Traffic Sign Recognition by Color Filtering and Particle Swarm Optimization

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Abstract. In this paper a comprehensive approach to traffic sign detection and recognition is proposed. An RGB roadside image is acquired. Color filtering and segmentation is used to detect the boundary of traffic sign in binary mode. At the feature extraction stage, the RGB traffic sign region is cropped. The image is resized to 100x100 pixels. Finally, particle swarm optimization is used to identify the traffic sign. Experimental results show that our system can give a high recognition rate for all types of traffic signs used in Thailand: namely, prohibitory signs (red or blue), general warning signs (yellow) and construction area warning signs (amber).

Keywords: traffic sign, recognition, color, filtering, Particle Swarm Optimization

1. Introduction

Traffic signs carry essential information for drivers. They define prohibitions, give warnings, etc. Ignoring the presence of such signs can lead drivers into dangerous situations or even accidents. Automatic road sign detection and recognition systems can be used both to warn drivers in these situations and supply additional environmental information [1]. With the development of autonomous Driver Support Systems (DSS) [2], automatic detection and classification of traffic signs is becoming increasingly important.

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 [3]-[7] and then to use this information to identify the region of the roadside image that could contain a traffic sign. Approaches to traffic sign detection which rely on color images are usually based on RGB color space. RGB color space requires no transformation; or only a very simple one. However, it requires more sophisticated segmentation algorithms than other color modes, since the boundary between colors is fuzzier [10]. 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 [7] or neural networks [3]. In [8], [9] a different strategy was developed based on the idea of representing a candidate sign as a set of similarities to stored prototype images.

In this paper we present an algorithm for detecting a traffic sign in a roadside image based on color filtering. Color segmentation is adopted to extract the inner features of a traffic sign. Further, we apply Particle Swarm Optimization (PSO) to classify the traffic sign in the recognition stage. MATLAB programs have been developed to implement all stages of the traffic sign recognition system.

Table 1. Examples of traffic sign in Thailand

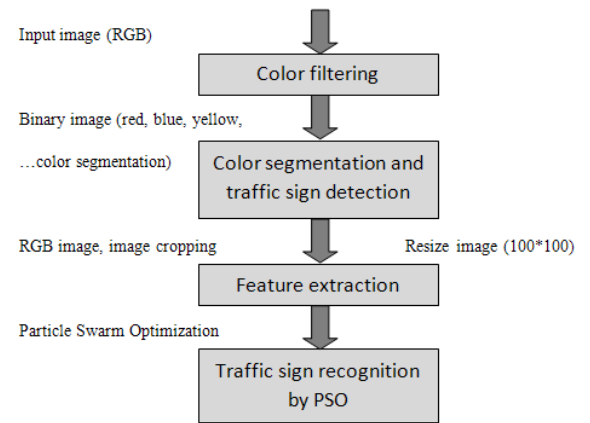| Traffic Sign Types	Examples		
	Example 1	*Example 2*	*Example 3*
Prohibitory signs (Red signs)			
Prohibitory signs (Blue signs)			
General warning signs (Yellow signs)			
Warning signs at construction areas (Amber signs)			

Fig. 1: Flow of processing in proposed system

This paper is organized as follows: Section 2 gives an overview of the proposed system. In section 3, concepts of traffic sign detection by using an RGB pixel relevance model and color filtering are discussed. Section 4 describes a color segmentation method for extracting inner information from a traffic sign. Section 5 presents an application of PSO to traffic sign recognition. Section 6 shows experimental results of our methods for traffic sign detection and recognition from roadside images. Section 7 gives a discussion and conclusions.

2. Overview of Proposed System

Traffic signs provide important information for drivers about road condition and hazards. Their shapes and colors are selected by traffic authorities to make them easily recognizable by humans. In Thailand, traffic signs are divided into three main classes: prohibitory signs (red and blue signs), general warning signs (yellow signs), and warning signs at construction areas (amber signs). Examples of traffic signs in Thailand are shown in Table 1.

Fig 1. shows an overview of the proposed traffic sign recognition system. The main stages of our implementation are: color filtering, color segmentation and traffic sign detection, feature extraction, traffic sign recognition by PSO. We describe each step in detail in the following sections.

3. Traffic Sign Detection

The RGB color roadside image is input to the traffic sign detection and recognition system. Red, green and blue values for each pixel are captured. RGB values for each pixel are shown in Table 2.

Color filtering and segmentation technique are applied to define location of traffic sign in original road side image. Red, blue, yellow and amber filtering are performed on the image. Then 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, traffic sign is detected by this process.

TABLE 2. RGB VALUES FOR EACH COLOR IN TRAFFIC SIGN

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

4. 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. Fig. 2 shows examples of yellow signs in the standard test library of the recognition system.

5. Traffic Sign Recognition

PSO is a simple but powerful optimization algorithm introduced by Kennedy and Eberhart [10]. 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.

PSO searches for the optimum of a fitness function, following rules inspired by the behavior of flocks of birds in search of food. A population of particles move within the fitness function domain (usually termed their search space), sampling the function in the points corresponding to their position. This means that, after each particle's move, the fitness computed at its new position is evaluated. In their motion, particles preserve part of their velocity, while undergoing two attraction forces: the first one, called cognitive attraction, attracts a particle towards the best position it has visited so far, while the second one, called social attraction, pulls the particle towards the best position found up to that time by the whole swarm [1]. A flow chart of PSO algorithm is shown in Fig 3.

In this paper, we apply PSO for the traffic sign recognition stage. The mechanism of PSO is a simulation of the behavior of living as a group. The individuals in the population will adjust themselves in the best position for the group and at the same time they try to adjust themselves to the best position among members of the population.

Our PSO implementation has been subdivided into the following three kernels.

