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Classification of Traffic Signs Using Artificial Neural Networks

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Abstract

A traffic sign classification method based on artificial neural network is proposed in this paper. The proposed method for classifying traffic signs first detects traffic signs by using on the property of color probability model and then classifies the detected traffic signals. In both of detection and classification processes, two artificial neural network models are utilized. Experiments on practical image data sets show that the proposed method can detect and classify traffic signs with favorable accuracy.

Keywords: traffic sign, artificial neural networks, image classification, color map

1 Introduction

Research on smart cars has been one of the most emerging topics in computer vision community [1]-[3]. One of the most important features for smart cars, or computer-controlled vehicles, is understanding various traffic signs so that the computer-controlled vehicles can move with the traffic without accidents. In order for the smart cars to understand various traffic signs, it requires first to detect traffic signs from the scene obtained through camera and then to classify the detected traffic signs properly. Therefore, accurate detection of traffic signs is one of the most primary tasks in designing smart cars because the safety of smart cars is of unparalled importance. The specific features include specific shapes for different purposes with fixed and bright colors. When applying computer vision techniques to traffic sign detection and understanding tasks, various conditions are encountered. The difficult situations include undesirable image data conditions obtained through camera due to speed of vehicles and environmental changes. Furthermore, the images obtained through cameras under low or dark light conditions makes the traffic sign understanding tasks even more difficult.

As the first step for understanding traffic signs, it is necessary to develop a detection procedure for traffic signs. Various schemes have been introduced for this purpose of traffic sign detection. The first group of schemes tend to utilize the color information of traffic signs because most of the traffic signs are in fixed bright colors. Conventional methods for extracting traffic signs by using color information generate a continuous color map in HSI (Hue-Saturation-Intensity) space [4]. Even though this approach is relatively simple and effective, it sometimes yields inaccurate extraction of traffic signs. In order to alleviate problems with the color threshold approach for extracting traffic signs from images, color probability models have been proposed. The color probability model determines a specific color range in HSI space and then generate a color probability model based on all values of the specific color. The color probability model is then transformed to a Color Probability Map (CPM) by the Look-Up-Table (LUT) method [5] or training the color probability model with an artificial neural network [6]. The CPM is then generated by the LUT or calculating each pixel of the color input image data with trained artificial neural network. In order to detect the location of a specific traffic sign in color input image, the shape of traffic signs with a specific color is first detected in CPM by using a shape detection procedure and the location of a target sign is then determined.

After extracting specific traffic signs from images, the extracted traffic signs are then to be classified using Convolutional Neural Network (CNN) [7]. The traffic signs to be studied in this paper are speed limit signs in red color. Note that the approach proposed in this paper can be easily extended to different traffic signs with various colors.

The remaining part of this paper is organized as follows. Section 2 gives a summary of related works including traffic sign detection methods and Convolutional Neural Network as an image classifier. Section 3 addresses the architecture of the target system for the traffic sign detection and classification. Experiments and results are presented in Section 4 and Section 5 concludes this paper.

2 Related Works

2.1 Color Probability Map

The color probability map (CPM) is generated from image data by using the color probability model. In order to search a specific color information on image data, a pixel-wise binary output method with a threshold for a specific color can be easily utilized in RGB color space. However, this pixel-wise binary output method can be very sensitive to various outdoor environments including illumination variations and different levels of faded traffic signs.

All colors that belong to prespecified range of red colors are collected for the Red Color Probability Model. In order to extract color information from images, Ohta color space is used [8]. The Ohta color space is defined by the following linear transformation:

$$P_1 = \frac{1}{\sqrt{2}}\frac{R-B}{R+G+B}, \quad P_2 = \frac{1}{\sqrt{6}}\frac{2G-R-B}{R+G+B} \tag{1}$$

When C_i is the $i-th$ color class, the following can be calculated:

$$P(C_i|\mathbf{x}) = \frac{P(\mathbf{x}|C_i)P(C_i)}{P(\mathbf{x})} \tag{2}$$

where $\mathbf{x} = (P_1, P_2)$ and $P(\mathbf{x}|C_i)$ denote the normalized Ohta color and the likelihood probability, respectively.

Without losing generality, we can assume that the probability distribution of a color class in Ohta color space be Gaussian. Then, the following can be obtained:

$$P(\mathbf{x}|C_i) = \frac{1}{(2\pi) \mid \Sigma_i \mid^{1/2}} \exp\{-\frac{1}{2}(\mathbf{x}-\mu_i)^T \Sigma_i^{-1}(\mathbf{x}-\mu_i)\} \tag{3}$$

where μ_i and Σ_i denote the mean vector and covariance matrix of the $i-th$ color in Ohta color space, respectively..

