Detection and Recognition of Traffic Sign using FCM with SVM

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Abstract

This paper mainly focuses on Traffic Sign and board Detection systems that have been placed on roads and highway. This system aims to deal with real-time traffic sign and traffic board recognition, i.e. localizing what type of traffic sign and traffic board are appears in which area of an input image at a fast processing time. Our detection module is based on proposed extraction and classification of traffic signs built upon a color probability model using HAAR feature Extraction and color Histogram of Orientated Gradients (HOG).HOG technique is used to convert original image into gray color then applies RGB for foreground. Then the Support Vector Machine (SVM) fetches the object from the above result and compares with database. At the same time Fuzzy Cmeans cluster (FCM) technique get the same output from above result and then to compare with the database images. By using this method, accuracy of identifying the signs could be improved. Also the dynamic updating of new signals can be done. The goal of this work is to provide optimized prediction on the given sign.

Keywords: Histogram of Orientated Gradients, Color and HAAR Feature extraction, ROI, SVM, Fuzzy C-means clustering.

I. INTRODUCTION

Indian road conditions require development of an automated driver guidance system. Human lives are becoming uncertain day by day. Since traffic Concentration is increasing day by day worldwide, roads are occupied by overloaded vehicles. Accidents are occurring due to the inaccuracy of the drivers. A driver cannot easily predict the sudden pot holes or bumps or sudden turns where the road signs are not very prominent. Although image processing plays a vital role in the road signs recognition, mainly in color analysis, but the paper points to many problems concerning the constancy of the received information of colors, distinctions of these colors with respect to the daylight circumstances, and absence of a color model that can led to a good solution. This means that there is a lot of work to be complete in the field, and a lot of improvement can be achieved. Soft computing techniques were widely used in the detection and the recognition of the road signal. The majority of the authors used neural networks as a recognizer, and as classifier. Some other methods such as template matching or classical classifiers were also used. New techniques should be involved to increase the forcefulness, and to get faster systems for real-time applications.

Road and traffic sign recognition is one of the essential fields in the modern transport system. This is due to the importance of the road signs and traffic signals in everyday life. They define a visual language that can be interpreted by the drivers. They denote the current traffic situation on the road, show the danger and difficulties nearby the drivers, give notices to them, and help them with their navigation by providing useful information that makes the driving safe and convenient. The field of road signal recognition is not very old; the first paper looked in Japan in 1984. The goal was to try various computer vision methods for the detection of objects in outdoor scenes. Since that time various research groups and companies are interested and conducted research in the field, and enormous amount of work has been completed. Different methods have been used, and big improvements have been achieved during the last decade.

The identification of the road signals is achieved by two main stages: detection, and recognition. Suppose if there is a system with merged motion camera and a merged onboard computer with the vehicle, a simple driver guidance system based on frame by frame examination of the motion frames can be developed and there by generate the alarm signals accordingly, in order to make driving quite easier. Road image examinations are very important aspect for automated driver support system. Real-time qualitative road data examination is the cornerstone for any modern transport system. So far, most of the use of image processing techniques for qualitative examination is still at its early stage and examination is done manually. In this paper description about different image processing algorithms together with the results is given, which assign a qualitative explanation to a road scene. The qualitative description of a road scene can be used for controlling road lights and placing hazard signals on the road. Road safety is always a problem everywhere, especially in developed countries like US, Japan etc. Most of the cases, they are not aware of the traffic signs. In many cases, accidents happen during bad weather or in occlusion. Drivers could not identify the road signs due to bad weathers. Shadows, at night time and cloudy weather are some complex that drivers face. Recently many techniques have been discovered to detect road signs for safe journey. Many of them implemented to segment the road sign using the shape and color information.

