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Recognition of Sign and Text Using LVQ and SVM

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Abstract— *Traffic Sign Recognition (TSR) is used to regulate traffic signs, warn a driver, and command or prohibit certain actions. Fast real-time and robust automatic traffic sign detection and recognition can support and disburden the driver and significantly increase driving safety and comfort. Automatic recognition of traffic signs is also important for an automated intelligent driving vehicle or for driver assistance systems. Traffic signs or road signs are signs erected at the side of or above roads to give instructions or provide information to road users. There are many more other types of traffic signs such as special regulation signs, signs for direction and position, welcome sign etc. This report work aims to present a colour segmentation approach for traffic sign recognition based on Linear Vector Quantization (LVQ) neural network and also focuses on triangular edge detection and feature extraction based on Hough transformation and Histogram of Oriented Gradient (HOG) respectively. At first samples of images in different weather conditions are collected and then Red Green Blue (RGB) images are converted into Hue Saturation Value (HSV) colour space. The samples are then trained using LVQ depending on the hue and saturation values of each pixel and then tested for colour segmentation. The edges of the triangular segmented images are then detected using Hough Transformation. Then samples are taken to extract features using HOG. Finally they are trained and tested using Support Vector Machine (SVM) to get the output image. The algorithms were applied to around 100 sampled images which are taken in different Despite the varying conditions, the algorithms worked almost accurately in all situations and the success rate was quite satisfactory with a very good response time of a few milliseconds. Individual text characters are detected as Maximally Stable External Region (MSER) and are grouped into lines, before being interpreted using optimal character recognition (OCR). Recognition accuracy is vastly improved through the temporal fusion of text results across consecutive frames.*

Keywords— *TSR, LVQ, SVM, HOG.*

I. INTRODUCTION

Automatic traffic sign detection and recognition is an important part of an advanced driver assistance system. Traffic symbols have several distinguishing features that may be used for their detection and identification. They are designed in specific colors and shapes, with the text or symbol in high contrast to the background. Because traffic signs are generally oriented upright and facing the camera, the amount of rotational and geometric distortion is limited. Information about traffic symbols, such as shape and color can be used to place traffic symbols into specific groups; however, there are several factors that can hinder effective detection and recognition of traffic signs. Road scenes are also generally much cluttered and contain many strong geometric shapes that could easily be misclassified as road signs. Accuracy is a key consideration, because even one misclassified or undetected sign could have an adverse impact on the driver. The various traffic sign boards are illustrated in the figure 1.

Fig. 1. Traffic sign boards

Traffic sign recognition is an important part of a Driver Assistance System (DAS). Traffic signs enhance safety by informing the driver of speed limits, warning him against possible dangers such as slippery roads, imminent road works or pedestrian crossings. Three of the main challenges facing traffic sign detection systems are

- The poor image quality due to low resolution, bad weather conditions or poor illumination,
- The rotation, occlusion and deterioration of the signs,
- The need for are spouse in real-time in a DAS .In this project, we proposed a real-time HOG-based traffic sign detection combined with an image segmentation. The detected candidates are passed on to a SVM classifier to determine the nature of the sign.

The proposed system is accurate at high vehicle speeds, operates under a range of weather conditions, runs at an average speed of 20 frames per second, and recognizes all classes of ideogram-based (non-text) traffic symbols from an online road sign database. Comprehensive comparative results to illustrate the performance of the system are presented. Reliable traffic sign recognition can be considered as a key aspect of driver assistance systems. In this work we deal with the problem of large scale traffic sign recognition where we have to process a wide variety of different traffic sign classes. Our motivations to the problem are driven by the needs of a street inspection company. Cameras are mounted on inspection cars and images of the road scene are taken every four meters while the car moves along. Our goal is to find all traffic signs. The cameras observe the scene from different viewing angles, which means that the traffic signs are more likely to be distorted as it would be the case with frontal views. Our system has to differentiate between visually very

