Comparing Classification Performances between Neural Networks and Particle Swarm Optimization for Traffic Sign Recognition

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Abstract: - This paper compares classification performances of two techniques for traffic sign recognition, namely, neural networks and particle swarm optimization. Neural networks and particle swarm optimization are applied to the problem of identifying all types of traffic signs used in Thailand, namely, prohibitory signs (red or blue), general warning signs (yellow) and construction area warning signs (amber). The comparison indicates that the neural network technique has higher correct recognition rates than particle swarm optimization for traffic sign recognition. Moreover, neural networks require less computer processing time than particle swarm optimization in the traffic sign recognition system.

Key-Words: - Classification techniques, traffic sign recognition, neural networks, particle swarm optimization

1 Introduction

Traffic sign recognition has been a challenging problem for many years. It is now 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, e.g., Besserer et al. [3].

Subsequently, 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 [6,7] and Japan [8], intensive research on traffic sign recognition is nowadays conducted by both academic and industrial groups all over the world, often with close association with the car industry [9].

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 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 [4].

A new evolutionary computation technique, called particle swarm optimization (PSO), inspired

by social behaviour simulation, was originally proposed by Eberhart and Kennedy [11].

This paper compares classification performances between neural network and particle swarm optimization techniques for traffic sign recognition. Concepts of these techniques are first reviewed. The focus is on the practical implementation of these techniques for recognition of traffic signs used in Thailand. Examples of the Thai traffic signs are shown in Table 1.

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Traffic Sign Types	Examples		
	Example 1	Example 2	Example 3
Prohibitory signs (33 Red signs)	หยุด	$\mathbf{\overline{N}}$	
Prohibitory signs (19 Blue signs)		×	
General warning signs (53 Yellow signs)		\blacklozenge	$\langle \mathbf{F} \rangle$
Warning signs at construction areas (24 Amber signs)	*	1111/18d514 construction	-

2 Review of Classification Techniques

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 might be more efficient than the particle swarm optimization technique 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 [1,2]?

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

2.1 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 [1].

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.



Fig. 1 The overview of training stage and testing stage of neural network modules

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 Table 1. 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 $(M_1, M_2, M_3 \text{ and } M_4 \text{ for red, blue, yellow and amber group).}$

At this 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 Figure 1.

2.2 Particle Swarm Optimization

Particle swarm optimization is a high performance classifier [2]. This technique was designed and developed by Eberhart and Kennedy in 1995 [9]. 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 Figure 2.

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

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

The new position of a particle is calculated using

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

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.



Fig. 2 Diagram of PSO

Particle swarm optimization has 6 processes as shown in Figure 2. Firstly, position and velocity for each particle was generated randomly. Secondly, fitness value for each particle was computed. Thirdly, each particle was compared and velocity was updated by using equation (1). Fourthly, the updated velocity was used for position update calculation by using equation (2). Fifthly, processes 1 to 5 in loop were repeated until it reached stopping criteria. Finally, it could find the best position.

If the swarm size s is too large, the cost time will also be too large. If the swarm size s is too small, the recognition rate will be low, although the cost time will be short.

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.

3 Analysis

To facilitate comparison of classified performances between neural networks and particle swarm optimization, a group of roadside images were used for testing.

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.

3.1 Traffic Sign Recognition

Table 2 illustrates the test results of traffic sign recognition by the neural network and particle swarm optimization techniques.

Туре	Number	Neural Network		PSO	
of sign inputs	of inputs	Number Correct	(%) Correct	Number Correct	(%) Correct
Red	36	36	100	35	97
Blue	27	27	100	26	96
Yellow	50	48	96	47	94
Amber	23	23	100	22	96
Total	136	134	98.5	130	95.6

Table 2. Test result of traffic sign recognition

From the results shown in Table 2, it can be seen that the traffic sign recognition by neural network has an accuracy of approximately 98.5%, whereas the traffic sign recognition by particle swarm optimization has a lower accuracy of approximately 95.6%.

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. Further testing will be required to compare the two methods when the roadside images are distorted or blurred, or occluded by other objects in the input roadside image. Insufficient feature extraction of an input sign contributes little to the uniqueness of a given sign, and therefore it is more difficult to identify at recognition stage.

3.2 Processing Time

Table 3. 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.

The form	Processing time (Second)			
Type of signs	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		

Table 3. Processing time of traffic sign recognition

Although the performance of the particle swarm optimization technique 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 above 95% 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 particle swarm optimization in order to increase its performance in terms of classification and processing time.

4 Conclusion

In this paper, classification performances between neural networks and particle swarm optimization are compared for traffic sign recognition. The comparison indicates 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.

Although particle swarm optimization has lower performance than neural network for traffic sign recognition at this time, it can be improved and is a potential classifier for traffic sign recognition in future.

5 Acknowledgments

Financial assistance for Thongchai Surinwarangkoon was provided by a scholarship from Department of Business Computer, Suan Sunandha Rajabhat University, Bangkok, Thailand.

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