A traffic sign detection and recognition system

Thongchai Surinwarangkoon, Supot Nitsuwat, and Elvin J. Moore

Abstract— In a visual driver assistance system, traffic sign detection and recognition are important functions. This paper presents automatic traffic sign detection and recognition systems based on neural networks and particle swarm optimization. Our system is able to detect and recognize all types of traffic signs used in Thailand, namely, prohibitory signs (red or blue), general warning signs (yellow) and construction area warning signs (amber). Traffic signs provide drivers with important information that help them to drive more safely and easily by guiding and warning them. The systems consist of four main stages: 1) color filtering according to color of RGB pixels; 2) color segmentation and traffic sign detection by black-white color transformation; 3) feature extraction; 4) traffic sign recognition based on classification techniques. Experiments show that system has high accuracy of traffic sign detection and recognition for the traffic signs used in Thailand.

Keywords—Traffic sign detection and recognition systems, color filtering, color segmentation, neural networks, particle swarm optimization.

I. Introduction

TRAFFIC-SIGN detection and recognition have been an important issue for research recently because they are becoming increasingly important for the development of intelligent vehicles. The first work in this area can be traced back to the late 1960s and significant advances were made in the 1980s and 1990s. An example of this early work was the Traffic Sign Recognition (TSR) project that was begun in 1988. In this project, color was ignored because insufficient processing power was available at that time to handle color information. The main work was based on the detection and extraction of relevant shapes, known as form primitives, from the images [1].

The idea of computer vision-based driver assistance attracted worldwide attention when video processing became more attainable. Originating from large-scale projects developed in the USA, Europe [2,3,4] and Japan [5], intensive research on traffic sign recognition is now being conducted by both academic and industrial groups all over the world, often in close association with the car industry [6].

In the majority of published work, a two-stage sequential approach has been adopted. The first stage aims at traffic sign detection, and the second stage aims at traffic sign recognition. For the traffic sign detection stage, a common approach is to first define the acceptable appearance of signs and the geometrical relationships between their parts with respect to color and shape [7]-[10] and then to use this information to identify the region of the roadside image that could contain a traffic sign. Different approaches have been used for different stages of the detection problem, such as color segmentation, control theory and feature extraction. For the traffic sign recognition stage, a pixel-based approach is often used and the class of a detected sign might be determined by cross-correlation template matching [11], [12] or classification techniques [7], [13]. In [14], [15] a different strategy was developed based on the idea of representing a candidate sign as a set of similarities to stored prototype images. Related research on the detection and extraction of text characters on road traffic panels can be found in [16]. A vehicle detecting and tracking system has recently been proposed for dynamic environments where shapes and sizes of vehicles are changing all the time [17].

For automatic traffic sign recognition systems, it is necessary to create templates of characteristic patterns for different classes of sign. A classification technique defines an object into a class by using object features. For traffic sign recognition, there are broadly 3 major methods, namely, color-based, shape-based, and classification techniques such as neural-network based recognition [18].

A computational intelligence technique, called particle swarm optimization (PSO), inspired by social behaviour simulation, has been proposed by Eberhart and Kennedy [19].

PSO is a simple but powerful optimization algorithm. In the last decade PSO algorithms have been developed and successfully applied to many problems in image analysis. In fact, image analysis tasks can often be reformulated as the optimization of an objective function.

This paper focuses on the task of automatic traffic sign recognition from video and the use of that information in a driver assistance system. We use detection and recognition methods based on color filtering, color segmentation, neural networks and particle swarm optimization. Color filtering and color segmentation are used in the traffic sign detection stage. Two classification techniques: neural networks and particle swarm optimization, are used in the traffic sign recognition stage. Experimental tests have been carried out on the four main types of traffic signs used in Thailand to compare the

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accuracy and the processing time of these two classification techniques for traffic sign recognition. MATLAB programs have been developed to implement all stages of the traffic sign detection and recognition methods.

This paper is organized as follows: Section II describes feature of traffic signs used in Thailand. Section III gives an overview of the proposed detection and classification system. In section IV, concepts of traffic sign detection by using an RGB pixel relevance model, color filtering and color segmentation are discussed. Section V presents applications of two classification techniques to traffic sign recognition; neural networks and PSO. Section VI shows experimental results of tests of our methods for traffic sign detection and recognition systems from roadside images. Section VII gives a discussion and conclusions.

II. TRAFFIC SIGN

Traffic signs are designed to be recognized rapidly by human drivers under a variety of conditions, so their colors and shapes are selected to be significantly different from natural environments.