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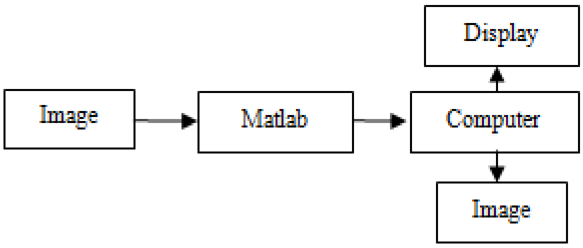
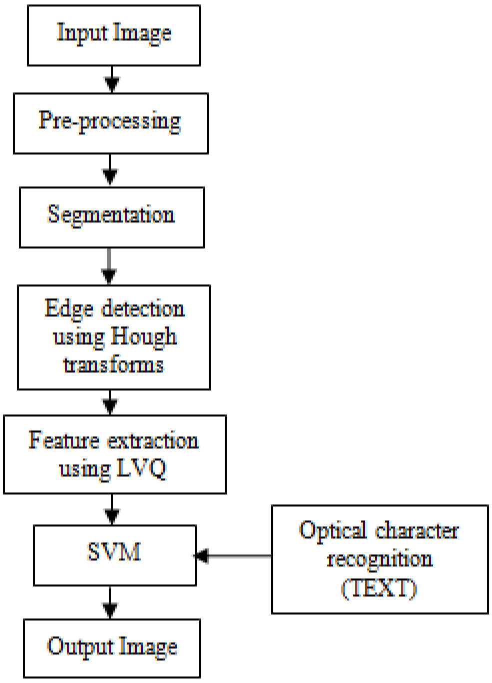
similar traffic sign, for example different speed limitation signs

II. Block Diagram

In this block diagram, the required image to be processed is given as the input to MATLAB. The image is44 pre-processed by using following techniques: resizing, filtering, gray scale conversion, thresholding and edge detection. These techniques are used to remove the noise present in the image. Traffic sign and symbol is detected by using LVQ technique and the output obtained in the form of voice and pop-up message. Text is recognized by using SVM classifier and OCR methods. Recognized text is printed in the text file.



Flow Chart



A. Preprocessing

Removing low-frequency background noise. Normalizing the intensity of the individual particles images removing reflections and masking portions of images. Image pre-processing is the technique of enhancing data images prior to computational processing.

B. Segmentation

Speech segmentation is the process of identifying the boundaries between words, syllables, or phonemes in spoken natural languages. The term applies both to the mental processes used by humans, and to artificial processes of natural language processing.

C. Edge Detection

Process of identifying and locating sharp discontinuities in an image and reduces the amount of data and filters out useless information. The Hough transform is a feature extraction technique used in image analysis, computer vision, and digital image processing [8].The purpose of the technique is to find imperfect instances of objects within a certain class of shapes by a voting procedure.

D. HOG

The histogram of oriented gradients (HOG) is a feature descriptor 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. This method is similar to that of edge orientation histograms, scale-invariant feature transform descriptors, and shape contexts.

E. SVM

SVM stands for Support Vector Machine. SVM Classifier is used to recognize the pattern. A topic of pattern recognition in computer vision is an approach of classification based on contextual information in images. "Contextual" means this approach is focusing on the relationship of the nearby pixels, which is also called neighborhood. The goal of this approach is to classify the images by using the contextual information.

F. Optimal Character Recognition (OCR)

Mechanical or electronic conversion of images of typed, handwritten or printed text into machine-encoded text. It is widely used as a form of data entry from printed paper data records, whether passport documents, bank statements, business cards, mail, printouts of static-data, or any suitable documentation. OCR is a field of research in pattern recognition, artificial intelligence and computer vision.

