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Recognition of Traffic Sign using Support Vector Machine and Fuzzy Cluster

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Abstract

Traffic sign recognition plays an important role in driver assistant systems and intelligent autonomous vehicles. Its real-time performance is highly desirable in addition to its recognition performance. This system aims to deal with real-time traffic sign recognition, i.e., localizing what type of traffic sign appears in which area of an input image at a fast processing time. Our detection module is based on traffic sign proposal extraction and classification built upon a color probability model and color HOG(Histogram of Orientated Gradients). HOG technique performs conversion of original image into gray color then applies red or blue color for foreground. Maximally Stable External Region (MSER) take stable object in the previous output by the use of multiple frames. Next Support Vector Machine(SVM) fetch the object from MSER output and compares with database. At the same time fuzzy pattern cluster technique fetch the MSER output and apply the RGB(RED,GREEN,BLUE) colors then compares with the database images. In the above two methods, the one which produce the output first is considered. Then voice output narrating the traffic sign is produced.
Keywords: BHOG, MSER, SVM, FEZZY

I. INTRODUCTION

A. Image processing

Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image. Usually Image Processing system includes treating images as two dimensional signals while applying already set signal processing methods to them**.**

Traffic sign recognition has high industrial potential in Driver Assistant System and Intelligent Autonomous Vehicles. There are two tasks in a typical traffic sign recognition system: finding the locations and sizes of traffic signs in natural scene images (traffic sign detection) and classifying the detected traffic signs into their specific sub-classes (traffic sign classification). It is a crucial factor in the real-world applications of traffic sign recognition and cannot be ignored.

B. Motivation

Existing system consist of many techniques such as ROI(region of interest),MSER(maximally stable external region),SFC(split flow cascade) tree detection, HCRE(high contrast region extraction), ESRC(extended sparce representation classification) . MSER is first used in existing system for detecting maximally stable images. It takes more time to detect.Proposed system uses HOG technique first then use MSER. SVM and cluster nearer fuzzy method for classification. It reduces time for classification.

The process of the ROI extraction. (a) is the input image. (b) is the color enhancement image. (c) is the voting image. (d) is to show the extraction regions using the mask; the gray region in (d) is the mask.

The most popular previous ROI extraction methods [3]–[12] rely on thresholding of the input image in a particular color space; these methods are not robust to color variance in the input images. The other ROI extraction methods that do not rely on thresholding [13]–[15] or rely on extreme region detection [31] are often complex and time consuming. To address these problems, a novel ROI extraction method, called the Hig Contrast Region Extraction (HCRE), is proposed. Motivated by the cascaded detection methods [24], [38], the HCRE utilizes integral image and rectangle features to quickly extract ROI regions; unlike the features used in cascaded detection method [24], [38], the features used by the HCRE are not position-fixe in the detection window. The voting of neighbouring features decides whether the corresponding region is a ROI region. Taking advantage of the observation that different types of traffic signs have relative high contrast in local regions, the HCRE can effectively remove non-interesting regions with small local contrast, such as sky, road and some buildings, and can boost the detection speed of the SFC-tree detector [2] from 5 frames per second to more than 10 frames per second in our experiments. After the process of ROI extraction and traffic sign detection, multiclass traffic signs are detected and roughly classified into various categories. We design a verification method based on the OvR SVM classification method [36] to ensure the correct classification of the SFC-tree detector.