2.2 Look-Up-Table for Color Probability Map Image

The Look-Up-Table (LUT) method can generate Color Probability Map (CPM) by using a LUT [5]. The LUT method for red color traffic signs, for example, collects pixels in red color and calculates the probability of red colors on reference images. When an image data is given, CPM image can be obtained by using the LUT for each pixel of the image. LUT method for CPM image is very fast and accurate. However, the quality of CPM image heavily depends on the LUT. When the reference image data does not fill enough the all possible entries of LUT, some holes are inevitable in LUT. Note that there will be 253^3 possible entries for LUT.

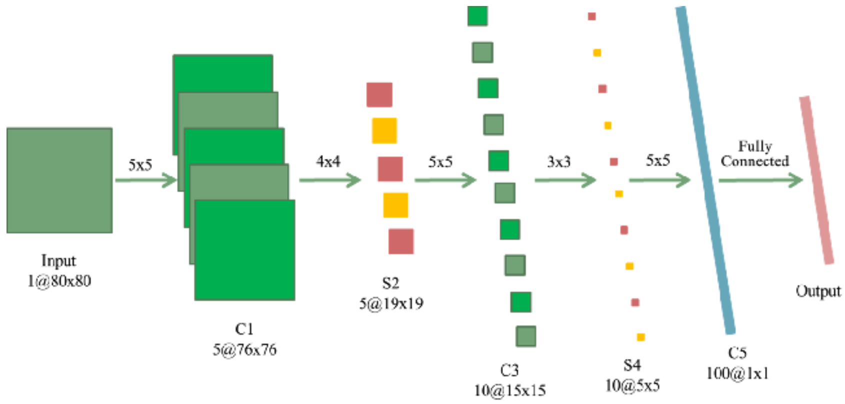

Figure 1: Convolutional neural network

2.3 Artificial Neural Networks for Color Probability Map Image

Since Artificial Neural Network (ANN) can generate a moderate output to an input data that was not contained in the training dataset, ANN has been successfully applied to CPM image generation. In order to apply ANN to CPM image generation, it is not necessary to train all color probability models. When compared with LUT method, ANN requires only a fraction of memory space for weights instead of all possible cases of color values. For a ANN architecture of 3-5-15-1, ANN requires only 126 ($3\times5+5\times15+15\times1+5+15+1$) memory space while LUT method needs at most 256^3 memory space. ANN can generate an interpolated result even though the ANN was never trained with the identical input data.

2.4 Convolutional Neural Network

The convolutional neural network (CNN), a supervised learning algorithm with the deep learning concept, have been successfully applied to various pattern recognition problems including handwritten character recognition, and pedestrian detection [7]. CNNs can be considered as an integrated model for feature extraction and classification. Input data for the CNNs utilized in this paper are extracted traffic signs of speed limits. An example of CNN is given in Fig.1.

The CNNs consist of two parts: feature extraction layers and classification layers. The first feature extraction layers include convolution layers and subsampling layers. The convolution layers have several 2-dimensional weights. The convolution operation in convolution layers is as following:

$$h_j = \tanh(\sum_{i=1}^{N} x_i * k_{ij} + bias) \tag{4}$$

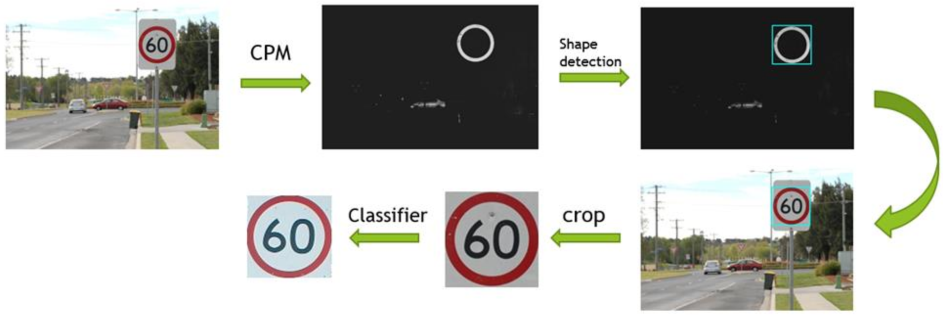

Figure 2: Flow Diagram of the traffic sign classification system

where x denotes the data of the previous layer and k represents the weight matrix.

