# **Research on Traffic Sign Classification Algorithm Based on SVM**

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#### Abstract

A coarse-to-fine traffic sign classification algorithm is proposed. The task for traffic sign classification is to analyze the detected regions and determine the class of the sign in the region. By analyzing existing traffic sign classification algorithms, the major problem affecting the classification accuracy is pointed out. Based on this analysis, a coarse-to-fine classification algorithm is proposed. The algorithm first classifies traffic signs into several super classes, then performs class-specific shape adjustment, and finally gets the fine classification result. Experimental results show that the proposed algorithm outperforms other existing algorithms in classification accuracy, and is robust to many adverse situations.

**Keywords:** Traffic Sign Recognition, Image Restoration, Object Detection, Image Classification, Support Vector Machine

# **1. Introduction**

Traffic sign classification task is receiving traffic sign detection module output region of interest (ROI), and judge sign area included the categories. Due to the type of traffic sign up to tens or even hundreds of species, so the traffic signs classification is a complicated multi class classification problem. This paper first introduces the basic process of symbol classification algorithm and the analysis of existing traffic sign classification algorithms, and then proposes a classification algorithm of stepwise refinement based on support vector machine, gives the algorithm on the classification results of traffic sign classification of German public dataset GTSRB, and compared with several existing optimal algorithms [1].

# 2. Traffic Sign Classification Algorithm Based on Support Vector Machine

The existing traffic sign classification algorithm can correct rate is roughly classified into two grades: the first grade of the convolutional neural network advantage obviously, classification in GTSRB data set. The correct rate is about 99%, but the classification speed is very slow. Most of the second grades of the algorithm are characterized by HOG, based on the support vector machine, random forest, such as linear discriminant analysis classifier. The correctly rate of classification on the GTSRB data set is about 95%~97%. The advantage lies in the classification speed.

This paper presents a classification of traffic signs gradually thinning based on support vector machine algorithm. The classification process is divided into two stages: the first stage mark divided into several categories, second got specific categories in the internal sub categories. Look from the structure, the algorithm and Boi algorithm are similar [2], tree support vector machine network, but the correction algorithm is proposed to a high reliability of the shape, placed before the second class classification, significantly enhance

the rate of correct classification. The whole algorithm in classification accuracy and the convolutional neural network is similar, but the computing complexity is much lower.

In order to fully compared with the existing algorithms, this thesis algorithm implementation methods for the GTSRB data set. Although the GTSRB data set collected from Germany, mark but algorithm is applied in other countries, only in the concrete implementation method with minor modifications.

## 2.1. The GTSRB Data Set

GTSRB data sets published in the 2011 IJCNN conference; aim to provide an open platform for all kinds of traffic sign classification comparison algorithm. The data set consists of 43 kinds of traffic signs, it is shown in figure1. The entire data set consists of more than 50000 images collected from the image of a real traffic environment, each image corresponds to a region of interest, contains only one traffic sign.

The data set includes a large number of low light intensity, low resolution, from the angle of tilt, occlusion and other adverse conditions in the sample, can better reflect the comprehensive ability of classification algorithm. The entire data set was divided into training set and test set in two parts, Table1 is according to the categories list the specific number of various types of traffic signs.

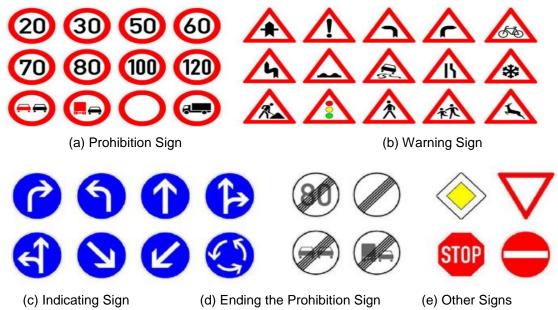


Figure 1. Illustration of All Traffic Sign Categories in GTSRB

	Sign	The number of training samples	The number of the test
	type		sample
Prohibition	12	17310	5670
Sign			
Warning	15	8980	2790
Sign			
Indicating	8	5639	1770
Sign			
Ending the	4	1140	360
prohibition			
Sign			
Other signs	4	6150	2040

# Table 1. Number of Traffic Signs for Each Category in GTSRB

#### 2.2. The Basic Ideas and the Whole Structure of Algorithm

Although the number of markers from GTSRB data up to 43, but in accordance with the color, shape is divided into five categories. Mark each class has a specific color and shape, it is shown in Table2, the markers in each image belong to which category is not very difficult.