C. *Architecture*

1) *Existing system*

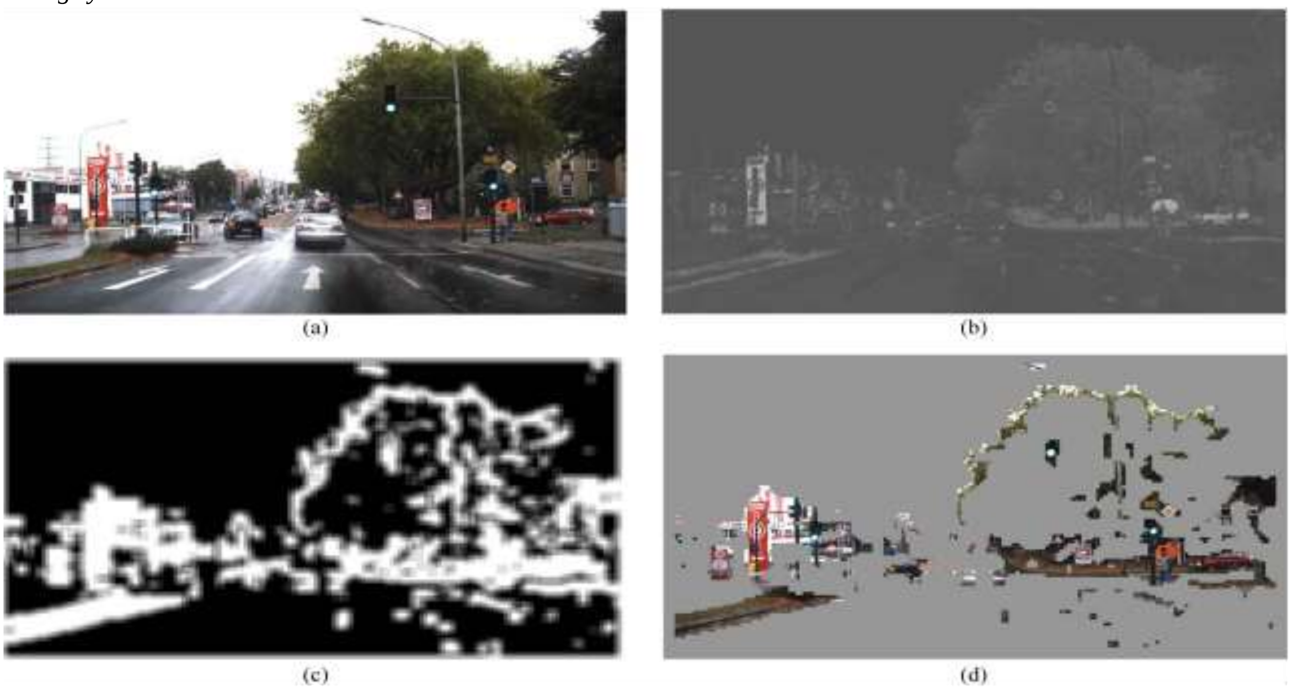


Fig. 1:

This verification method is more time saving than directly classifying these detected categories. After the verification process, the categories that contain different types of traffic signs have deeper classification performed. For the traffic sign classification task, many TSR methods have been developed, such as the SVM-based methods [31],[32], the NN-based methods [26]–[28] and the tree-based methods [33]–[35]; yet, the SVM-based and tree-based methods are not robust at classifying signs with partial occlusions or isolated samples, and the NN-based methods are often too slow to be applied in real applications. Recently, some SRC-based TSR methods [29], [30] have been developed and employed for traffic sign classification. By introducing an identity occlusion dictionary, the SRC-based methods have robust recognition results against partial occlusion and isolated samples. The success of the existing SRC-based methods [29], [30] inspires us to design an occlusion-robust SRC-based TSR method; the existing problem is that the accuracy of the SRC-based methods [29], [30] largely relies on an over-complete dictionary, which often results in high computational complexity. We design a rapid occlusion-robust traffic sign recognition method based on the Extended Sparse Representation Classification (ESRC) [37] to improve the previous SRC-based methods in recognition time. The proposed ESRC-based method has two dictionaries: the content dictionary and the occlusion dictionary. The content dictionary can represent the inter-class differences, whereas the occlusion dictionary is shared by different objects and is utilized to represent the common occlusions of different signs .The introduction of the content dictionary and the common occlusion dictionary makes the sparse representation compact.
All of these methods are combined into our efficient multiclass

TSR system, which can detect and recognize different types of traffic signs in high resolution images at approximately 8 to 12 frames per second on the GTSDB dataset [40]. The framework can reach accuracy as high as that of the-state-of the- art methods, and the processing time is performed quickly in high-resolution images. The remainder of this paper is organized as follows: In

Section II, the ROI extraction method of the HCRE is introduced. Section III shows the TSD method based on the SFC tree detector and the verification method. Section IV shows the occlusion-robust classification method based on the ESRC.

D. Explanation

For recognition purpose first detection is perform. Detection side use HOG and MSER methods then only start recognition. First take original image then HOG convert that image into gray color image, after apply RED or GREEN color to foreground and BLACK color to background .MSER region detector take HOG output and identify the stable images by the use of many images. MSER compares the each frame to other frames so differentiate the each image object which one is move and which stable all image. Because traffic signs are not moved.SVM takes stable images and converts into some values .Then the value is compared with database. In this system GLOBAL TRADE SYSTEM DATABASE (GTSDB) is used. At the same time fuzzy cluster technique take the same output of the MSER then applies the RGB colors to stable image. Then take the common visual in the image. Finally compared the same GTSDB. Above both matches which one is produced output first that give the instruction. If the value match with the database image that traffic sign is narrated to the driver.