The problem of traffic sign recognition has some favorable characteristics. First, the design of traffic signs is unique, thus, object differences are small. Further, sign colors often contrast very well against the environment. Moreover, signs are inflexibly positioned relative to the environment, often set up in clear sight to the driver. The traffic sign detection algorithms are commonly on shape and color of the traffic signs. Shape based methods detect the signs using a set of predefined templates and hence is sensitive to total or partial occlusion and target rotation. Color based methods detect signs in a scene using the pixel Concentration in RGB or HSI color spaces. HSI is the most commonly used color space since it gives different pieces of information in every component. More over HSI color space is suitable to extract color features against rough conditions like adverse climate and damaged road signs. It describes a general framework for the detection and classification of traffic signs from image sequences using color information. Color based segmentation techniques are engaged for traffic sign segmentation. Red, blue, yellow and white colors are the most commonly used signs in road traffic.

This work focuses on converting the signs in to textual data in a minimum time giving the driver an extra time to manipulate and take decisions quickly while driving, thereby providing a chance for safe and correct travel.

II.RELATED WORK

According to [1], the first work on automated traffic sign detection was reported in Japan in 1984. This attempt was tracked by several methods presented by different researchers to develop an efficient DRTS system and minimize all the issues stated above. An efficient DRTS system can be divided into several stages: preprocessing, detection, tracking and recognition. In the preprocessing phase the visual presence of images has been enhanced. Different color and shape based approaches are used to decrease the effect of environment on the test images [2-5]. The goal of traffic sign detection is to classify the region of interest (ROI) in which a traffic sign is supposed to be found and verify the signal after a large-scale search for candidates within an image [6]. The ROI is detect through different color and shape based methods are used by the researchers. The popular color based detection methods are HOG Transformation, Region Growing [7], Color Indexing [8], and YCbCr color space transform [9]. As the color information can be unreliable due to brightness and weather change, shape based algorithm is introduced. The popular shape based approaches are Canny Edge Detection, and Edges with Haar-like features [10, 11].The tracking stage is necessary to ensure real-time recognition. In addition, the data provided by the images of the traffic signs will help verify the correct identification and thus detect and follow the object [12]. The most common tracker adapted is the Kalman filter [10, 13,14]. Several methods have been used by the scholars for recognizing traffic signal. Ohara et al. [15] and Torresen et al. [16] used the Template Matching method, which is a fast and straightforward method. Greenhalgh and Mirmehdi [17,18] showed a comparison between SVM,HOG-based classifiers, and Decision Trees and found that a Decision Tree has the highest accuracy rate and the lowest computational time. Its correctness is approximately 94.2%, whereas the accuracy of the SVM is 87.8%. Neural Network is flexible, adaptive, and robust [19]. Support Vector Machine (SVM) is another popular method used by the researchers which is robust against brightness and rotation with a very high accuracy. Yang et al. [20] and García-Garrido et al. [21] used SVM with Gaussian Kernels for the recognition whereas Park and Kim [22] used SVM method that enhanced the computational time and the precision rate for gray scale images. For improving the recognition rate of the impaired or partially occluded sign, Soheilian et al. in [23] used template matching followed by a 3D reconstruction algorithm.

In our approach, for decreasing the processing time RGB segmentation and shape toning based detection and SVM with bagged Fuzzy Cmean cluster are used for recognizing the red traffic signs. Grey-scale images are used to make our detection and recognition algorithm stronger to changes in illumination. So we have to classify using Fuzzy Cmean cluster with help of Support vector machine. The combination of unsupervised and supervised machine learning produce the high level accuracy. The complicated traffic signs are easily detect and recognized by this combination.

