Traffic Signs Recognition via Adaptive Histogram Equalization and Committee of CNNs

Guang Yi Chen and Wenfang Xie

***Abstract* - Traffic signs recognition is very important in today's autonomous driving. In existing traffic signs datasets, many images are of very bad quality, which need to be improved in visual quality. In this paper, we enhance the traffic signs images by color adaptive histogram equalization, and feed the enhanced image, its (R, G, B) channels and its grayscale image to a committee of five convolutional neural networks (CNNs). We take the average of the five CNN output probabilities to determine the final class label of the unknown traffic sign. Experiments demonstrate that our new method achieves relatively high correct recognition rate (98.75%) for traffic signs recognition with German traffic sign benchmarks.**

***Index Terms* - Adaptive histogram equalization, convolutional neural networks (CNNs), traffic signs recognition; pattern recognition.**

I. INTRODUCTION

TRAFFIC signs recognition is of vital importance in the literature. It is a safety system which recognizes traffic signs from the acquired images and displays the recognized signs to the driver through the instrument cluster, front screen, or head-up display. Traffic signs recognition systems can identify speed limit, stop, 'do not enter', and many other kinds of traffic signs. Traffic signs normally do not change over time, so it is preferable to use deep learning for its recognition tasks since deep learning normally outperforms conventional techniques, which utilize hand-crafted features for pattern recognition.

We briefly review several existing methods here about this topic. Lim et al. [1] recently reviewed the advances and datasets in traffic sign recognition. Li and Wang [2] studied real-time traffic sign recognition based on efficient convolutional neural networks (CNNs) in the wild. Zhu and Yan [3] analyzed traffic sign recognition according to deep learning. Bangquan and Xiong [4] worked on real-time embedded traffic sign recognition using efficient CNNs. Zaibi et al. [5] studied a lightweight model for traffic sign classification based on enhanced LeNet-5 network. Mishra and Goyal [6] invented an effective automatic traffic sign classification and recognition deep convolutional networks. Haque et al. [7] studied DeepThin: A novel lightweight CNN architecture for traffic sign recognition without GPU requirements. Li et al. [8] hand-crafted features for traffic sign recognition with good recognition results. Liu et al. [9] studied fast traffic sign recognition via high-contrast region extraction and extended sparse representation. Guo et al. [10] worked on mixed vertical-and-horizontal-text traffic sign detection and recognition for street-level scene. Luo et al. [11] investigated detection and recognition of obscured traffic signs during vehicle movement. An et al. [12] worked on road traffic sign recognition algorithm based on cascade attention-modulation fusion mechanism. Cao et al. [13] proposed an improved YOLOv4 lightweight traffic sign detection algorithm.

In this paper, we propose a new method for traffic signs recognition. We enhance the traffic sign images with color adaptive histogram equalization (AHE [14]), and feed the enhanced image, its (R, G, B) channels and its grayscale image to a committee of five CNNs [15]. We take the average of the five CNN output probabilities to determine the final class label of the unknown traffic sign. Experiments show that our new method performs very well for traffic signs recognition with the German traffic sign benchmarks dataset.

The organization of the paper is given as follows. Section II invents a new method for traffic signs recognition. Section III performs some experiments to test the robustness of our new method. Finally, Section IV draws the conclusion of the paper and proposes future research directions.

II. PROPOSED METHOD

Traffic signs recognition is a constantly evolving research area. Due to low light conditions, some traffic signs images are very dark in traffic sign datasets, so certain preprocessing is needed to improve the quality of traffic sign images. In this paper, we propose a novel algorithm for traffic signs recognition by performing color adaptive histogram equalization to the input color traffic sign image, feeding the enhanced color image, its (R, G, B) channels, and its grayscale image to a committee of five CNNs, taking the average of CNNs' five output class probabilities, and then determining the final class label of the unknown traffic sign. Our new method improves the correct recognition rates significantly for traffic signs recognition.