Traffic signs have two roles. Firstly, they regulate the traffic. Secondly, they indicate the state of the road, guiding and warning drivers and pedestrians. These signs can be classified according to their color and shape.

In Thailand, the Department of Traffic and Transportation of the Royal Thai government is in charge of defining the appearance of all traffic signs. They divide signs into three main classes: prohibitory signs, general warning signs, and warning sign at construction areas.

A. Prohibitory Signs

A prohibitory traffic sign is used to prohibit certain types of maneuvers or some types of traffic. In Thailand, they are separated into a red group and a blue group. The red signs are typically circular and have red borders and white backgrounds with information in red and black. The exceptions are the international standard stop sign that is an octagon with red background and white border, and the yield or give-way sign which is triangular. The blue signs usually give direction information, and they are typically circular with blue borders and backgrounds and instructions in white. Examples of the red and blue groups are shown in Fig. 1.

Fig. 1 examples of prohibitory signs (red and blue signs)

B. General Warning Signs

A warning sign is a type of traffic sign that indicates a hazard ahead on the road. In Thailand, general warning signs are diamond-shaped with black border and yellow background and with instructions in black. The Thai standard is in contrast to the standards of most other countries which typically use triangular warning signs with white backgrounds.

Fig. 2 examples of general warning signs (yellow signs)

C. Warning Signs at Construction Areas

Warning signs at construction areas are used to set the obligations of all traffic which use a specific area of road. Unlike prohibitory or general warning signs, a warning sign at construction areas tells traffic what it must do, rather than must not do. In Thailand, all warning signs at construction areas are diamond-shaped with black border and amber background and with information given in black. Examples of construction area signs are shown in Fig. 3.

Fig. 3 examples of warning signs at construction areas (amber signs)

III. OVERVIEW OF PROPOSED SYSTEM

In this paper, we present a system for traffic sign detection and recognition that we have successfully applied to Thai traffic signs. Fig. 4 shows the main stages of our implementation: color filtering, color segmentation and traffic sign detection, feature extraction and traffic sign recognition by neural networks and PSO. We describe each step in detail in the following sections.

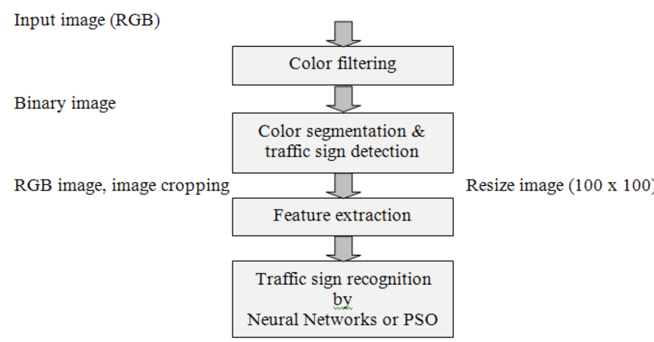

Fig. 4 stages of traffic sign detection and recognition system

IV. Traffic Sign Detection

This stage is composed of color filtering, color segmentation and traffic sign detection, and feature extraction. We describe each step in detail in the following subsections.

A. Color Filtering

The RGB color roadside image is input to the traffic sign detection and recognition system (see Fig. 5). Red, green and blue values for each pixel are captured. RGB values for each pixel are shown in Table I. Then images from red, blue, yellow and amber filtering are transformed to binary mode.

Fig. 5 an example of road sign image

TABLE I RGB Values for each Color in Traffic Signs

Color	RGB Value		
	R	***G***	***B***
Black	0	0	0
Blue	0	0	255
Red	255	0	0
Yellow	255	255	0
Amber	150	70	0
White	255	255	255

B. Color Segmentation and Traffic Sign Detection

RGB color is transformed to binary mode and color segmentation is applied in order to find the contour of the traffic sign. After that, the size of sign is checked to see if it is a traffic sign. If its size is too small or if it is not a traffic sign, then the image will be discarded. Therefore, a traffic sign is detected by this process. Fig. 6 shows an example of an image after the color segmentation and traffic sign detection stage.

C. Feature Extraction

In this stage, an RGB image of the traffic sign is cropped and resized to 100 x 100 pixels in order to match with images in a standard test library containing: 33 red signs, 19 blue signs, 53 yellow signs and 24 amber signs. After that, the image information is sent to the traffic sign recognition stage. Fig. 7 shows an example of an RGB cropped image at feature extraction stage. Fig. 8 shows examples of red signs in the standard test library of the traffic sign detection and recognition system.