III.METHODOLOGIES

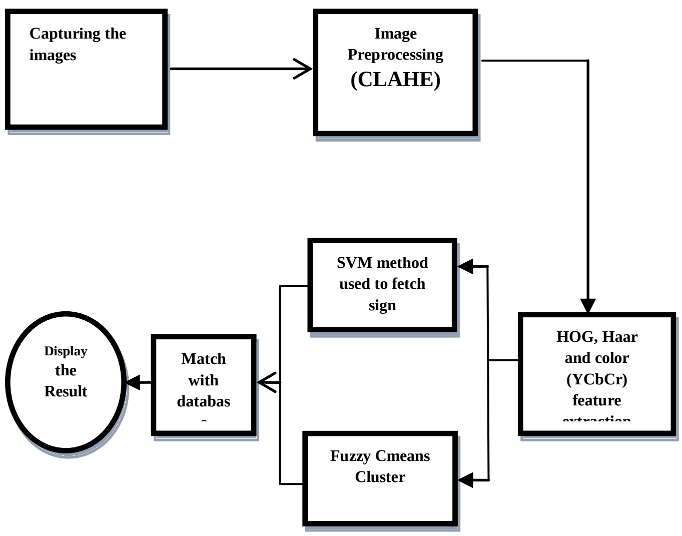

Fig 3.1.Block Diagram

3.1 Image Pre-Processing

Our system use contrast-limited adaptive histogram equalization (CLAHE) to stabilize colors in the input 2D or 3D images. In Figure 3.1 we can infer that type of histogram equalization which works on slates in the image, in order to diminish the excessive contrast and noise that may rise from ordinary histogram equalization. Normal histogram equalization is done by mapping pixels to a altered value based on the cumulative distribution function (CDF) of pixel values in the dimensional image. Adaptive Histogram Equalization (AHE), is marginally easy than CLAHE, works by acting this transformation for all pixel only by considering the CDF of pixels near —a tile. This means that contrast is locally promoted.

3.1.1 CLAHE

Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm splits images into contextual regions. Histogram equalization is applied to each.

Fig 3.2.CLAHE

This evens out the used grey values and brings out hidden features in the image. In Figure 3.2 we can infer that the contrast limited histogram equalization (CLAHE), the histogram is cut at slide threshold and then equalization is implemented. Contrast Limited Adaptive Histogram Equalization for Images in Color Space. Contrast limited adaptive histogram equalization (CLAHE) is flexible contrast histogram normalization method, where the contrast of an image is upgraded by applying CLAHE on small data regions called tiles rather than the entire image.

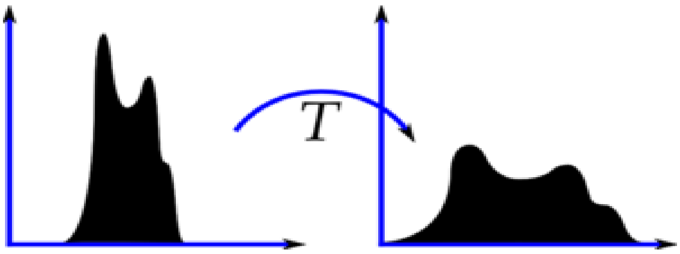

Fig 3.3.CLAHE process

The resulting nearer tiles is then stitched back seamlessly using bilinear interpolation. The contrast in the homogeneous region can be incomplete so that noise amplification can be avoided. In Figure 3.3 we can infer that that the image which is read in RGB space is transformed into the color space with a luminance (Y) and two chrominance components (Cb, Cr) by using the relation given in Equation. It is advantageous not to dispose the part of the histogram that exceeds the clip limit but to redistribute it equally among all histogram bins.

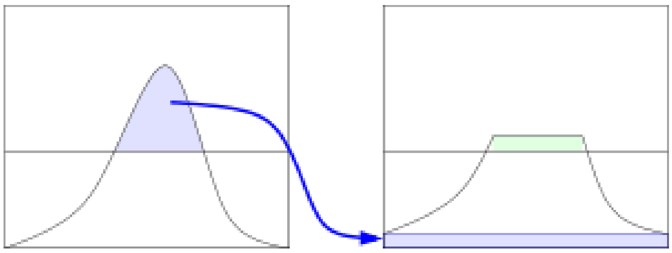

Fig 3.4.Threshold frequency

In Figure 3.4 we can infer that the redistribution will push some bins over the clip limit another time (region shaded green in the figure), resulting in an effective clip limit that is larger than the given limit and the exact value of which rest on the image. If this is undesirable, In Figure 3.5 we can infer that the redistribution procedure can be persistent recursively until the excess is insignificant.

Fig 3.5.Image Pre-processing using CLAHE

3.2 ROI Selection

Pre-Processing output is given as a input for ROI Selection. Afterwards, some pre-processing takes place, usually color normalization after this an ROI-selection if necessary. Typically the ROI is hardcoded in recently, but saliency measures may also be used. Region of Interest is the way of crop the specific region of object in the image by eliminating background. ROI can be gained by using binary edge curve image to find the position of circle, triangle, and square in image.

