Development of Road Sign Recognition for ADAS Using OpenCV

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***Abstract*—Real time Road sign recognition technology of advanced driver assistance systems (ADAS) provide necessary information and instructions to help the driver to drive safely. Road sign recognition is the technology of driver assistance system which interprets the signs to the driver. Recognition is dependent on the combination of detection and classification. Among the various available methods the most efficient one is chosen. Thus detection of region of interest is performed by using Histogram of oriented gradient and classification by using support vector machine. Training data is generated from our own database. This paper represents a study to recognize road signs using OpenCv techniques. This is implemented in visual studio and ported on NVIDIA's TK1 platform. The experimental results shows good performance for recognition of ideogram based signs with an average speed of 25 frames per second having accuracy up to 94%.**

***Index Terms*—Hough Transform (HT), histogram of oriented gradient (HOG), road sign recognition, region of interest (ROI), support vector machine (SVM).**

I. Introduction

The only seek for development of vehicle is to assure traffic safety. Driver support system that provides the prior indication to the driver can greatly assure safety. Recognition system is dependent on the combination of detection and classification techniques. The detection of road traffic sign is dependent on information obtained from shape and color of sign. Classification technique enables to recognize the sign by differentiating the sign from others. There are several factors like variations in perspective, variations in illumination, occlusion of signs, motion blur and snowy area that can greatly affect the recognition.

Road side area is normally disarranged and contains many of the strong geometric shapes that lead to misclassification or remains undetected which will cause adverse impact on the driver [1]. Thus it is a challenging job to develop a robust system which is still intensively studied from the past two decades. It has become more feasible since the processing power of computer is increasing day by day. Many researchers are proposing variety of solutions to recover the efficiency of the system.

A significant number of documents relating to the recognition in the form of ideogram specifying - on the basis of road signs in real road scenes were published [2]. The common approach reasonably consists of two main stages: detection and classification. The Detection phase determines the area of interest and is performed using the color segmentation or shape features and then in one form or another form of recognition. Detected candidates and then either recognized or rejected during the classification stage employing, for example, template matching [3] or some other classifier such as SVMs [4], or neural networks [5].

For segmentation/ partitioning of the image, majority of systems utilize the color information method. Moreover, the color based road sign detection performance is less in adverse weather conditions such as snow, fog and also due to strong illumination, poor lighting. To overcome these problems various color models like hue-saturation-value (HSV) [6], YUV [7], and CIECAM97 [8] are chosen. For instance, Shadeed et al [7] accomplished segmentation by using the U and V chrominance channels of the YUV space, with U and V being positive and negative respectively for red colors.

In contrast, there are many more approaches, which completely refuse the color information and instead use the only shape information to determine the information from the image with grayscale. For instance, Loi and Zelinksy [9] proposed system, that used local radial symmetry for the allocation of points of interest on each of the image and the detection of octagonal, square and triangular road signs. Some of the most recent methods such as [9] use Histogram oriented gradient (HOG) features for road sign feature extraction. To include the color information using the CIELAB and YCbCr color space, Creusen et al [9] enlarged HOG algorithm. Overett et al introduced the two alternative formulations of HOG features for the detection of signs of speed in New Zealand.

The HOG features is the one to assist our classification process and will be explained later why they are found to be the most suitable for this application. Other methods for detection are edge detection which is a fundamental step in image processing, template matching where the detection is performed by comparing with the previously defined lot of templates. Also Hough Transform (HT) is a detection method which is used to detect circles, rectangles with large amount of computation time. Among the various classification methods

SVM is the most efficient binary classifier which provides better performance.

The vast majority of existing systems consist of classifiers that were prepared using the manual marked with real images, for example [4], [5], which is repetitive, time-consuming and errors. In addition, although many of the existing systems report of the high-level segment of the rates, the total number of traffic sign classes recognized is usually very limited, for example, 42 classes in the [2] and are therefore less likely to suffer inconsistencies in regard to similar signs which were missing from their databases.

In this paper, our purpose is to design a road sign detection and classification system which is robust for object scaling, occlusion, rotation and projection distortion. The system is divided into two phases: one phase for detection and the other for classification. In detection phase, HOG features are extracted from normalized candidate regions and in classification phase linear SVM classifiers are used for different color shape have been applied to the features classification.

