Neurocomputing 128 (2014) 153–159

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Application of BW-ELM model on traffic sign recognition

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ARTICLE INFO

Article history:
Received 26 August 2012
Received in revised form
8 November 2012
Accepted 11 November 2012
Available online 24 October 2013

Keywords:
Traffic sign recognition
Extreme learning machine
Histograms of oriented gradient

ABSTRACT

Traffic sign recognition is an important and active research topic of intelligent transport system. With a constant increasing of the training database size, not only the recognition accuracy, but also the computation complexity should be considered in designing a feasible recognition approach. In this paper, an effective and efficient algorithm based on a relatively new artificial neural network, extreme learning machine (ELM), is proposed for traffic sign recognition. In the proposed algorithm, the locally normalized histograms of the oriented gradient (HOG) descriptors, which are extracted from the traffic sign images, are used as the features and the inputs of the ELM classification model. Moreover, the ratio of feature's between-category to within-category sums of squares (BW) is designed as a feature selection criterion to improve the recognition accuracy and to decrease the computation burden. Application on a well known database, German traffic sign recognition benchmark (GTSRB) dataset, demonstrates the feasibility and efficiency of the proposed BW-ELM model.

1. Introduction

With the development of intelligent techniques, driver assistance system (DAS) has been exploited as an important component of intelligent transportation system [1]. In the DAS, traffic sign detection and recognition is one major approach to acquire safety and precaution information. In a real environment, it becomes a difficult task to recognize the traffic signs timely and accurately because the visibility of traffic signs may be decreased greatly by some unfavorable factors.

So far, many algorithms have been proposed for traffic sign recognition [2,3]. In [2], a novel evolutionary version of Adaboost is proposed for sign detection, and a battery of classifiers are trained to split classes in an error-correcting output code framework. Constructed by SimBoost or a fuzzy regression tree framework, a robust sign similarity measure is proposed in [4] for road sign recognition. Support vector machines (SVM) [5] is a popular classifier and has been applied in many fields [6,7]. An automatic road-sign detection and recognition system is presented in [8], in which a SVM is used for traffic sign detection while a Gaussian kernel SVM is adopted for traffic sign recognition. An eigen-based traffic sign recognition is proposed in [9] by using principal component analysis (PCA) algorithm [10–12] to choose the most effective components of traffic sign images to classify an unknown traffic sign. Boosted by the successful applications on handwritten digits recognition, convolutional neural network (CNN) has also been employed on traffic sign classification [3,13]. In [3], instead of various features, a CNN is trained directly with the raw pixel values of traffic sign images. Moreover, a better result is obtained by integrating the results obtained by a CNN and a multilayer perceptrons (MLP).

Gradient orientation is one kind of useful information in various object recognition, including the traffic signs. In [14], a novel local feature representation, the so-called histogram of oriented gradients (HOG), is initially proposed for pedestrian detection. Subsequently, HOG is adapted to traffic sign detection or traffic sign recognition in several works. Just as expected, the HOG descriptors achieved relatively good performances in both traffic sign detection and traffic sign recognition, because of its fine-scale gradients, fine orientation binning, relatively coarse spatial binning, and high-quality local contrast normalization in its overlapping descriptor blocks. MLP, a popular feedforward artificial neural network (ANN) [15], is adopted in [3] to classify the HOG features extracted from traffic sign images. In [16], the classification performance of k-d trees and random forests are evaluated for traffic signs with different sizes of HOG descriptors and distance transforms.

Recently, a relatively novel learning algorithm for single-hidden layer feedforward neural networks (SLFNs), called extreme

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0925-2312/$ - see front matter © 2013 Published by Elsevier B.V.
http://dx.doi.org/10.1016/j.neucom.2012.11.057

learning machine (ELM), has been proposed [17,18] and widely applied in various fields [19–21]. In ELM, the input weights and hidden biases are randomly chosen, and the output weights are analytically determined by using Moore–Penrose generalized inverse. ELM not only learns much faster with a higher generalization performance than the traditional gradient-based learning algorithms, but it also avoids many difficulties that are faced by gradient-based learning methods, such as stopping criteria, learning rate, learning epochs, local minima, and overtuning issues [17].

In this paper, a HOG-based ELM classification scheme is proposed for traffic sign recognition. In the proposed method, the HOG descriptors extracted from traffic sign images are used as the features. Moreover, the ratio of feature's between-category to within-category sums of squares (BW) is designed as a feature selection criterion to improve the recognition accuracy and to decrease the computation burden. Since ELM has a competitive classification performance to most popular classifiers, and the strategy of BW can effectively improve the recognition accuracy, the proposed BW-ELM model has a comparable performance to the state-of-the-art traffic sign recognition algorithms. Moreover, as ELM has a far less computation burden and has only one parameter to be adjusted, the proposed BW-ELM model has a less computation complexity compared to the existing methods.

The remainder of the paper is organized as follows. The proposed method is presented in Section 2. Experimental results and related discussions are given in Section 3. Finally, conclusions are made in Section 4.