3.2.1 Region identifying and region clustering using altered fuzzy c-means clustering

Fuzzy c-mean (FCM) is one of the most used approaches for image segmentation and its success chiefly attributes to the introduction of fuzziness for the appropriate of each image pixels. Compared with crisp or hard segmentation methods, FCM is able to retain more facts from the original image. However, one difficulty of standard FCM is not to consider any spatial information in image perspective, which marks it very sensitive to clatter and other imaging artifacts. Fuzzy c-means (FCM) is based on minimization of the following objective.

$$JP_{mn} = \sum_{i=1}^{N} \sum_{j1=1}^{ca} uk_{ij1}^{mn} \,||x_i - c_{j1b}||^2, \; 1 \leq mn < \propto$$

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where m is any real number greater than 1, uk_{ij1} is the degree of membership of xi in the cluster j1, xi is the ith of d-dimensional measured data, cj1 is the d-dimension centre of the cluster, and ||*|| is any norm expressing the comparison between any dignified data and the centre. But for this research to detect the image in a better way a altered approach is used to detect the images in the bad illumination conditions. We introduce a special factor RSij combining both the local spatial relationship (called Srs_ij) and the local gray level relationship (called Srg_ij) to change the parameter α and make it play a more important role in clustering. Its definition is presented as below:

$$RS_{ij} = \begin{cases} S_{rs\_ij} X \, S_{rg\_ij} & j \neq i \\ 0 & j = i \end{cases}$$

Where the ith pixel is the mid of the local window (for example, 3×3) and jth pixel are the set of the10 neighbors falling into a window around the ith pixel. Srs_ij makes the influence of the pixels within the native window change and adapt according to their space from the central pixel and thus more local information can be used.

3.3 Feature extraction

It is based on color and shape feature extraction. The color extraction is based on RGB and HSV. The Haar-like features are used for summing up blocks of pixels at various scales.

3.3.1 Color Feature Extraction

1. In Figure 3.6 we can infer that the color histograms are used to detect the color distribution in an image.
2. Mainly, the color histogram approach counts the number of occurrences of each identity color on a sample image.
3. In Figure 3.7 we can infer that by examining the color histogram of an image, the colors standing on the image can be identified with their matching areas as the number of pixels.
4. Histogram search attributes an image by its color distribution.

Fig 3.6.ROI selection based on color

Fig 3.7.Best & worst process

3.3.2. Haar feature

Haar-like features are digital image features implemented in object recognition. They owe their name to their native similarity with Haar wavelets and were used in the first real-time face detector.

Historically, working with only image strengths (i.e., the RGB pixel values at each and every pixel of image) made the task of feature calculation computationally costly. A publication by Papageorgiou et al. described working with substitute feature set based on Haar wavelets as an alternative of the usual image strengths. Viola and Jones adapted the idea of using Haar wavelets and recognized the so-called Haar-like features.

A Haar-like feature reflects adjacent rectangular regions at a exact position in a detection window, sums up the pixel intensities in each region and calculates the difference between these sums. This variance is then used to categorize subsections of an image.

3.3.3 Histogram of Oriented Gradients (HOG)

The feature descriptor implemented using histogram of oriented gradients (HOG) in computer vision and image processing for the reason of object detection. The technique counts occurrences of gradient orientation in localized area of an image. This method is similar to that of edge orientation histograms, scale-invariant feature transform descriptors, and shape contexts, but varies in that it is computed on a dense grid of uniformly spaced cells and routines overlapping local contrast normalization for improved accuracy.

Histogram of oriented gradients (HOG) is a feature identifier used to detect substances in computer vision and image processing. The HOG descriptor technique finds occurrences of gradient orientation in contained portions of an image - detection window, or region of interest (ROI).