E. Proposed System

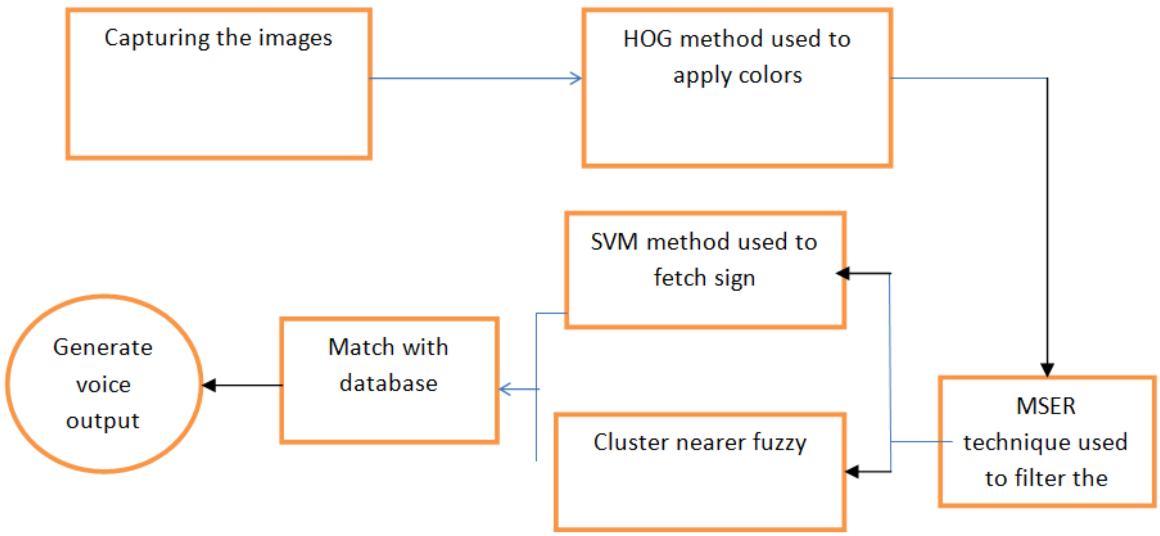


Fig. 2:

1) For Example

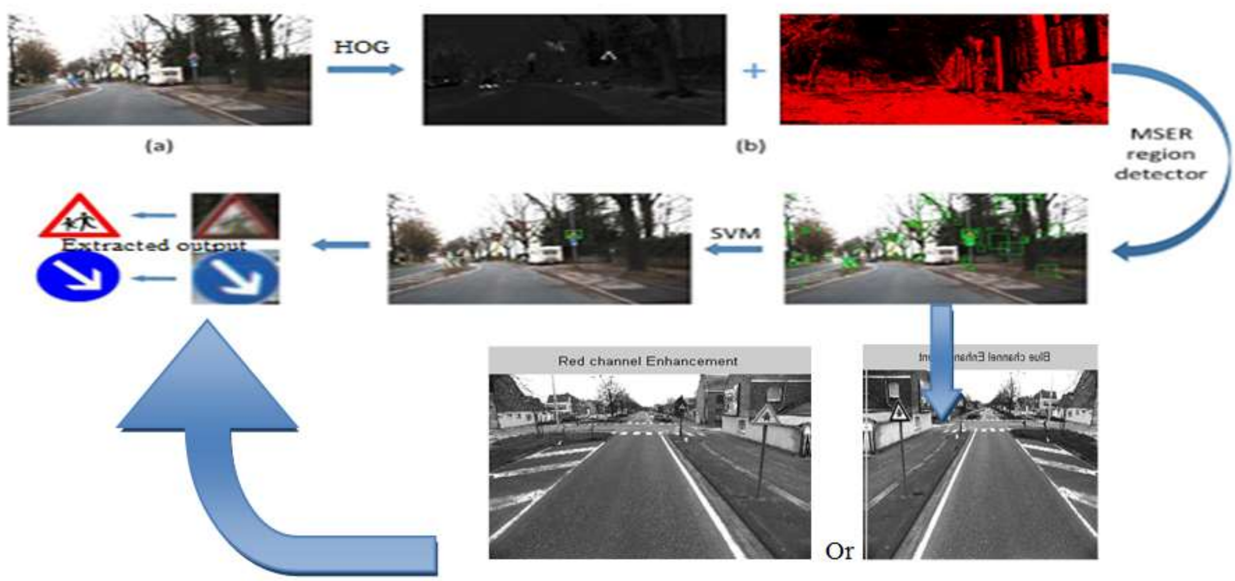


Fig. 3:

II. IMAGE CAPTURING AND PREROCESSING

In our system capturing the images above the 10 meter into the vehicle. Because the drivers also seeing the the blow 10 meter. Image color as well as nature color and image takes in the all the resolution also all formats. In the image size depends on that image resolution. That vehicle camera boundary is the users required pixels. Then that original images send to the pre-processing unit. That unit take all image formats such as jpeg, png and etc. this phase performed convert to original resolution image into the constant image format used the resized Bomb and filter functions.

The size of filter kernel in both of the two convolution layers is 5 ×5 and L2-pooling is used in sub sampling layers. The size of input image is 32×32, after the

III. HISTOGRAM OF ORIENTEDED GRADIENT

It is descriptors, or hog descriptors, are feature descriptors used in computer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image.

The purpose of this system is to implement the algorithm of extracting histogram of gradient orientation(HOG) feature. These features will be used then for classification and object recognition. There are two benefits of using HOG-based methods. First, traffic signs have distinctive shapes, and the patterns on that the gray images are converted dark images used to magnitude of gradients.

different layers may have strong edges. Therefore, the gradient can efficiently capture these features. Second ,using HOG can help to achieve scale invariance .In addition, inspired by feature selection in face detection, we designed an over complete set of the Hoar-like features, from which we can select features that can best describe and distinguish different signs.

HOG method used to in this system is take the original images the converting that original image into the gray color images because RGB (colors are finding very large process, black(111) and white(000) is take 2 times to find images, so we are use gray(0.5) so finding easily and quickly.

STEP 1: Calculating the computation of the gradient values In this step filtering the gray image with following filter values

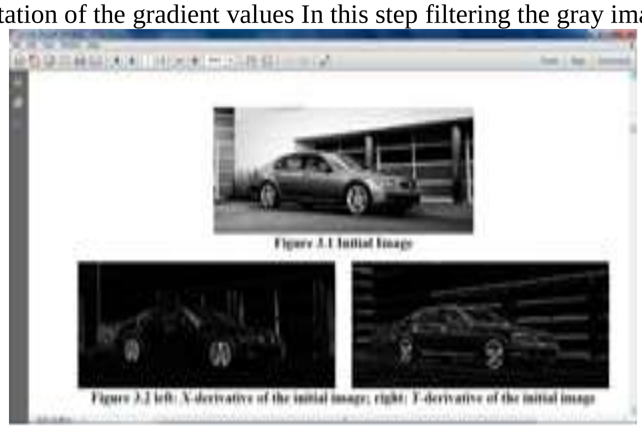


Fig. 4:

STEP 2: Calculation involves creating the cell histogram. This step weighted vote oriented based the histogram base on the values found on the gradients computation. The cells spred over first convolution layer, there are 16 feature maps with the size of 28×28.

We used constant size of the resizing the image is 256×256. And that resized images store in the particular folder

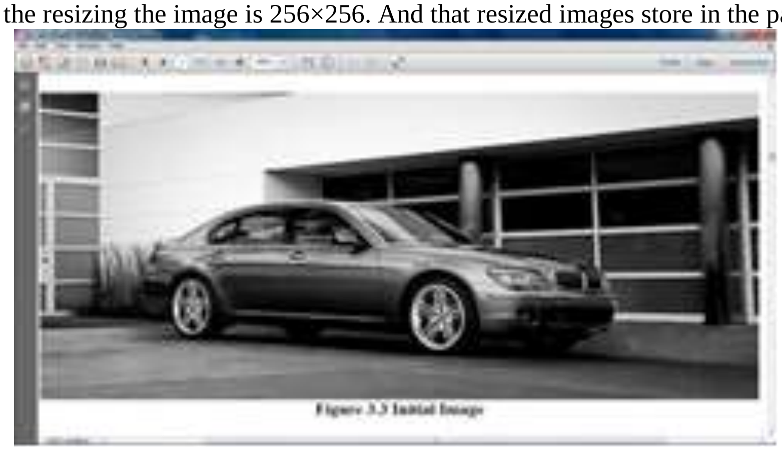


Fig. 5:

for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image.