The adaptive histogram equalization is an image processing method for improving grayscale image contrast. It is different from standard histogram equalization by computing several histograms of different distinct sections of

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the image and using them to redistribute the lightness values in the image. It is very good for improving the local contrast and enhancing the edges in each region of a grayscale image. For color traffic sign image, we convert it to the L*a*b color space, enhance the L channel by standard AHE, and then convert it back to the color space. We then normalize the enhanced traffic sign images to the range of [0,255] to facilitate display. The Matlab code for our color adaptive histogram equalization is given as follows:

```
% Adaptive histogram equalization for color
% images
function Out = AdaptiveHistogramEqualization
(Image)

% Convert the RGB image to the L*a*b* color
% space
LAB = rgb2lab(Image);

% Scale values to the range expected by the
% adapthisteq function, [0 1]
L = LAB(:,:,1)/100;

% Perform adaptive histogram equalization on
% the L channel. Scale the result to get back to
% the range used by the L*a*b* color space
L = adapthisteq(L,'NumTiles',[8 8],'ClipLimit',
0.005);
LAB(:,:,1) = L*100;

% Convert the resulting image back to the
% RGB color space
GrayF = lab2rgb(LAB);

% Normalization
GrayF=(GrayF-min(GrayF(:)))/(max(GrayF(:))-
min(GrayF(:)))*255;
Out=uint8(GrayF);
```

A CNN is a regularized kind of feed-forward neural network that learns features by itself via filter (or kernel) optimization. This kind of deep learning network can make predictions from different types of data including text, images and audio. CNNs are the standard in deep learning-based approaches to computer vision and image processing, which have been replaced in some cases by newer deep learning architectures such as the transformer. Vanishing gradients and exploding gradients as seen during backpropagation in earlier neural networks are prevented by using regularized weights over fewer connections. CNNs can be used for image and video recognition, recommender systems, image classification, image segmentation, medical image analysis, natural language processing, brain–computer interfaces, and financial time series. Our CNN has four convolutional layers, four batch normalization layers, four Rectified Linear Unit (ReLU) layers, three maxPooling layers, and one fully connected layer. The input traffic sign images are cropped and scaled to 28×28 pixels. The number of channels (NumCh) of the input images to CNNs is set to 3 for color images, and to 1 for single channels (R, G, B) and grayscale images. We crop the traffic sign images based on their region of interest (ROI) and then scale them to the size of 28×28 pixels as the input to our CNNs. Our CNN structure is defined in Matlab as follows.

```
layers = [
imageInputLayer([28 28 NumCh])

convolution2dLayer(3,8,Padding="same")
batchNormalizationLayer
reluLayer
maxPooling2dLayer(2,Stride=2)

convolution2dLayer(3,16,Padding="same")
batchNormalizationLayer
reluLayer
maxPooling2dLayer(2,Stride=2)

convolution2dLayer(3,32,Padding="same")
batchNormalizationLayer
reluLayer
maxPooling2dLayer(2,Stride=2)

convolution2dLayer(3,64,Padding="same")
batchNormalizationLayer
reluLayer

fullyConnectedLayer(43)
softmaxLayer];
```

We explain two figures for traffic sign recognition here. Fig. 1 shows one original traffic sign, the enhanced image by color adaptive histogram equalization (Color), its R, G, B channels, and its grayscale image (Gray). As can be seen from the figure, the enhanced image, its (R, G, B) channels, and its grayscale image are much better than the original traffic sign image in visual quality. This is the main reason why our new method performs very well for traffic signs recognition. Fig. 2 depicts the flow-chart of our proposed method (The original traffic sign image is the input. We perform color adaptive histogram equalization to the input traffic sign image, feed the enhanced image, its R, G, B channels and the grayscale image to a committee of five CNNs. We take the average of the five CNN output probabilities to determine the final class label of the input traffic sign). Experiments in the next section confirm that this new algorithm works very well for traffic signs recognition.

The major advantage and disadvantage of this paper can be given as follows. The advantage is that we enhance the traffic sign images significantly in visual quality by means of color adaptive histogram equalization. We feed the enhanced traffic sign image, its (R, G, B) channels, and its grayscale image to CNNs separately. We take the average of the five CNN output probabilities to determine the final class label of the unknown traffic sign. In this way, better results can be obtained for traffic signs recognition. Experiments in the next section confirm the success of our new method proposed in this paper. The disadvantage of our new method is that our new method is implemented with unoptimized Matlab code, and it needs more central processing unit (CPU) computation time than a single CNN for traffic signs recognition. Nevertheless, we can port our slower Matlab implementation with a faster programming language such as C/C++ or Python and run it on graphics processing units (GPUs). We can also parallelize our code so that we can take advantage of today's modern computers, which have multiple cores to run codes. In this way, faster implementation can be done for traffic sign recognition.