Fig. 6 stage of color segmentation and traffic sign detection

Fig. 7 an example of RGB cropped image at feature extraction stage

Fig. 8 examples of red signs in the standard test library

V. TRAFFIC SIGN RECOGNITION

Traffic sign recognition requires classification techniques in order to identify each traffic sign. The central goal of this study is to evaluate whether the neural network technique or the particle swarm optimization technique is the more efficient for traffic sign recognition. There are several research questions associated with this goal. First, what is the difference between neural networks and particle swarm optimization techniques? Second, how well are traffic signs classified by these techniques? Third, how much computer time is required by these techniques for recognition of Thai traffic signs [20,21]?

To begin with, a brief review of the neural network and particle swarm optimization techniques will be given in the following subsections.

A. Neural Networks

Neural networks are based on biological neural systems. They are made up of an interconnected system of nodes (neurons). A neural network can identify patterns in numeric data through a training process. To date, neural networks have received limited application for traffic sign recognition and no studies comparing them to particle swarm optimization technique for traffic sign recognition have been performed [20].

There are many neural network models, but the basic structure involves a system of layered, interconnected nodes. The nodes are arranged to form an input layer, one or more hidden layers, and an output layer, with nodes in each layer connected to all nodes in neighboring layers.

Information enters the network at the input layer nodes and moves along weighted links to nodes in the hidden and output layers. Each node combines information from all nodes in the previous layer, resulting in a final output.

Complexities in the data are captured through the number of nodes in the hidden layers. The weights are determined by iteration to produce the lowest error in the output. To avoid overfitting to the data, a neural network is usually trained on a subset of inputs and outputs to determine weights and subsequently validated on the remaining data to measure the accuracy of predictions. In this paper, neural networks are used in classification and recognition of traffic signs.

In our experiment, four neural network modules are used to identify signs in each of the red, blue, yellow and amber groups as shown in section II. At the training stage, a neural network module for a color group is trained to recognize each of the different signs in that color group. Then, the training weights for a module are generated and stored in neural network modules (M_1, M_2, M_3 and M_4 for red, blue, yellow and amber group). The training images are selected to have a range of color intensity, shape distortion and lighting conditions so that the neural network will be able to recognize signs from images likely to be found under real driving conditions. Examples of training red sign images for neural networks are shown in Fig. 9.

Fig. 9 examples of training red sign images for neural networks

At this training step, each group has 49 input nodes in the network but a different number of output nodes; 33 output nodes for red, 19 for blue, 53 for yellow and 24 for amber.

At the testing stage, a roadside image is input into the system. After the traffic sign has been detected by, for example, a color filtering stage the sign color type is checked against matching groups and its features are extracted. The sign is then sent to the appropriate neural network color module for identification. An overview of the training and testing stages of the neural network method are shown in Fig. 10.

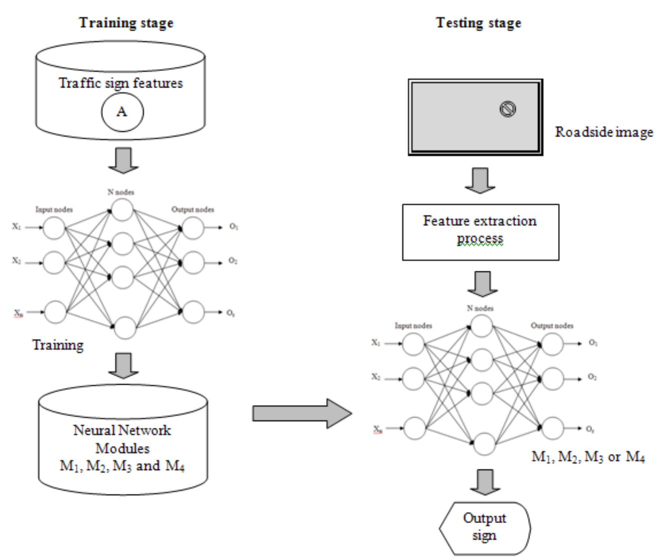

Fig. 10 the overview of training stage and testing stage of neural network modules

B. Particle Swarm Optimization

Particle swarm optimization is a high performance classifier [21]. This technique was designed and developed by Eberhart and Kennedy in 1995 [19]. Particle swarm optimization searches for the optimum of a fitness function, following rules inspired by the behavior of flocks of birds in search of food.

In traffic sign recognition, the mechanism of PSO is a simulation of the behavior of living as a group. The individuals in the population will adjust themselves in two ways, first to give the best position for the group and second to give themselves the best position among members of the group. An algorithm for particle swarm optimization is shown in Fig. 11.