The purpose of this system is to implement the algorithm of extracting histogram of gradient orientation(HOG) feature. These features will be used then for classification and object recognition. There are two benefits of using HOG-based methods. First, traffic signs have distinctive shapes, and the patterns on that the gray images are converted dark images used to magnitude of gradients.

Fig. 6:

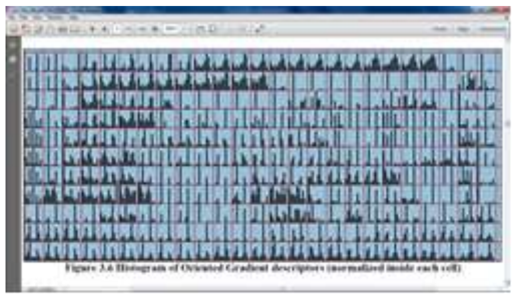
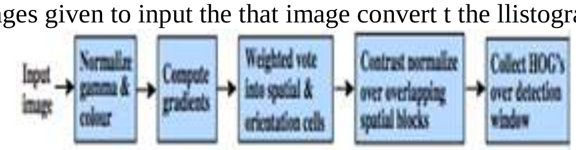


Fig. 7:

This figure is the that previous images given to input the that image convert t the llistogram of Oriented Gradient descriptor



Above figure is change the original color into the lite gray image, because the original image have the lot of color (ex.RGB compination colors That above fig is comparing the each other image

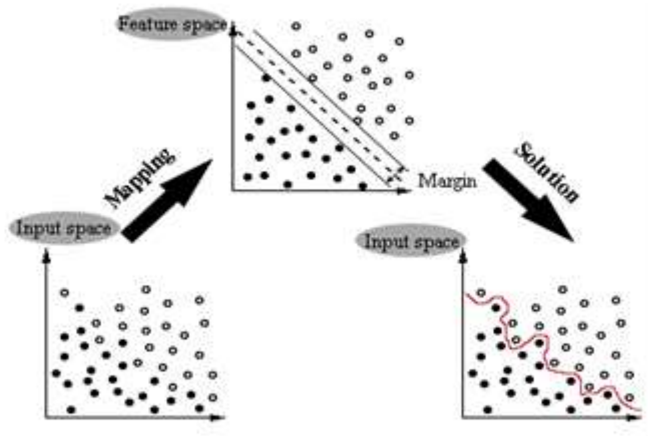
IV. SUPPORT VECTOR MACHINE (SVM)

In recognition stage, to confirm the shape of candidate region as traffic sign and exact type of sign, HOG features are extracted from the image, which represent the occurrence of gradient orientations in the image. Gradient histograms measure the orientations and strengths of image gradients within an image region. Here we divide the extracted image into 4 × 4 cell i.e total 16 cells as shown in Fig. 4(a). Here we use the Canny edge detector to detect a wide range of edges in image. Canny algorithm uses four filters to detect horizontal, vertical and two diagonal edges in the blurred image. The angle of edge direction is rounded to one of four angles(for example 0, 45, 90 and 135 degrees) representing vertical ,horizontal and the two diagonals. Here, for each cell we are calculating 4 directions. Therefore we get total 64 features .Here each cell is divided into 3 × 3 pixel as shown in Fig.4(b). For central pixel, we are calculating position of neighborhood pixel i.e. b0 to b7 and calculating the 4 feature vectors. Fig. 4 (c) shows the histogram of oriented gradient features, where x-axis shows orientations and y-axis shows the frequency of gradient features .After extraction of HOG features, the SVM classifier is applied to the HOG features to classify the traffic symbol .Here, SVM classifier with Radial Basis Function Kernel is used. A SVM is a binary classifier i.e. it classifies data between two classes. But traffic sign data cannot be classified using two classes. Hence to train the SVM classifier, the pair wise classification method of training images is used. Here ,the classifier is trained for each possible pair 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 binarclassifiers and count how many times point x was assigned to that class label. Class label with highest count is then considered the label for unknown point x. The SVM with RBF is illustrated as