2. The BW-ELM model

2.1. Feature extraction of HOG

Fig. 1 shows the flowchart of the feature extraction of HOG [14,22]. In this figure, the rectangle represents the input or output data while the ellipse represents the operation. Before the feature extraction, all color images were scaled to a size of 40×40 pixel and converted to grayscale images. The image of a traffic sign is first divided into overlapping blocks. Then, each block is divided into non-overlapping cells. For each pixel of every cell, the gradients are computed by using Gaussian smoothing followed by a simple 1-D mask $[-1,\ 0,\ 1]$. A histogram of the gradient orientations of each cell is formed, and then weighted by the gradient magnitude. Finally, the histograms of the cells are concatenated to constitute a final descriptor of this block. The above parameter setting of HOG provided by [14] has been verified to be effective for traffic sign recognition [3].

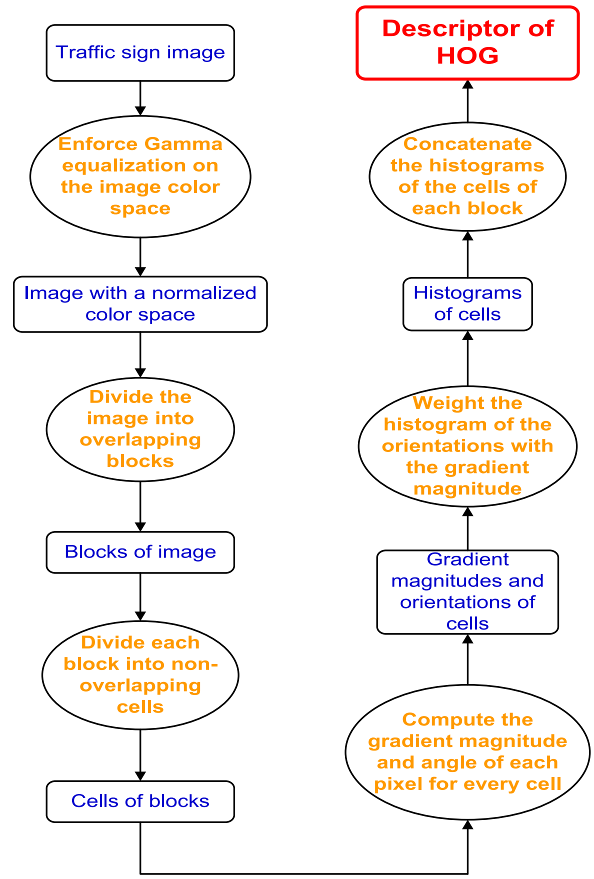

Fig. 1. Flowchart of the feature extraction of HOG. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

2.2. Feature selection with BW

The strategy of BW is to select the features with large between-category distances and small within-category distances. Assume that there are N samples $\mathbf{x}_i, i=1,\ldots,N$, where $\mathbf{x}_i=(x_{i1},x_{i2},\ldots,x_{in})^T \in R^n$. For the jth feature, the mean of the samples can be computed as

$$\mu_j = \frac{1}{N}\sum_{i=1}^{N}\mathbf{x}_{ij}. \tag{1}$$

The mean of the kth class samples can be obtained by

$$\mu_{kj} = \frac{1}{n_k}\sum_{i=1}^{n_k}\mathbf{x}_{ij}, \quad \mathbf{x}_i \in \mathbf{X}_k, \tag{2}$$

where $\mathbf{X}_k$ denotes a sample set of the kth class, n_k is the number of the samples in $\mathbf{X}_k$. With the obtained μ_{kj}, the sum of the distances within the kth class can be computed by

$$s_{kj}^{w} = \sum_{i=1}^{n_k}(\mathbf{x}_{ij}-\mu_{kj})^2, \quad \mathbf{x}_i \in \mathbf{X}_k. \tag{3}$$

Given μ_j and μ_{kj}, the mean distance between the kth class and all classes can be calculated as

$$s_{kj}^{b} = (\mu_{kj}-\mu_j)^2. \tag{4}$$

The ratio of feature's between-category to within-category sums of squares can be given by

$$\lambda_j = \frac{\sum_{k=1}^{m} s_{kj}^{b}}{\sum_{k=1}^{m} s_{kj}^{w}}, \quad j=1,\ldots,n. \tag{5}$$

Finally, the features with large λ_j values are selected for classification.

2.3. Classification using the ELM model

The following is a detailed description of the classification of the HOG features with the ELM model [17], as shown in Fig. 2. Given N distinct samples $(\mathbf{x}_i,\mathbf{t}_i)$, where $(\mathbf{x}_i=(x_{i1},x_{i2},\ldots,x_{in})^T \in R^n$, $\mathbf{t}_i=(t_{i1},t_{i2},\ldots,t_{im})^T \in R^m$, the standard SLFNs with $\tilde{N}$ hidden nodes and activation function $g(x)$ are mathematically modeled as

$$\sum_{i=1}^{\tilde{N}}\beta_i g_i(\mathbf{x}_j) = \sum_{i=1}^{\tilde{N}}\beta_i g(\mathbf{w}_i\cdot\mathbf{x}_j+b_i)=\mathbf{o}_j, \quad j=1,\ldots,N, \tag{6}$$

where $\mathbf{w}_i=(w_{i1},\ldots,w_{in})^T$ is the weight vector connecting the ith hidden node and the input nodes, $\beta_i=(\beta_{i1},\ldots,\beta_{im})^T$, is the weight vector connecting the ith hidden node and the output nodes, and