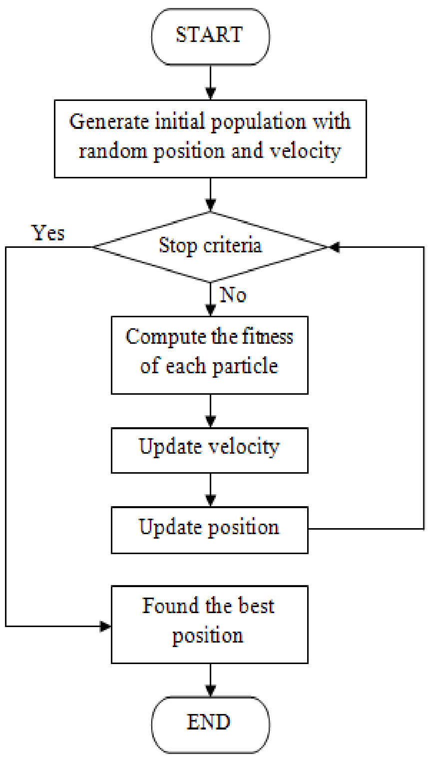

Fig. 11 diagram of PSO

The mathematical details of the PSO method are as follows. The swarm size of the PSO is denoted by *s*. Each particle has the following attributes: a current position x_i in the search space, a current velocity v_i and a personal best position p_i in the search space.

The variable ϖ is the inertia weight, this value is typically set to vary linearly from 0 to 1 during the course of a training run.

The variables c_1 and c_2 are acceleration coefficients, which control how far a particle will move in a single iteration.

The variables r_1 and r_2 are two random numbers in the range (0,1). The variable p_g is the global best position found by all particles. The velocity v_i of each particle can be clamped to the range [-v_{max}, v_{max}] to reduce the likelihood of particles leaving the search space.

During each iteration, each particle in the swarm is updated using (1) and (2);

$$v_{i+1} = \varpi v_i + c_1 r_1 (p_i - x_i) + c_2 r_2 (p_g - x_i) \qquad (1)$$

The new position of a particle is calculated using

$$x_{i+1} = x_i + v_{i+1} \qquad (2)$$

As shown in Figure 11, particle swarm optimization has 6 processes . Firstly, positions and velocities for each particle are generated randomly. Secondly, a fitness value for each particle is computed. Thirdly, each particle is compared and then its velocity is updated by using (1). Fourthly, the updated velocity is used to update the position of each particle update by using (2). Fifthly, processes 1 to 5 in the loop are repeated until the stopping criteria are satisfied. Finally, the best position of the swarm is found.

If the swarm size *s* is too large, the computational time will also be too large. If the swarm size *s* is too small, the computational time will be short, but the recognition rate will be low.

In this test, the swarm size *s* was set to 40, the inertia weight ϖ was 1.0, the acceleration coefficients c_1 and c_2 were 1.5 and the iterative time was 500. A fitness function was applied to compute distance for fitness value and find similarity of features for each particle.

VI. Experiment Results

Thirty roadside images were used to verify the traffic sign detection and recognition system before testing. The following figures show an example of the processes of traffic sign detection and recognition of a sign in the blue group; Fig. 12 shows the input roadside image in RGB color space, Fig. 13 shows the binary color segmentation at the traffic sign detection stage, Fig. 14 show image cropping in RGB mode and Fig. 15 shows the output from the traffic sign recognition.

Fig. 12 input roadside image in RGB color space

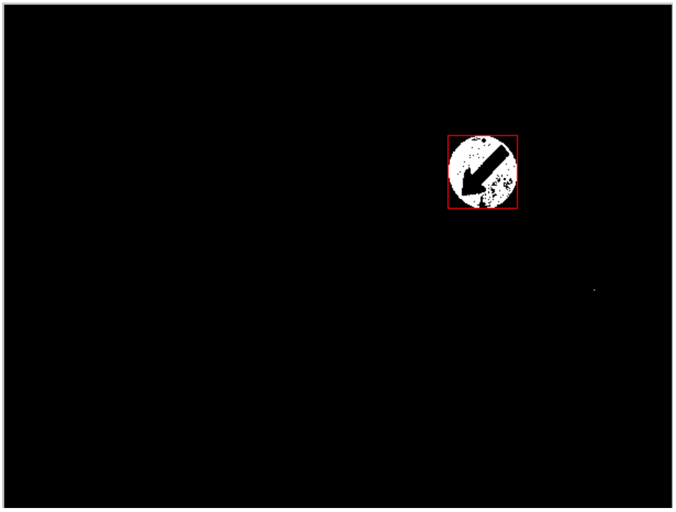

Fig. 13 color segmentation in binary mode

Fig. 14 image cropping at feature attraction stage

Fig. 15 output from traffic sign recognition stage

Particle swarm optimization and neural networks were examined to identify all types of traffic signs used in Thailand: 33 red prohibitory signs, 19 blue prohibitory signs, 53 general warning signs (yellow) and 24 construction area warning signs (amber).