III. EXPERIMENTAL RESULTS

We use the German traffic sign benchmark [16] for our experiments, which is a multi-class, single-image classification challenge held at the International Joint Conference on Neural Networks (IJCNN), 2011. Fig. 3 shows a sample of traffic sign images in the German traffic sign benchmark. As can be seen, some traffic sign images are very dark, which need to be improved. This benchmark considers a single-image, multi-class classification problem with 43 classes and 51,839 images in total. The input traffic sign images are cropped and scaled to 28×28 pixels. We enhance the traffic sign images by color adaptive histogram equalization, and then use the enhanced images and its (R, G, B) channels and its grayscale images for CNNs. We take the average of the five CNN output probabilities to determine the final class label of the unknown traffic signs. We train the CNNs with 50, 100, 150, 200, and 250 epochs separately. Our new method is implemented in Matlab instead of Python.

Table 1 tabulates the correct recognition rates (%) of different methods (adaptive histogram equalization normalized color image, R, G, B, grayscale, and proposed) for German traffic signs dataset. The best results are highlighted in bold font. From the table, we can see that our new method achieves the best classification results for German traffic sign recognition for all epochs (50, 100, 150, 200, and 250). The highest recognition rate for our new method is 98.75% with 200 epochs, which is reasonably high for German traffic sign recognition. In addition, the recognition rate improvements from the color images to our new method are significant for all epochs as shown in the last column of Table 1. As can be seen, the highest net improvement in percentage is 1.95% for epochs 50. This demonstrates the success of our new method proposed in this paper for German traffic sign recognition.

Table 2 shows the correct recognition rates (%) of three methods (HOG + SVM, AHE + HOG + SVM, and the proposed method) for the German traffic signs dataset. The best result is highlighted in bold font. We extract histogram of oriented gradients (HOG [17]) features from the original traffic sign images without AHE, classify them with support vector machines (SVM [18]), and we get the correct recognition rate of 92.93%. We also extract HOG features from the traffic sign images enhanced with AHE, classify them with the SVM, and we obtain the correct recognition rate of 93.36%. Nevertheless, our proposed method in this paper achieves 98.75% correct recognition rate for traffic sign recognition. As can be seen, the improvement in correct recognition rate is 5.39%, which is significant. This confirms the usefulness of our proposed method in this paper for traffic sign recognition.

IV. CONCLUSIONS

Traffic sign recognition is very important in computer vision. It is a very challenging task since the acquired traffic sign images may be very dark, very blurry and may contain significant amount of noise. As a result, enhancing the quality of traffic sign images is needed for successful traffic sign recognition systems.

In this paper, we have proposed a novel method for traffic signs recognition. We enhance the traffic sign images by color adaptive histogram equalization, and feed the enhanced image, its (R, G, B) channels and its grayscale image to a committee of five CNNs. We take the average of the five CNN output probabilities to determine the final class label of the unknown traffic sign. Experiments demonstrate that our new method performs very well for German traffic sign benchmarks dataset.

Future research for traffic sign recognition will be conducted in the following manners:

(a) We can extract invariant features from the traffic sign images and then feed them to CNNs to see if better results can be obtained.
(b) We can increase the number of CNNs for our committee of CNNs so that higher recognition rate can be achieved for traffic sign recognition. For example, we can smooth the traffic sign images with different low-pass filters and we can scale the traffic sign images with different scaling factors.
(c) We can reduce the noise in traffic sign images selectively by detecting the noise level automatically and then performing denoising if noise level is high. We do not reduce noise from traffic sign images otherwise. In this way, higher recognition rates can be expected for traffic sign recognition.
(d) We can improve this paper by smoothing the traffic sign images with different smoothing filters, feeding them to a committee of CNNs, and then determining the class

labels of the testing traffic sign images. In this way, better classification rates can be obtained.

(e) We can extract filter faces (FFs [19]) from traffic sign images so that illumination variation can be minimized. As we know that some traffic sign images are dark and some are bright. As a result, extracting FFs from traffic sign images can improve the recognition accuracy.

(f) We may also apply the basic idea of this paper to iris recognition or palmprint recognition so that better recognition results can be achieved.