Position update: A computation grid, divided into a number of blocks of threads, updates the position of all particles. Each block updates the data of one particle, while each thread in a thread block updates one element of the position and velocity arrays of the particles. In the beginning, the particle's current position, personal best position, velocity and local best information are loaded.

1) Fitness evaluation: This kernel is scheduled as a computation grid composed by one block for each particle being simulated. Each block comprises a number of threads equal to the total number of points that describe a sign so that the projection of all points on the current image is performed in parallel. The thread index determines to which set the projected point under consideration belongs. Finally the fitness value is computed. Then similarity is assessed in parallel.

2) Best update: Each thread loads in shared memory both the current and the best fitness values of its corresponding particle. The best fitness value is found by computing the best fitness of each particle's neighborhood, comparing it to the best value found so far, and then updating it, when necessary.

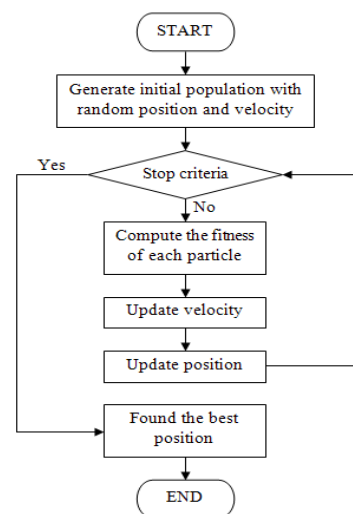Fig. 2: Examples of yellow signs in the standard test library

Fig. 3: Diagram of PSO

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);

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

The new position of a particle is calculated using

$$X_{i+1} = X_i + V_{i+1} \qquad (2)$$

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 can 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.

If the swarm size s is too large, the cost time will be increased. If the swarm size s is too small, the recognition rate will be low, although the cost time will be short. For our experiments, the swarm size s was 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. We show in section 6 that the recognition results can be achieved at a high recognition rate.

6. Experimental Results

25 roadside images were used to verify the traffic sign recognition system by PSO before testing. The following figures show an example of the processes of traffic sign detection and recognition of a sign in the yellow group; Fig. 4 shows the input roadside image in RGB color space, Fig 5. shows the binary color segmentation at traffic sign detection stage, Fig 6. shows the image cropping in RGB mode and Fig. 7 shows the output from the traffic sign recognition by PSO.
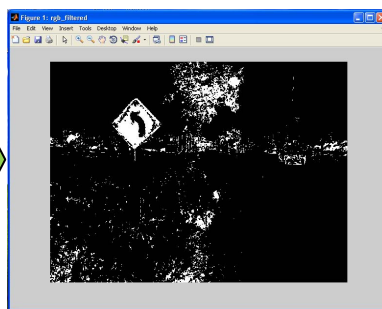

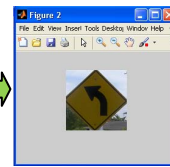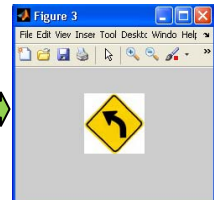Fig. 4: Input image in RGB mode   Fig. 5: Color segmentation   Fig. 6: Cropping   Fig. 7: Output

A group of roadside images were used for testing. All roadside images for testing were detected at a physical distance from the camera of approximately 10-30 meters. The testing results are shown in Table 3. It can be seen that the system can detect and recognize traffic signs with high correct recognition rate.

TABLE 3. TEST RESULT OF TRAFFIC SIGN RECOGNITION

Type of sign	Test Results		
	Number of inputs	Number Correct	Percentage Correct
Red	36	35	97
Blue	27	26	96
Yellow	50	47	94
Amber	23	22	96

TABLE 4. TEST RESULT OF PROCESSING TIME

Stages	Processing Time (Seconds)				
	Red Signs	Blue Signs	Yellow Signs	Amber Signs	Average
Image Reading	0.082	0.080	0.076	0.078	0.079
Color Filtering	0.252	0.250	0.247	0.246	0.249
Color Segmentation and Detection	0.937	0.932	0.924	0.943	0.934
Feature Extraction	0.232	0.231	0.234	0.226	0.231
Recognition by PSO	0.316	0.301	0.325	0.313	0.314
Total	1.819	1.794	1.806	1.806	1.806

The majority of detection failures were caused by insufficient contrast between a sign's boundary and the background, especially for a sign in shade. In a few cases this low contrast was caused by the dye on the sign.

Table 4 shows processing time for each stage of traffic sign recognition system. We achieve a mean processing time of 1.806 seconds for traffic sign recognition system on a 3.1-GHz Intel Core i5, where the frame dimensions are 720 x 576 pixels. By inspecting the obtained results, the system approximately required 0.079s at image reading stage, 0.249s at color filtering stage, 0.934s at color segmentation and detection stage, 0.231s at feature extraction stage and 0.314s at recognition stage by PSO. The total processing time for all stages of the system is around 1.806 seconds. It is clear that the proposed traffic sign recognition system not only employ low computation time but also perform classification efficiently.

7. Conclusion

In this paper, an algorithm for traffic sign detection and recognition is proposed based on color filtering, color segmentation and PSO. Color filtering and color segmentation is used to detect the boundary of a traffic sign from a roadside image. PSO is used to recognize a traffic sign from its extracted features. Experiments have been carried out on original roadside images and show that the algorithm can successfully 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). The size of the template database used in our experiment is significantly greater than those reported previously in Thailand.

Future work will mainly focus on improving the efficiency of the traffic sign detection stage in order to reduce the overall processing time of the system. We will also apply ontology-based knowledge in order to improve traffic sign recognition, guide image interpretation and contain more detailed description of recommendation information for driver assistance system.

8. Acknowledgements

9. References

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