The subsampling layer after convolution layer performs average pooling operation and max-pooling operation. The following max-pooling operation is often used:

$$p_j = \tanh(\arg\max_{k=1}^{r}(h_{jk}^{n\times m}) + bias) \tag{5}$$

where p_j is the output data of the subsampling layer.

The final outputs from the feature extraction layers become the input values to the classification layer. The classification layer in CNN is a MLPNN.

3 Traffic Sign Classification System

Traffic Sign Classification System (TSCS) developed in this paper is shown in Fig. 2. As can be depicted in Fig. 2, the TSCS consists of three parts: CPM generation by using MLPNN, shape detection and extraction by using circle detection procedure, and classification procedure by using CNN. The CPM is generated with the 3-5-15-1 architecture of MLPNN which is trained with 15,000 data. The circle shape detection procedure by using the randomized algorithm can effectively detect circles with high speed. The detected and extracted red circle signs are then applied to CNN for the classification of speed limit signs.

4 Experiments and Results

In order to evaluate the proposed TSCS, image data are collected from internet, Traffic Sign UAH Dataset (TSUAHD) [9] and LT Tam Test Database (LTTTD) [10]. These image datasets include some undesirable data in various weather conditions. In experiments, speed limit signs with numbers of 30, 50, 60, 70, and 90 inside and red circle outside are used. 40 image data in each

Figure 3: Examples of training data

category of speed limit are used for experiments. Fig. 3 shows some examples of image data.

For the experiments, we utilize a 10-fold cross-validation method. This method has been successfully used when the size of data samples is small but to evaluate a classifier fairly. That is, the data samples are first divided into ten groups randomly with equal samples. For training a classifier, the first nine groups of samples are then used. For evaluating the trained classifier, the remaining one group of samples are used. 10 different combinations of training data groups and test data group are used for experiments in order to evaluate the classifier. The following computing resource is used: Intel Core i5-6600k CPU (3.50 GHz) and 16.00GB DDR4.

The results are summarized in Table 1 in terms of classification accuracy. Note that the training procedure takes 29.6 sec on average. The classification accuracy is 97.2 % on average. As can be seen from Table 1, the CNN clasisfier accurately classifies the speed limit signs. This preliminary result can be further expanded to more complex cases including various traffic signs.

5 Conclusion

A traffic sign classification method based on artificial neural network is proposed in this paper. The proposed method for classifying traffic signs first detects traffic signs by using on the property of color probability model and then classifies the detected traffic signals. In both of detection and classification processes, two artificial neural network models are utilized. Experiments on practical image data sets show that the proposed method can detect and classify traffic signs with favorable accuracy. The preliminary results show that the proposed procedure can be favorably utilized for practical situations when we consider its performance in terms of classification accuracy and training speed. A more sophisticated procedure for various traffic signs should be further studied in future research.

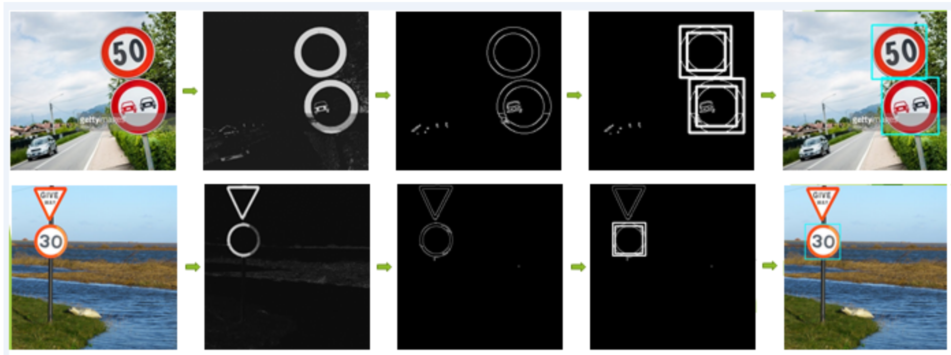

Figure 4: Examples of detection procedures

Table 1: Confusion table (%)

	30	50	60	70	90
30	98.2	0.9	0.8	0.0	0.1
50	2.2	96.4	1.2	0.0	0.2
60	0.0	0.7	97.1	0.5	1.7
70	0.0	0.0	0.9	96.8	2.3
90	0.0	0.0	0.8	1.6	97.6

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