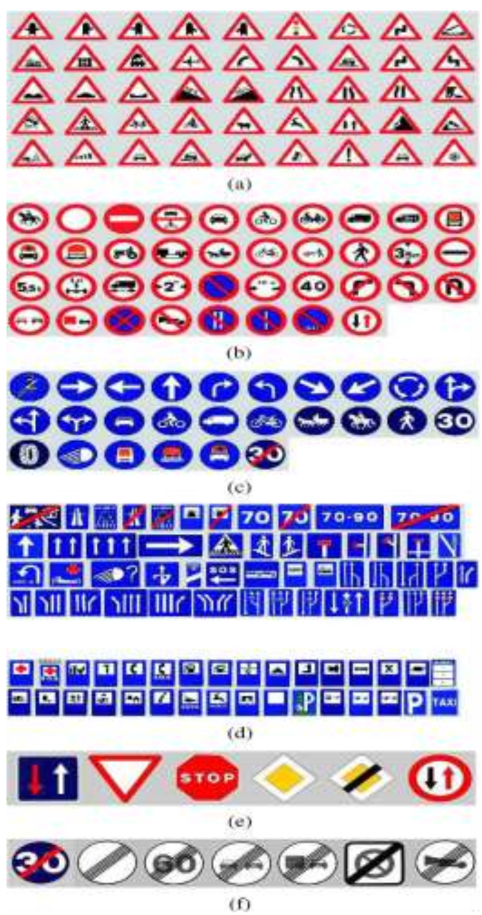
$$f\ x = \alpha i\ yi \exp - |\ x - xi\ |22\ \sigma 2 + bNi \quad (2)$$

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 separates the two groups in normalized data space, αi is
the vector of weights for the support vectors.

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



Overview of SVM process



Traffic-sign database. (a) Danger. (b) Prohibition. (c) Obligation. (d) Warning and information. (e) Priority. (f) End of prohibition.

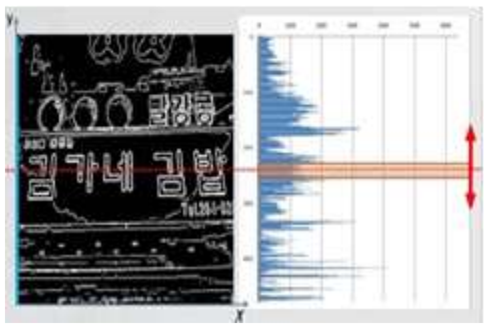
V. REGION IDENTIFYING AND REGION CLUSTERING USING MODIFIED FUZZY C-MEANS CLUSTERING

Fuzzy c-mean (FCM) is one of the most used methods for image segmentation [11] and its success chiefly attributes to the introduction of fuzziness for the belongingness of each image pixels. Compared with crisp or hard segmentation methods [12], FCM is able to retain more information from the original image. However, one disadvantage of standard FCM is not to consider any spatial information in image context, which makes it very sensitive to noise and other imaging artefacts. Fuzzy c-means (FCM) is based on minimization of the following objective.

where m is any real number greater than 1, uij is the degree of membership of xi in the cluster j, xi is the ith of d-dimensional measured data, cj is the d-dimension centre of the cluster, and ||*|| is any norm expressing the similarity between any measured data and the centre. But for this research to detect the image in a better way a modified approach is used to detect the images in the bad illumination conditions. We introduce a special factor Sij incorporating both the local spatial relationship (called Ss_ij) and the local gray level relationship (called Sg_ij) to replace the parameter α and make it play a more important role in clustering. Its definition is presented as below: where the ith pixel is the centre of the local window (for example, 3×3) and jth pixel are the set of the10 neighbours falling into a window around the ith pixel. Ss_ij makes the influence of the pixels within the local window change flexibly according to their distance from the central pixel and thus more local information can be used. Here the definition of Ss_ij is given as in equation

A. *Modified Fuzzy C-Means (MFCM) Algorithm*

1) Step1. 1) Set the number c of the cluster prototypes change from 2 to Cmax (predefined or set by some validity criterion or a priori knowledge);
2) Initialize randomly those prototypes and set ε>0 to a very small value.
3) Step2. Compute the local similarity measures Sij using (9) for all neighbour windows over the image.
4) Step3. Compute linearly-weighted summed image ξ in terms
5) Step4. Update the partition matrix using
6) Step5. Update the prototypes using (9).
7) Repeat Steps4–5 until the following termination criterion is satisfied:



VI. CONCLUSION

The software developed and implemented for “Detection and Recognition of Road Traffic Signs in various illumination and weather conditions” works satisfactorily and thefollowing conclusions are drawn.The developed software gives the satisfactory results under various illumination and weather conditions.Accuracy of detection of sign high (≥ 89.47%) which mostly satisfies the requirement of sign detection. Fezzy cluster also ceck the particular sign Both above methods which one is produce first that give voice alert.

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