A group of roadside images was input to the systems in order to compare performances between the neural network and the particle swarm optimization. The results of the testing are as follows.

A. Accuracy of Traffic Sign Recognition

Table II illustrates the test results of traffic sign recognition by the neural network and particle swarm optimization techniques.

TABLE II TEST RESULT OF TRAFFIC SIGN RECOGNITION

Type of sign	Number of inputs	Neural Network		PSO	
		Number Correct	(%) Correct	Number Correct	(%) Correct
Red	46	46	100	44	96
Blue	37	37	100	35	95
Yellow	60	58	97	57	95
Amber	33	32	97	31	94
Total	176	173	98.3	167	94.9

From the results shown in Table II, it can be seen that the traffic sign recognition by neural network has an accuracy of approximately 98.3%, whereas the traffic sign recognition by particle swarm optimization has a lower accuracy of approximately 94.9%. Moreover, it can be seen that neural networks have a higher accuracy recognition rate than PSO for all types of traffic signs.

In the test roadside images used in this comparison, the color filtering stage gave a clear detection and classification of the color type of the traffic sign image.

Although the detailed results are not shown in this paper, we found by comparing the performance of the neural network and PSO on high quality and on poorer quality images that the neural network technique gave more accurate and faster recognition rates than the PSO technique in both cases. Therefore a neural network will be able to recognize more accurately than PSO when the roadside images are distorted or blurred, or occluded by other objects in the input roadside image. However, since both neural network and PSO techniques will have reduced efficiency on poor quality images it is very important that the detection and feature extraction stages produce images containing sufficient information for input into the recognition stage.

B. Processing Time

Table III shows the processing times of traffic sign recognition by neural networks and particle swarm optimization techniques. These results were obtained on a 3.1-GHz Intel Core i5 with frame dimensions of 720 x 576 pixels.

Average processing time for traffic sign recognition by neural networks is 0.289 second. Average processing time for traffic sign recognition by particle swarm optimization is 0.314 second.

It is clear that traffic sign recognition by neural networks not only requires lower computation time but it also has higher correct recognition rate compared with the particle swarm optimization technique.

The neural network technique requires a training stage before testing. A group of traffic sign images of each traffic sign type must be prepared and used to train the network. In this paper, the training took approximately 30 minutes total for the four neural network modules. Hence, the system can learn quickly and give accurate recognition rates. If more traffic sign images were used at the training stage, then the system would run a longer time at this stage, but the trained system should have a more accurate recognition rate.

Although the performance of the PSO was not as good as that of the neural network technique in terms of recognition rate and computational time, it still performed satisfactorily. Its recognition rate was approximately 94.9% and its processing time was much less than 1 second. However, the processing time of particle swarm optimization will become much larger when the sample size in the database is increased. Further study is required to improve the formulation of PSO in order to increase its performance in terms of classification and processing time.

TABLE III PROCESSING TIME OF TRAFFIC SIGN RECOGNITION

Type of signs	Processing time (Second)	
	Neural Network	PSO
Red	0.290	0.316
Blue	0.286	0.301
Yellow	0.295	0.325
Amber	0.285	0.313
Average	0.289	0.314

VII. CONCLUSION

In this paper, an overview of traffic sign detection and recognition system is given. Processes of traffic sign detection are discussed. Traffic signs from roadside images are detected successfully at color filtering and color segmentation stages. Classification performances between neural networks and particle swarm optimization are compared for traffic sign recognition. The experiments indicate that the neural network technique has a more accurate recognition rate than particle swarm optimization for all types of traffic signs used in Thailand and that its computer processing time is also less. Although an efficient training stage is required for neural networks before they can be used for traffic sign recognition, this training is done off-line and the on-line recognition rate of the trained network is faster than that of the particle swarm optimization technique.

Future work will mainly focus on improving the efficiency of the traffic sign detection stage in order to decrease noise and increase quality of input roadside image. This task will allow us to investigate and develop new procedures that will contribute to the design of a versatile system. We will also apply ontology-based knowledge in order to improve traffic sign recognition, guide image interpretation and to give more detailed descriptions of traffic conditions and improved recommendations in a driver assistance system.

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