The main difficulty lies in the same class in a number of different subclasses only subtle differences. It is shown in figure2. The classifier accurately capture these differences are often difficult, and when the sign to have the displacement, angle of inclination, will be more difficult. Most of the traffic signs classification algorithm for misclassification occurred mainly in the larger class of internal similarity between the subclasses [3].

	Shape	Color
Prohibition Sign	Round	Red, white, black
Warning Sign	Triangle	Red, white, black
Indicating Sign	Round	Blue, white
Ending the prohibition Sign	Round	white, black
Other signs	Various kinds	Various kinds

Table 2. Color and Shape of Each Super Class in the GTSRB Dataset



Figure 2. Traffic Signs with Similar Appearances

Based on the above analysis, this paper proposes a classification of traffic signs algorithm based on support vector machine. The algorithm is divided into two levels, the first level used by HOG and SVM on the input image classification, which belongs to the signs that a large class, the second level categories is according to specific categories of the image into shape correction, and then again uses HOG features and fine SVM for image classification, obtains a final classification result.

#### 2.3. Prohibition Sign Shape Corrections Based on Mirror Symmetry Algorithm

Prohibition Sign shape is round, in order to get the exact position in the input image, the round detection or ellipse detection algorithm, this paper uses the circle detection algorithm, for the following reasons:

(1) Accurate shape correction requires six conditions, and the oval shape is only 5 degrees of freedoms, cannot be completely correct. When the flag is close to a circle, ellipse detection algorithm may even rotation angle error estimates are given, but reduce the rate of correct classification.

(2) The input image prohibition signs angle inclination are usually small. Basic is round, the circle detection algorithm is to accurately positioning.

(3) Circle detection algorithm is generally faster than the ellipse detection algorithm, more suiTable for driving assistance and high real-time occasion.

Existing Circle detection algorithm is more [4-5], the mirror symmetry detection algorithm [6] algorithm is a fast, high reliability. In this paper, used mirror symmetry algorithm to locate the prohibition signs, concrete steps are as follows:

(1) From red Bitmap  $B_{R}$  used Sobel operator to extract edge Bitmap  $E_{R}$ 

(2) Used  $E_{R}$  each edge to gradient direction of  $f_{R}(x)$  reddish, radius parameter  $(x_{c}, y_{c}, r)$  voting statistical results obtained three dimensional vote  $V(x_{c}, y_{c}, r)$ , only consider the direction from high to low, so as to ensure only detect prohibition signs inside the circle

(3) To achieve three dimensional mean filter on  $V(x_c, y_c, r)$ , to get

 $V(x_c, y_c, r)$ .

This is aimed at the prohibition signs of mirror symmetry detection algorithm are an important improvement. For low quality images, that is not very accurately the gradient direction of the edge point, resulting in a vote position deviation. The  $V(x_c, y_c, r)$  mean filter can be a mild deviation vote refocus, to significantly improve detection precision;

(4) Find out group of circle parameters  $(x_c^*, y_c^*, r^*)$  the highest number of

 $V'(x_c, y_c, r)$  as the final detection result.

Figure3 shows the above correction algorithm to correct results image on GTSRB prohibition sign, the first act is the input image, the second act is the correction results. As you can see, the correction algorithm for shelter, low-resolution, motion blur and other issues has better adaptability.