G. Recognition of Text Using LVQ AND SVM

An automated Road sign detection system captures real time images every two seconds and saves them as JPG format files. The system processes the images to find out whether they contain images of road sign or not. The road sign information of the road signs is detected and extracted from the images. It extracts and classifies the detected sign according to colors of the traffic sign. There were various parameters we could adjust in order to control the overall performance. Some of the most important include the vertexes of the radial division in the chrominance segmentation and the choosing of the thresholds in the luminance segmentation. We had also to choose some thresholds for the area, size, and relation aspect filter. Besides of that, some other parameters were adjusted for the character arrangement into words. After testing with various road sign panels, we have finally chosen the configuration which better results offered. Classification is inherently a discrimination problem. Contrary to the real nature of the problem, the classical approach to classification solves the problem by first estimating the class specific densities and by calculating posterior probabilities of classes, which in turn define the discrimination function [3, 8]. Recent research [10] shows that for problems where discrimination is the main concern, attacking discrimination problems by density estimation may be inferior to more direct approaches. In traffic environments, signs regulate traffic, warn the driver, and command or prohibit certain actions. Real-time and robust automatic traffic sign recognition can support and disburden the driver and thus significantly increase driving safety and comfort. For instance, it can remind the driver of the current speed limit, prevent him from performing inappropriate actions such as entering a one-way street, passing another car in a no passing zone, unwanted speeding etc. Further, it can be integrated into an adaptive cruise control (ACC) for a less stressful driving. In more global context, it can contribute to the scene understanding of traffic context (e.g., if the car is driving in a city or on a freeway). In recent years, the performance of many object detection applications has received a boost by an approach that discriminates object from non-object image patches with help of machine learning techniques. Its main idea is to generate an over-complete set of (up to 100000) efficiently commutable Haar wavelet features, combine them with simple threshold classifiers and utilize Ada Boost to select and weight the most discrimination subset of wavelet features and threshold classifiers. Supported by an efficient wavelet feature computation with help of the so-called integral image and a cascaded classifier setup. The vast majority of published traffic sign recognition approaches utilizes at least two steps, one aiming at detection, the other one at classification, that is, the task of mapping the detected sign image into its semantic category. Regarding the detection problem, several different approaches have been proposed. Among those, a few rely solely on gray-scale data. It shows that [5] employs a template based approach in combination with a distance transform. Since radial symmetry corresponds to a simplified (i.e., fast) circular Hough transform, it is particularly applicable for detecting possible occurrences of circular signs. Hypothesis verification is integrated within the classification. The authors report very fast processing with this method in [6] the authors used template matching for recognition of the road signs in the regions of interest (ROI) in the captured image. The ROI of the road image is determined by expecting the possible location(s) of the sign or by using the color information of the road image. The approach inherits the difficulties of the template matching schemes, namely, the relatively slowness and the need for various shapes for each template to consider different deformations resulted from changes in scale, orientation, rotation, etc. The template matching approach used in [8] doesn’t suffer from the square signs case. However, it still doesn’t respond to strong shape distortion at all in addition to the relatively long time consumed in template matching In [10], the authors used a combination between physics-based approach for color detection and a template matching- based approach for sign recognition. The use of a physics-based approach for detection requires well knowledge of the appropriate physical model and needs to keep in mind the changes in the model parameters to accommodate the natural variations like illumination and lighting conditions. On the other hand, the difficulties of using template matching as mentioned before still exist.

III. Proposed Method

Traffic Sign Recognition is a technology by which a vehicle is able to recognize the traffic signs on the road e.g. "speed limit" or "turn ahead". This paper aims to focus on edge detection and feature extraction based on Hough transformation and HOG respectively. Finally they are trained and tested using classifier and Optical character recognition used for text recognition.

IV. LVQ

Learning Vector Quantization is a supervised classification scheme which was introduced by Kohonen in 1986 (Kohonen, 1986).LVQ is appealing for several reasons: The classifiers are sparse and define a clustering of the data distribution by means of the prototypes. Multi-class problems can be treated by LVQ without modifying need to be replaced, but can simply be ignored for the comparison between prototypes and input data; given a training pattern with missing features, the prototype update only affects the known dimensions. Furthermore, unlike other neural classification schemes like the support vector machine or feed-forward networks, LVQ classifiers do not suffer from a black box character, but are intuitive. The prototypes reflect the characteristic class-specific attributes of the input samples. The Learning Vector Quantization (LVQ) is an algorithm for learning classifiers from labeled data samples. Instead of modeling the class densities, it models the discrimination function defined by the set of labeled codebook vectors and the nearest neighborhood search between the codebook and data.

Learning vector quantization (LVQ) intuitive and simple but powerful classification scheme [4] which is very appealing for several reasons: the method is easy to implement; the complexity of the resulting classifier can be controlled by the user; the classifier can naturally deal with multiclass problems and unlike many alternative neural classification schemes such as feed forward networks and support vector machines, the resulting classifier is human understandable because of the intuitive classification of data points to the class of their closest prototypes. For these reasons, LVQ has been used in a variety of academic and commercial applications such as image analysis, telecommunication, robotics, etc. Original LVQ, however, suffers from several drawbacks such as slow convergence and instable behavior because of which a variety of alternatives have been proposed, as explained e.g. in [5]. Still, there are two major drawbacks of these Methods, which have only recently been tackled. Several proposals for cost functions can be found in the literature, the first one being generalized LVQ. Recently, a generalization of LVQ has been proposed based on the formulation as cost optimization in [10] which allows the incorporating of every differentiable similarity measure. At the same time, it allows easy interpretation of the result because the relevance profile can directly be interpreted as the contribution of the dimensions to the classification [6]. For an adaptive diagonal metric,