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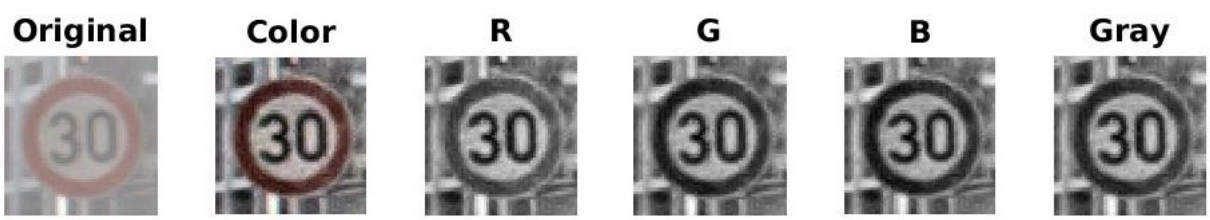

Fig. 1. One original traffic sign image, the enhanced image by color adaptive histogram equalization (Color), its R, G, B channels, and its grayscale image (Gray). The visual quality is much better than before after our enhancement.

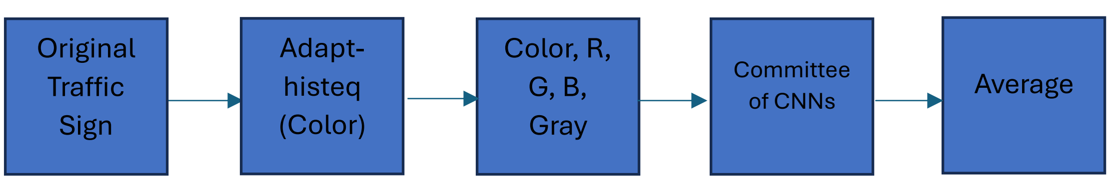

Fig. 2. The flow-chart of the proposed method: The original traffic sign image is the input. We perform color adaptive histogram equalization to the input traffic sign image, feed the enhanced image, its R, G, B channels and the grayscale image to a committee of five CNNs. We take the average of the five CNN output probabilities to determine the final class label of the input traffic sign.

Fig. 3. A sample of traffic sign images in the German traffic sign benchmark.

TABLE 1
THE CORRECT RECOGNITION RATES (%) OF DIFFERENT METHODS: ADAPTIVE HISTOGRAM EQUALIZATION NORMALIZED COLOR IMAGE (COLOR), R, G, B, GRAYSCALE, AND THE PROPOSED METHOD FOR THE GERMAN TRAFFIC SIGNS DATASET. THE BEST RESULTS ARE HIGHLIGHTED IN BOLD FONT.

Epochs	Color	R	G	B	Gray	Proposed	Proposed - Color
50	96.44	96.36	96.41	96.19	96.35	**98.38**	**1.95**
100	96.94	96.14	96.00	96.45	96.87	**98.51**	**1.57**
150	96.84	95.68	96.59	96.22	96.45	**98.46**	**1.62**
200	97.08	96.56	96.14	96.48	97.17	**98.75**	**1.67**
250	97.14	96.44	96.43	96.47	96.96	**98.46**	**1.32**

TABLE 2
THE CORRECT RECOGNITION RATES (%) OF THREE METHODS (HOG + SVM, AHE + HOG + SVM, AND THE PROPOSED METHOD) FOR THE GERMAN TRAFFIC SIGNS DATASET. THE BEST RESULT IS HIGHLIGHTED IN BOLD FONT.

Methods	Correct Recognition Rates
HOG + SVM	92.93
AHE + HOG + SVM	93.36
Proposed	**98.75**

Guang Yi Chen holds a B.Sc. in Applied Mathematics, an M.Sc. in Computing Mathematics, an M.Sc. in Computer Science, and a Ph.D. in Computer Science. During his graduate and postdoctoral studies in Canada, he was awarded many prestigious fellowships. He has published over seventy-five scientific journal papers in his fields and holds two granted US patents in image processing. He is currently affiliated to the Department of Computer Science and Software Engineering, Concordia University, Montreal, Quebec, Canada. He is the world's top 2% scientist ranked by Stanford University. He is also an IEEE Senior Member. His research interests include pattern recognition, image processing, machine learning, artificial intelligence, remote sensing, and scientific computing.

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