Figure 3. Adjustment Results of Prohibitory Signs

# 2.4. Correction of Warning Sign Based on Triangular Shape Detection

Warning signs in the shape of an equilateral triangle. In this paper the basic ideas for the first detection of the equilateral triangle line of Hof transform, then the detection line to find the most likely constitute three straight equilateral triangle as the three side of the triangle, the process is as follows:

(1) From the red bitmap  $B_R$ . Used in Hof transform to extract a set of lines  $\{l_i\}$ . Different from the conventional methods, here did not use the edge bitmap, but directly extracted from the red line in the bitmap

(2) Computing segment set  $\{l_i\}$  is in any of three segments  $l_a, l_b, l_c$  triangle and equilateral triangle with the degree of similarity  $fd_R(a, b, c)$ , method is as follows:

 $fd_{R}(a,b,c) = vl(a,b,c).eq(a,b,c).vt(a,b,c)$ 

(3)Find the maximum value  $fd_R^*(a,b,c)$  all in  $fd_R(a,b,c)$ . The corresponding triangle is red bitmap  $B_R$  optimal equilateral triangle.

(4)The input image is converted to gray image, and extracts the edge bitmap  $E_1$  by Canny operator.

(5)At the edge bitmap graphic  $E_i$  to repeat steps (1) (2) of the process, find out the most similar degree  $fd_i^*(a,b,c)$ , the corresponding  $E_i$  is best equilateral triangle.

(6)Comparison of  $fd_{I}^{*}(a,b,c)$  and  $fd_{R}^{*}(a,b,c)$  size, the larger the corresponding triangle is the final detection result.

Figure4 shows the correction results of warning signs by this algorithm; one of the first acts is the input image. The second act is corresponding to the correction results. As you can see, the correction method of rotation, occlusion, motion blur, fade, has good adaptability.



Figure 4. Adjustment Results of Warning Signs

#### 2.5. HOG Color Feature Extractions

Color is a significant feature of traffic signs. The fusion of the HOG characteristics of the color information can significantly improve the ability of distinguishing features of different categories. The original HOG algorithm [7] is in order to the use of color information, in the calculation of a x gradient direction, gradient calculated point X in RGB three components, the maximum amplitude is the gradient of X. The advantage of this approach is that the same HOG dimension and HOG dimension based on gray image, but the color information utilization ability is limited. Another method uses color information was calculated HOG image RGB three components, and the direct link is a long feature. This method can more effectively use color information, improve the rate of correct classification, but the feature length is three times of the original algorithm, the training and test speed of later stage classifier significantly decreased.

This paper presents a new method for the extraction of color HOG features, in the effective use of color information at the same time, shorten the training and classification time, the specific process is as follows:

(1) Respectively to calculate the gradient direction RGB three components, and statistics each unit gradient direction histogram, RGB three components are statistics, each unit has three histograms.

(2) Within the block normalization, each unit of three common normalized histogram

(3) The normalized histogram of each block is connected together, got the HOG feature.

# 3. Experiment Design and Discussion

In this paper, the GTSRB data set of the proposed algorithm is discussed in detail in the experiment. As previously mentioned, the GTSRB data set contains a total of 43 classes, 51839 pieces of traffic sign image, the training set of 39209 pieces, 12630 pieces of test set.

# **3.1. High Class Classifications**

In this paper, according to the shape and color of 43 kinds of sign in GTSRB is divided into five categories: prohibition signs, warning signs, signs, prohibition signs, termination of other signs, figure1 shows all the signs according to the schematic diagram of high class division. Among the four categories of color and shape features, 4 mark fifth categories of various characters, is not the same for the first four categories, which are classified as a category of the sample quantity equilibrium, and reduces the total number of categories.

High class classification process is relatively simple: the input image is first scaled to  $40 \times 40$  pixels, and then the HOG feature is extracted from SVM, and finally into categories.