3.3.4. Canny Edge Detector

Edges characterize boundaries and are therefore a problem of fundamental importance in image processing. Edges in images are spaces with solid concentration contrasts – a jump in intensity from one pixel to the next. Edge detecting an image considerably reduces the amount of data and filters out useless information, while conserving the significant structural properties in an image. Canny edge detection algorithm is also known as the finest edge detector. Canny's intentions were to improve the many edge detectors in the image.

(1)The first criterion should have small error rate and filter out undesirable information while the useful information preserve.

(2)The second criterion is to keep the lesser variation as possible between the original image and the processed image.

(3)Third criterion removes multiple replies to an edge.

Canny edge detector is a preprocessing filter, a method of smoothing and threshold processing, normalization filter, method of equalizing the luminance component and contrast, etc.

3.4 Support Vector Machine (SVM)

In recognition stage, to authorize the shape of candidate region as traffic sign and actual kind of sign, HOG features are extracted from the image, which state the occurrence of gradient positioning in the image. Here we practice the canny edge detector to detect a wide range of edges in image. Canny edge detection algorithm uses four filters to detect horizontal, vertical and two sloping edges in the blurred image. The angle of edge direction is rounded to one of 4 angles (for example 0, 45, 90 and 135 degrees) stating vertical, horizontal and the two diagonals. Here, for each cell we are computing four directions. Therefore we acquire total 64 features .Here each cell is divided into 3 × 3 pixel. For central pixel, we are calculating position of nearer pixel i.e. b0 to b7 and calculating the 4 feature vectors. The histogram of oriented gradient features, where x-axis displays orientations and y-axis displays the frequency of gradient features. Later extraction of HOG features, the SVM classifier is applied to the HOG features to classify the traffic symbol. At this time, SVM classifier with Radial Basis Function Kernel is utilized. A SVM is a binary classifier i.e. it categorizes data among two classes. But traffic sign data cannot be classified using two classes. Hence to train the SVM classifier, the pair based classification method of training images is used. Here, the classifier is trained for each possible couple of classes. For M classes, this results in (M−1)*M / 2 binary classifiers. Anon known point x is classified by applying each of the binary classifiers and count how many times point x was assigned to that class label. Class label with utmost count is then considered the label for unknown point x. The SVM with RBF is illustrated as

$fx = \alpha iyi$ exp −| x−xi |22 σ2 + bNi

Where N is the number of support vector, yi is either 1 or −1indicating the class to which the point xi belongs, xi is support vector, b is the bias i.e. intercepts of the hyper plane that divides the two groups in normalized data space, αi is the vector of weights for the support vectors.

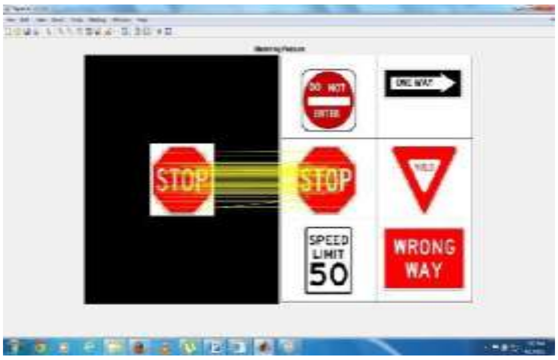

Fig 3.10.GTSDB

That above figure 3.10 is example for SVM data corresponding into the GTSDB. Detecting data is comparing with each database images, then find means show the alert to the driver.

3.5 Recently Fuzzy C-Means (AFCM) Algorithm

Step1: Set the number c of the cluster prototypes change from 2 to Cmax;
Step2: Initialize casually those prototypes and set ε>0 to a very lesser value.
Step3: Compute the local comparison methods Sij for all neighbor windows over the image.
Step4: Calculate linearly-weighted summed image ξ in terms
Step5: Update the partition matrix.
Step6: Update the prototypes.
Repeat Steps5-6 until the following termination criterion is satisfied

FCM algorithm is right to fall into the native optimization, and what fast FCM algorithm can find finest is greatly depended on the initialization. SVM-based FCM clustering algorithm excludes the local optima, and also is forceful to initialization. The fluctuation however has appeared in the new algorithm, and it had been detected that performance of the clustering algorithms deteriorate with more and more overlays in the data sets. SVM Classifier can handle linear devoted problems and has the advantages of high accuracy of classification. Motivated by this observation, in this work a new fuzzy clustering technique that SVM Combined with FCM for Classification problems has been recommended. Results of numerical experiments on two standard datasets show that the new algorithm is more efficient than the FCM clustering algorithms; it can not only avoid the local optima and is robust to initialization, and also increase accuracy of classification.