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dimensionality independent large margin generalization bounds can be derived. This fact is remarkable since it accompanies the good experimental classification results for high dimensional data by a theoretical counterpart. The same bounds also hold for Kernelized versions, but not for an arbitrary choice of the metric. For supervised classification tasks, however, an explicit metric which takes correlations into account has not yet been proposed. Based on the general framework as presented in [1], we develop an extension of LVQ to an adaptive full matrix which describes a general Euclidean metric and which can account for correlations of any two data dimensions in this article. This algorithm allows for an appropriate scaling and also an appropriate rotation of the data to learn a coordinate system which is optimum for the given classification task. Thereby, the matrix can be chosen as one global matrix, or as individual matrices attached to the prototypes, the latter accounting for local ellipsoidal shapes of the classes. Interestingly, one can derive generalization bounds which are similar to the case of a simple diagonal metric for this more complex case. The second step is to classify each blob's shape. This is done through the method described in [10], where FFT is applied to the signature of blobs.

V. Image Segmentation

In order to avoid low resolution of image and JPEG artifacts in the image, image segmentation is used. Segmentation was used to identify the object of image that we are interested. Luminance and chrominance analysis can help us to discriminate noisy regions. CIELAB is based on the CIE 1931 XYZ color space and it is considered one of the most complete color model used to describe all the gamut of colors visible to the human eye. It has been created to serve as a device independent model and the nonlinear relations for L*, a*, and b* are intended to mimic the logarithmic response of the eye. It is inherently parameter correctly, and thereby it always defines an exact color in contrast to RGB. We have three approaches to do it. The first is Edge detection. The second is to use of threshold. The third is the region-based segmentation.

VI. Thresholding

When the intensity distributions of objects and background pixels are sufficiently distinct, it is possible to use a single (global) threshold applicable over the entire image. The below figure 2 shows the threshold images for symbol 40 with various threshold values

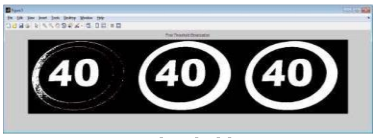

Fig. 2. Threshold image

VII. Histogram of the Image

When working in the LAB color space, we can compute a histogram of the two chromium components in a 3D plot which allows us to analyze graphically how pixels on the background image are distributed. As the fact that we need only the histogram of the image to segment it, segmenting images with Threshold Technique does not involve the spatial information of the images. Therefore, some problem may be caused by noise, blurred edges, or outlier in the image. That is why we say this method is the simplest concept to segment images. It's easy to know where the panel background lies, and thereby, how to apply a suitable segmentation that could allow us to distinguish the objects on the plane. The main consequence of this is that we don't need to know which color the panels are, we just examine the color histogram and then we apply a suitable segmentation. Several techniques have been studied in order to find the best geometrical approach that could define the histogram presents a clear maximum peak around a point which corresponds to the most repeated luminance value of the panel. Taking a threshold above and another one below the luminance histogram maximum, we can decide what background is and what background is not. This can be observed from the example obtained using the image 40 in the figure 3.

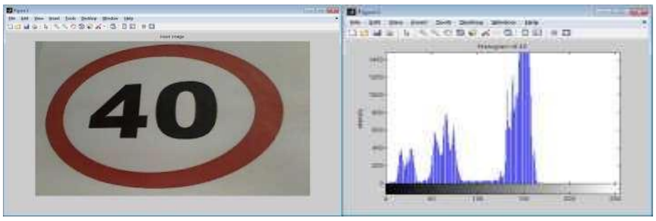

Fig. 3. Histogram

VIII. Basic Technique

The most common approach, quite sensibly consists of two main stages: detection and recognition.

A. Detection

In this part, the color and texture features used to identify the location of the road signs. Considering that the road speed signs are circular and marked with red areas in the edge of the circle so these features are used in the current study to identify the location of the road speed signs. Therefore, first the degree of the circularity of every connected region is in which area is an object area and perimeter is an object perimeter. The regions chosen as candidates and the red color is examined on that region due the red edge, that region is considered as the location of the road sign and is extracted from the main image shows the result from the main image is brought in the colored place of HSV then, its red pixels are detected by Equation, Is Red,

$$S \geq 0.45 \wedge V \geq 0.5 \wedge 0.8 \leq H \leq 0.94$$

Removing Noise and Extracting Numerals, the area that is exploited as a road sign, first probable noising and red color pixel are resolved, then road sign image is complemented till its writing of plate inside is seen such Removing Noise and Extracting Numerals, the area that is exploited as a road sign, first probable noising and red color pixel are resolved, then road sign image is complemented till its writing of plate inside is seen such white violence. Then this area is labeled and composed of R, G and B components is viewed