In the experiment, several groups of HOG parameters were tested, results show that, the unit pixel number 8. Number 8, histogram channel angle range of  $0 \sim 360$ , the correct classification rate were the highest. In addition, compared test color HOG features on several different extraction methods in experiment. Test method: the stochastic translation and rotation transformation to the training samples, HOG and 2.5 section were extracted from the gray level of three color HOG features, and training of linear SVM and histogram intersection kernel SVM, Finally, in the test set to the correct classification rate, the results are shown in Table3 and Table 4

HOG type	Training time	Test time (s)	The number of	The correct
	(s)		support vectors	rate (%)
Gray	67.78	27.16	1840	99.44
The original algorithm for color	66.79	27.50	1860	99.26
Creusen color	108.22	42.84	964	99.88
this paper color	101.11	38.63	864	99.84

Table 3. Comparison of Classification Results by Four Kinds of HOG
Features and Linear SVM

HOG type	Training time	Test time (s)	The number of	The correct
	(s)		support vectors	rate (%)
Gray	94.77	38.89	2676	99.52
The original	94.49	39.52	2706	99.43
algorithm for				
color				
Creusen color	221.92	95.85	2176	99.92
this paper	210.97	88.24	2005	99.89
color				

# Table 4. Comparison of Classification Results by Four Kinds of HOG Features and Intersection Kernel SVM

Table 3 and Table 4 showed. The number of support vectors corresponding color HOG features is proposed in this paper. In four kinds of HOG features in the least, color feature classification of color characteristics of the training and testing time is shorter than the accuracy of Creusen was significantly higher than that of gray scale HOG and the original algorithm.

But slightly lower is than Creusen of color feature. Integrated speed and classification accuracy considerations. In this paper, selected HOG feature of Creusen. Namely, feature extraction HOG RGB component, and is connected to a long feature vector.

In choosing the kernel function, histogram intersection kernel although slower than the linear kernel, but the rate of correct classification has the obvious advantage, so this paper selects the histogram intersection kernel function. Table 5 gives the final result classification.

	Classification error number	Classification correct rate
Prohibition Sign	4	99.93%
Warning Sign	2	99.93%
Indicating Sign	0	100%
Ending the prohibition Sign	1	99.72%
Other signs	3	99.85%

Table 5. Classification Results of Super Classes

Table 5 shows, categories of the classification results are ideal, in the 12630 test image classification error number is only 10, the average accuracy rate of 99.92%, mainly due to discriminative and HOG characteristics of the shape of strong and classification capabilities of the SVM

## 3.2. Prohibition Sign Classifications

High class classification, image is judged as prohibition signs into the prohibition signs fine classification procedure. Using the method of the shape correcting prohibition signs in section 2.3, and then be scaled to  $40 \times 40$  pixels, then extracting the HOG feature and SVM classification

Pattern image basically retained only sign corrected part. It is shown in figure3. Since the prohibition mark pattern part is black and white, so only HOG feature extraction to the gray image. The HOG parameter in the experiment: the unit pixel number 8. Number 8, histogram channel angle range of  $0 \sim 360$ , SVM kernel function for histogram intersection kernel. Training strategies and categories in the same set of test, obtained fine correct classification rate is 99.63%.

# 3.3. Warning Sign Classification

And the prohibition sign is similar, in the largest category of classification, image is judged as a warning sign of the first shape correction method using 2.4 sections, and then extract HOG feature and SVM classification. Figure1 shows, the warning signs of "mark" mark and the "signal" logo shape are very similar, the main difference is that the color, therefore, it is necessary to use color information signs to warn the fine classification. Method of classification and categories of similar, warning signs are characterized connected by HOG characteristics of the RGB three components

In addition, because some warning signs exist only some nuances, experiments found that only HOG features is difficult to accurately extract the inter class difference, the image resolution is low especially a problem. Therefore, in addition to the HOG feature, this algorithm will also correct image to scale. Contrast enhancement after adding the feature vector to improve the ability to distinguish between feature classes. Typically, gray level directly as features is difficult to obtain good results, but because the warning sign at this time has been accurate shape correction, the experimental results show that the correct rate of classification, gray value adding characteristics has significant improvement.

## 3.4. Classification of Indicator, Ending the Prohibition Sign and Other Signs

In the experiment, indicating, ending the prohibition "logo and other" three class without shape correction can obtain good classification results, the reason is that these three kinds of signs of similarity are not high. HOG features can be made effectively distinguish. Therefore, the three logo zoom to 40 x 40 pixels directly after the extraction of the gray HOG characteristics, and sent to the SVM classification.