Section II discusses about the database used for implementation. Overview of road sign recognition system, sign detection and classification. Section III presents the experimental results obtained. Finally, section IV presents the conclusion.

II. Road Sign Recognition System

The database for the implementation is taken from our own dataset of Indian road sign. Three types of signs used are represented in figure 1 below. The video of road side area in mp4 format running at speed of 25 frames per second is used as input for the system.

Figure 1: dataset

A. Overview of System

The recognition system consists of 2 main phases: Detection and Classification. The figure 2 represents the algorithm of road sign recognition system. The input image of the road side area from camera is extracted one by one and is given to detection phase. In detection phase the input color image is first resized, converted to grayscale and finally the features of the image is obtained by HOG computation. In classification phase the SVM classifier is used to classify the type of sign and finally display the recognized sign.

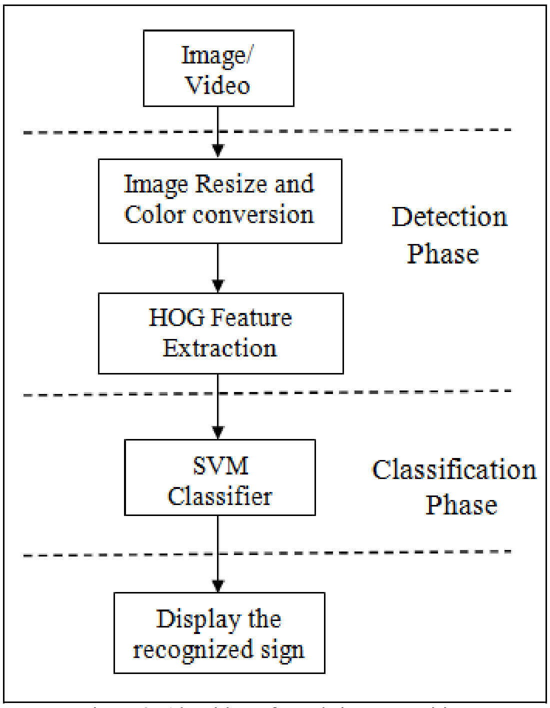

Figure 2: Algorithm of Road sign recognition

B. Units

To speed up the processing time the input image (1270 x 720) is downscaled to 640 x 360. Then the image is converted to grey scale by using gamma correction in order to reduce the noise interference. Histogram of oriented gradient features is extracted from the image. The extraction process includes three main steps: first is gradient computation. This step consists in computing the horizontal and vertical gradient for each pixel. It aims to capture the contour information and to weaken the interference of light. The horizontal gradient Gx(x,y) and the vertical gradient Gy(x,y) are obtained by performing convolution with sobel kernel. The gradient magnitude G(x, y) and gradient direction α(x, y) can be also obtained by the following equations:

$$G(x,y) = \sqrt{G_x(x,y)^2 + G_y(x,y)^2} \quad (1)$$

$$\alpha(x,y) = tan^{-1}\frac{G_y(x,y)}{G_x(x,y)} \quad (2)$$

The second step of calculation is creation of the cell histograms. Every single pixel within the cell casts a weighted vote for an orientation-based histogram channel dependent on the values found in the gradient computation. The cells can either be radial or rectangular in shape, and the histogram channels are evenly spread over 0 to 180 degrees or 0 to 360 degrees. The figure 3 shows the pictorial representation of formation of cells in the image.

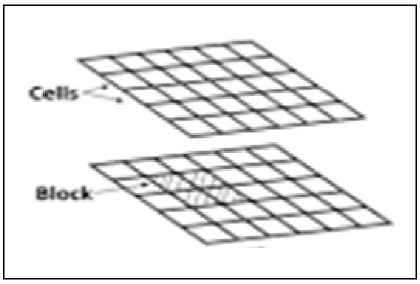

Figure 3: Cell formation

The third step is formation of descriptor block and normalization. To compromise for changes in illumination and contrast, the gradient strengths must be locally normalized, which needs grouping the cells together into larger, spatially connected blocks. The figure 4 shows the block normalization with the descriptor feature vectors. The HOG descriptor obtained are the concatenated vector of the components of the normalized cell histograms from all of the block regions. These descriptor feature vectors are then applied to a classifier.