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Fig. 4. Noise removed extracted road sign

The detection stage identifies the regions of interest and is mostly performed using color segmentation, followed by some form of shape recognition. Detected candidates are then either identified or rejected during the recognition stage using, for example, template matching or some form of classifier such as SVMs [4], [5], or neural networks [2]. The majority of systems make use of color information as a method for segmenting the image [9], [10]. The performance of color-based road sign detection is often reduced in scenes with strong illumination, poor lighting, or adverse weather conditions such as fog. Color models, such as hue–saturation–value (HSV) [9], [6], [19], [10] have been used in an attempt to overcome.

B. Recognition

The complete set of road signs used in our training data are recognized by the system. The recognition stage is used to confirm a candidate region as a traffic sign and classify the exact type of sign. Classifier is used to recognize the pattern. A topic of pattern recognition in computer vision is an approach of classification based on contextual information in images. For the classification of candidate regions, their HOG features are extracted from the image [8], which represent the occurrence of gradient orientations in the image.

C. HOG

The histogram of oriented gradients (HOG) is a feature descriptor used in computer vision and image processing for the purpose of object detection. HOG feature vectors are calculated for each candidate region. A Sobel filter is used to find the horizontal and vertical derivatives and, hence, the magnitude and orientation for each pixel. The technique counts occurrences of gradient orientation in localized portions of an image. This method is similar to that of edge orientation histograms, scale-invariant feature transform descriptors and shape contexts. We find the application of HOG in recognition of traffic symbols, given that traffic symbols are composed of strong geometric shapes and high-contrast edges that encompass a range of orientations. The HOG features are computed on a dense grid of cells using local contrast normalization on overlapping blocks. A nine-bin histogram of unsigned pixel orientations weighted by magnitude is created for each cell.

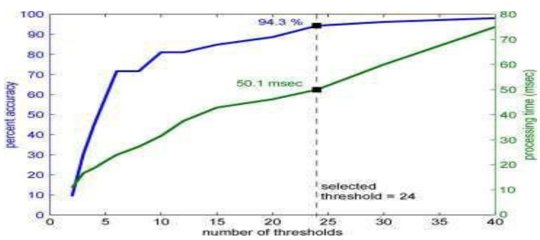

Fig. 5. Chart shows number of thresholds with accuracy

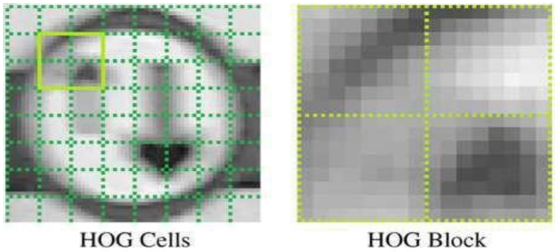

Fig. 6. HOG cells and blocks

D. SVM

SVM is a supervised learning method that constructs a hyper plane to separate data into classes. The “support vectors” are data points that define the maximum margin of the hyper plane. Although SVM is primarily a binary classifier, multi class classification can be achieved by training many values against one binary SVMs. SVM classification is fast, highly accurate, and less prone to over fitting compared to many other classification methods. It is also possible to very quickly train an SVM classifier, which significantly helps in our proposed method. We choose to use this feature for the traffic sign detection due to its scale in variance, local contrast normalization, coarse spatial sampling and fine weighted orientation binning. The unsigned gradients allow for the detection of both static signs as well as dynamic, illuminated signs with a single detector

E. Gray Scale Conversions

The road sign location in this paper are based on gray image, so the main function of the presentment algorithm is to convert color images to gray scale images for the latter operation. A color bitmap is road sign extract in this stage the road sign is extracted and its characters are distinguished. This stage involves road sign detection and probability noise removing for character extracting.

F. Mathematical Morphology

Mathematical morphology is the branch of image processing that argues about shape and appearance of object in images. The erosion and dilation operators are basically operators of mathematical morphology that are used in this part to improve the edge detection image. At this step, first erosion action is applied in the edge detection image. After erosion action on image, the dilation action is done.