3.6 FUZZY CLUSTERING BASED SVM CLSSIFIER ALGORITHM

Support Vector Machines (SVM) classifier is pointed to be done through the support of a linear or a nonlinear function. This method is based on the assessment of the most appropriate function to distinct the data from all other. The hyper plane geometry is for a generalization of the plane into a various number of dimensions. The cases where the data cannot be divided in linear or linear classifiers are not difficult enough sometimes, then the nonlinear classifiers can be utilized instead of the linear ones to map the data into a better off feature space including nonlinear ones by constructing a hyper plane in that space. The problem of the non-seperability of the data can be committed through the addition of nonnegative and error-indicative slack variables into the optimization model [24]. So, an active hybrid algorithm which is called as Fuzzy C-means clustering based Support Vector Machines (SVM) has been established by Esme & Karlik [25]. This hybrid algorithm contains of parallel combination of advanced unsupervised fuzzy clustering and supervised SVM algorithms. A number of data points are reduced by FCM clustering previously inputs are applied to SVM classifier.

IV. RESULTS

Properties of Road and Traffic Sign, Road and traffic signs have been designed to be principally distinguishable from the usual and/or man-made backgrounds. They are considered by many features make them recognizable with respect to the environment. Road signs are planned, contrived and installed according to tight regulations. They are designed in fixed 2-D shapes like triangles, circles, octagons, or rectangles. The colors of the signs are picked to be far left from the environment, which make them easily detectable by the drivers. The information on the sign has one color and the rest of the sign has additional color. The tint of the paint that covers the sign should correspond to an exact wavelength in the detectable spectrum. The signs are located in well-defined locations with respect to the road, so that the user (driver) can, more or less, expect the location of these signs. They may contain a pictogram, a string of characters or both. The road signs are categorized by using fixed text fonts, and character heights. They can look in different conditions, including partly occulted, slanted, scratched and clustered in a group of more than one sign.

Fig.4.1.Original Image using FCM mean classifier **Fig.4.2.Gray Image using FCM classifier**

Figure 4.1& 4.2 portrays that the captured original image is converted to gray image using FCM Classifier.

Fig.4.3.RGB Detection Image using FCM classifier   Fig.4.4.Result Image using FCM classifier

Figure 4.3 & 4.4 portrays that the gray scale image is subjected to RGB detection and is then processed using FCM Classifier for further detection.

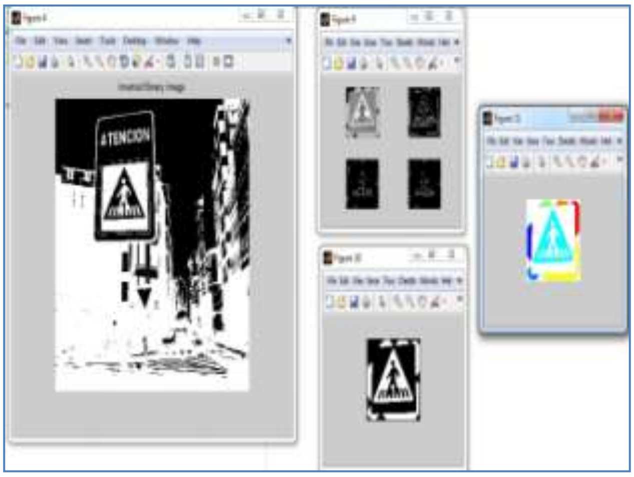

Fig.4.5.Inverted Binary Image using Fuzzy C mean Classifier

Figure 4.5 portrays that the processed image is converted to Inverted Binary Image for sign detection using FCM Classifier where just one sign is detected.

