is not possible. In this paper, we have showed a system for recognising traffic sign using adaptive neuro fuzzy model (ANFIS). There are some works on traffic sign recognition using other techniques on different shaped signs. Our proposed method works on circular signs and shows more than 98% accuracy. In future, we will work on the comparison of proposed ANFIS and neural network to find out the best soft computing technique for traffic sign recognition.

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