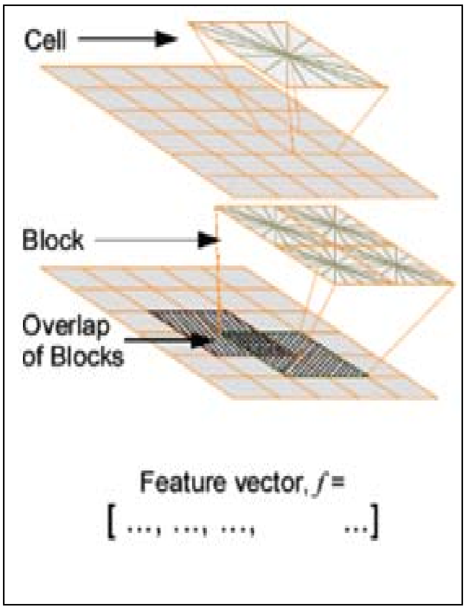

Figure 4: Block normalization

For window size of 32 x 32 with 8 x8 block size and 4 cells per block, the number of feature vector is calculated by using formulae given below:

$$N = \left(\frac{R_{width}}{C_{width}} - 1\right) * \left(\frac{R_{height}}{C_{height}} - 1\right) * B * H \qquad (3)$$

Where R is the region, C is the cell size, B is the number of cells per block and H is the number of histograms per cell. Thus the number of descriptor vectors obtained is 1764. The feature vectors are saved into the xml file.

C. Road Sign Classification

The feature vectors of the samples are given to train the Support Vector Machine (SVM) classifier. SVM is a discriminative classifier formally defined by a separating hyper-plane between two classes. The “support vectors” are data points that introduce the maximum margin of the hyper-plane. Even if SVM is basically a binary classifier, multiclass classification can be achieved by training several one against-one binary SVMs. SVM classification is fast, highly accurate, and less dependent to over fitting compared to several other classification methods. It is also possible to quickly train an SVM classifier, which considerably helps in our proposed method, given our huge quantity of training data and high number of classes. The OpenCV function of SVM is used to train the classifier. Thus for the input frame after computing descriptor vector, the classifier compares the descriptor vectors with the previously trained sample features and displays the recognized sign.

III. Experimental Results

In order to test the algorithm we collected different videos with the help of mobile camera placed on dashboard of vehicle, having resolution of 1280 x 720. The frame rate of the videos is 25 frames per second. The system has been implemented based on visual studio C/C++ and OpenCV. This is ported onto NVIDIA’s Jetson Tegra K1 platform to perform profiling of the code. Jetson TK1 is a tiny but full-featured computer designed for development of embedded and mobile applications. Tegra K1 has a quad core ARM CPU processor and Kepler GPU processor. Fig. 6a, 6b, 6c represents the experimental results of the Pedestrian cross, roundabout and right road sign recognition respectively. The green rectangular box represents the region of interest. This projected method can successfully detect the road sign boards under the different illumination environments, and is robust for the object rotation, object scaling and occlusion.

From the profiling we obtained that the time consumption to compute HOG in each frame of 640 x 360 is 0.8ms. To perform classification in each frame time consumed is 0.7ms. Table I shows the results of recognition with the count for number of false detection and number of missed detection. Various videos with total 10 in video-1, 10 in video-2, 12 in video-3, 15 in video-4, 16 in video-5 and 12 in video-6 signs boards and thus performance accuracy is measured in each video. Along with the correct detection there is false detection which decreases the performance.

TABLE 1: PERFORMANCE ANALYSIS

	Video 1	Video 2	Video 3	Video 4	Video 5	Video 6
Correct Detection	9	8	10	14	13	10
Missed Detection	1	2	2	1	3	2
False Positives	1	0	2	2	2	3
Total Signs	10	10	12	15	16	12
Precision	95%	94%	91%	93%	91%	90%

(a)

(b)

(c)

Figure 6: 6a, 6b, 6c represents pedestrian cross, roundabout and right turn sign recognition

IV. CONCLUSION

This paper proposed an effective and efficient method for road sign recognition. Simple color normalization is performed and shape analysis which is based on HOG feature extraction. Then, the linear SVM classifier is applied for the sign classification through using HOG descriptors in recognition phase.

From the experimental results, our system is robust. Besides there are false detection by the system which may lead to severe problem hence training has to be performed properly with more number of samples. So the only demerit of this method is that it requires large amount of training samples. Hence to improve the system performance the future scope is to collect maximum number of samples.

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