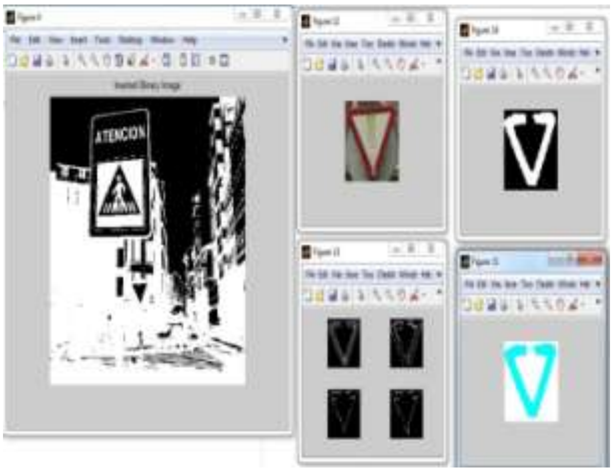

Fig.4.6.Detect the One More Sign on the Same Frame Using FCM with SVM

Figure 4.6 portrays that the processed image is converted to Inverted Binary Image for sign detection using FCM with SVM

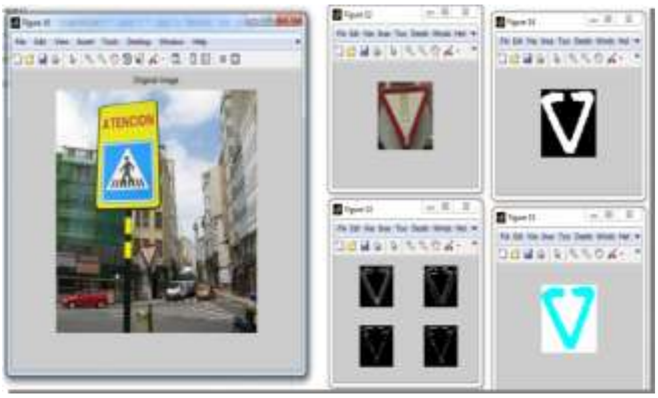

Fig.4.7.Result for additional Sign using FCM with SVM

Fig 4.7 portrays that the additional sign detected using FCM with SVM method is processed with the database to provide further instructions to the vehicle user.

V. FINAL DISCUSSION

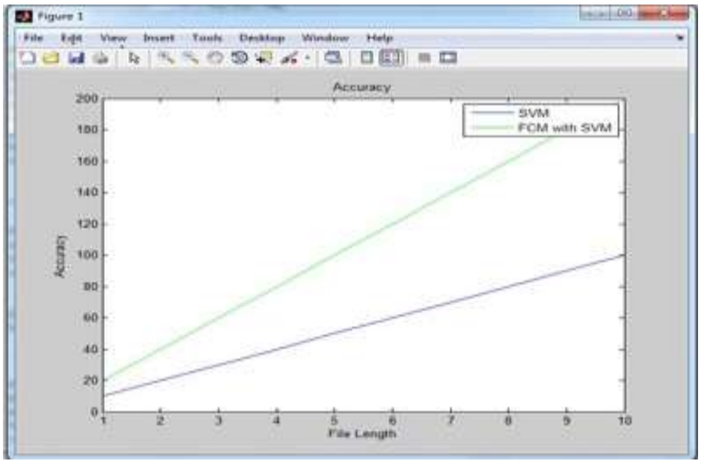

Fig.5.1.Detection Accuracy

Here we have used some images from database. These images may be in different data size (KB/MB). During the traffic sign detection SVM detect all edges and classify the futures of segmentation. In this SVM model can detection approximate traffic sign detection because, this is an supervised learning process. So this SVM method can't detect all type of sign. And FCM with SVM is entirely different from SVM. The FCM with SVM method can detect all edges and cluster the futures of segmentation. Classify the all type of shapes and find all type of sign. In Figure 5.1 we can infer that the FCM with SVM traffic sign detection's accuracy level is higher and better than the SVM.