HOG features and parameters of SVM classifier with ending the prohibition Sign are same. The correct rates of classification were 99.84%, 98.89%, 99.90% in the test set

## 3.5. Analysis of Results and Comparison

The experimental method and parameters by using the above described, this algorithm in the GTSRB data set classification for all test images of the correct total rate is 99.52%. The total number of classification error flag is 61. Figure 5 shows the image classification errors. Error condition can be roughly divided into six types. It is shown in Table 6.

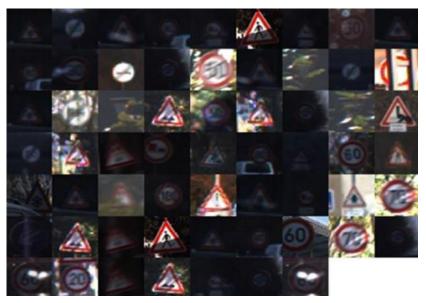


Figure 5. All Failure Cases of the Proposed Algorithm on GTSRB Dataset

	Low	Motion	Occlusi	Signs	Shad	Othe
	resolution	blur	on	similar	ow	r
Num	27	4	13	2	9	6
ber						

Table 6. Failure	Cause	<b>Statistical</b>	of the Pro	oposed Method

A source of error in the input image resolution is too low, a serious loss of image details, some of which have been almost impossible to make accurate classification; serious occlusion is another main cause of classification error, figure5 shows, some occlusion seriously though, but still may according to some local features to make correct classification, is a consider the improvement direction. Third main causes of errors is shadow interference, because most marks a white background, pattern is black, so the shadow on the mark pattern influence, HOG features of severe interference logo, lead to misclassification; while the other such as motion blur error can be added according to the preprocessing step to improve the correct classification rate.

In order to further illustrate the advanced nature of the algorithm, are presented in Table 7 comparison results of the improved algorithm and several representative classification algorithms, including the best classification algorithm MCDNN and artificial classification results [8]. Accuracy of the paper algorithm is better than the manual classification and the classification results of all the other algorithms. To see the results of the current, the correct rate of 99.52% of the algorithm is given the best results GTSRB datasets.

	Prohibiti	Warning	Instructi	Ending	Other	Total
	on		ons	the		
				prohibition		
LDA	95.75	93.73	97.18	85.83	98.63	9
Random	96.79	92.08	99.27	87.50	98.73	96.14
forest						
Artificia	98.73	99.21	100.00	98.89	100.00	99.22
1						
MCDN	99.59	99.07	99.89	99.72	99.22	99.46
Ν						
This	99.63	99.03	99.94	98.89	99.90	99.52
paper						
algorithm						

 Table 7. Comparison of the Classification Results between the Proposed and Existing Algorithm (%)

The efficiency of the algorithm, the MCDNN algorithm on the GTSRB test set all sign classification for hours [9]. By contrast, in this algorithm is only 520 seconds, the average of each image classification time of about is 40 ms, test the software and hardware platform is the Core I3 3.3GHz, 4GB DDR3, MATLAB 2011b. In addition, this code has been not for efficiency optimization, if used C++ rewriting algorithm, the speed should be improved significantly. In the real traffic environment, a frame in the marked by the number of usually is not more than 10; therefore, this paper algorithm is suiTable for real-time applications.

# 4. Conclusion

This paper mainly studies the traffic signs classification problem, through the analysis of the existing algorithms, proposed a stepwise refinement of traffic sign classification algorithm, the algorithm first divides the input image according to the color and shape of coarse divided into several categories, and then according to the characteristics of large class of shape correction and contrast enhancement on the logo, finally subdivision is given the final result.

This algorithm classification accuracy on GTSRB dataset reached 99.52%, exceeding all existing machine learning algorithms. In addition, the proposed algorithm is faster, the average time to process ROI is 40 milliseconds, which is much faster than the neural network algorithm based on convolution

By observing the classification error image in the GTSRB data set, this algorithm still has room for improvement. Considered to join the local feature enhancement algorithm for occlusion adaptive capacity, added some preprocessing steps of motion blur to enhance the adaptation ability.

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