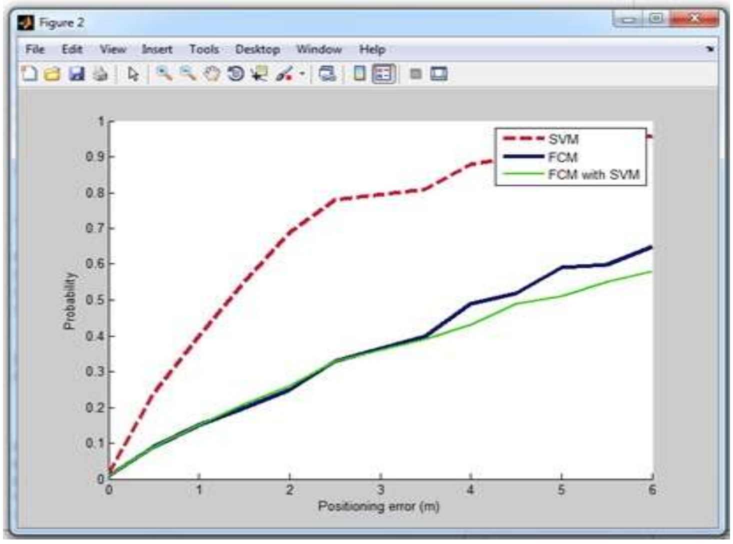

Fig.5.2.Error Occurrence Probability

Here have compared three techniques with themselves. In the image during edge detection may be occur positioning error, which means in some of images all edges not in clear. So our techniques may be can't detect all edges. The FCM with SVM is less probability to find out positioning error than the SVM and FCM. In Figure5.2 we can infer that the probability for the occurrence of error SVM and FCM techniques are higher but it is much reduced in FCM with SVM technique.

Technique	Error Probability
SVM	0.9
FCM	0.6
FCM with SVM	0.5

Table 5.1. Error Probability

We can infer from table 5.1 that the error probability in FCM with SVM technique is lesser compared to the techniques FCM and SVM used individually.

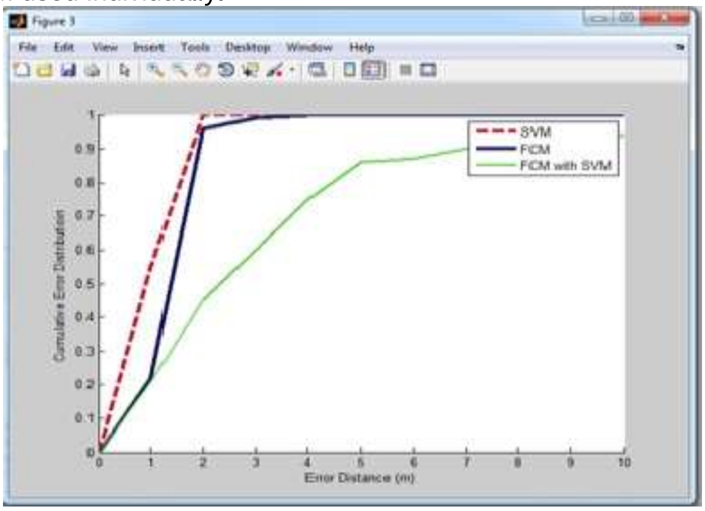

Fig.5.3.Cumlative Error Distribution

Here also have compared three techniques with themselves. In the image during edge detection may be occur error distance, which means in some of images all edges not in clear. So our techniques may be can't detect all edges. The FCM with SVM is less cumulative error in the error distance finding than the SVM and FCM. In Figure5.3 we can infer that Error distance of SVM and FCM techniques are higher but it is much reduced in FCM with SVM technique.

VI. Conclusion

In our result gives that the better detection performance for all type of traffic sign. This could able to reduce the rate of accident with the help of traffic signs notification application. To better understand the influences of individual components in detection for different signs with the help of SVM and Fuzzy Cmeans cluster, we have run detectors using hue channels and shape channels get the result from the above channel and it will send it to the two different Classifiers. Finally we combine both the techniques of SVM and Fuzzy Cmeans, which produce the best result in accuracy and also detection of many unknown traffic sign simultaneously in effective way. In our conclusion is that shape is a stronger cue than color and Fuzzy Cmeans with SVM prediction is greater.

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