(a). Original image (b) Gray scale image
(c). Edge detected image (d). Extracted connected component
Fig. 7. Mathematical morphology

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In our system we computed features based on transit and angel of contour pixels of the images as follows: First we found the bounding box (minimum rectangle containing the numeral) of each input image which is a two-tone image. Then for better result and in dependency of features to size, font and position (invariant to scale and translation). In a normalized image with its bounding box is shown. We extracted the contour of the normalized Image. This work is implemented for still images, for future work we have planned to extend it for road sign detection and recognition in video stream. Also occasionally accuracy decreased when the back ground was so complex, for solving this problem in the future work we will express the method based on edge analysis stage for reducing complexity and solving this problem.

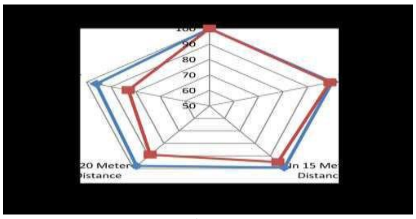

Fig. 8. Quality of proposed approach

High detection rate shows the quality of proposed approach to use in every applications, which are needed a road speed sign detection and recognition stage. Low complexity in computation and time are some of other advantages of the proposed approach. The ROIs are found using the time consuming region growing method and classified by matching their Color Distance Transforms to a template. This matching is not applicable to occluded or rotated signs. In this paper, we adapt the color enhancement stage and improve the classification
Step using a HOG-based SVM detector.

IX. Simulation Result

Symbol Detection

a) Input image

This input image that is captured using the camera and the output is obtained on the MATLAB

Fig. 9. Captured images

b) Resized image

The input image that is obtained is resized in using MATLAB and used for processing

Fig. 10. Resized image

c) Output message

This is the output image which is obtained as a pop up message

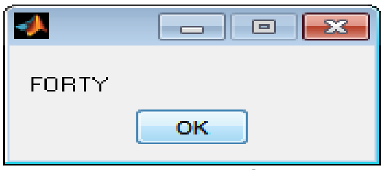

Fig. 11. Message box

d) Overview of symbol detection

The below images shows the overall view of the output of symbol detection. Here the symbol 70 is captured and processed to get the required output.

Fig. 12. overview of symbol detection

e) Sign detection

The input image that is captured using the camera and the output image is obtained on the MATLAB


Fig. 13. Captured image

f) Resized image

The input image that is obtained is resized in using MATLAB and used for processing

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Fig. 14. Resized image

g) Gray scale Image

The resized image is converted into a gray scale image.

Fig. 15. Gray scale converted image

h) Threshold Image

The image that is converted into gray scale is converted into threshold image in MATLAB.

Fig. 16. Threshold image

i) Output Message

This is the output image which is obtained as a pop up message.

Fig. 17. Resized image

X. Voice Output

It is used to alert the driver when the detected sign or symbol is matched with the trained symbol. For this we use the audio file in which we record the sign and symbol names in the form of audio file.wav format which is called when the detected sign is matched with the trained sign or symbol.

A. Text recognition by OCR

This input image that is captured using the camera and the output is obtained on the MATLAB.

Fig. 18. Input image

B. Gray scale image

The image that is resized is converted into a gray scale image (filtered image).

Fig. 19. Gray scale image

C. Edge detected image

The image which is converted into gray scale is then edge detected in order to extract the words from the image.

Fig. 20. Edge detected image

D. Output message

The image which is converted into gray scale is then edge detected in order to extract the words from the image.

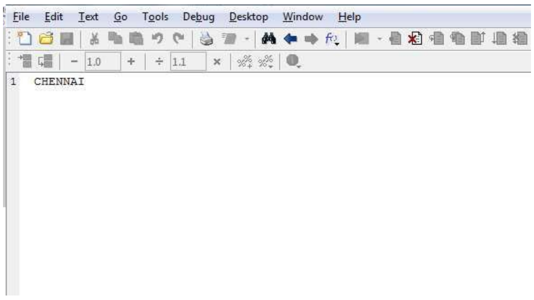

Fig. 21. Output image

E. Text recognition by lookup table method using SVM

The below images shows the overall view of the output of text recognition. Here the text "Hyderabad International Airport" is captured and processed to get the required output.

Fig. 22. Over view of text recognition

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XI. Conclusion

In this project, we implemented road sign and text recognition using Linear Vector Quantization (LVQ) and Support Vector Machine (SVM) models. Approach of text recognition uses OCR algorithm. Results of these both systems give output in the form of pop-up message and voice. The extension work of this system can be implemented with hardware interfacing, so it meets the social need of transport assistance to avoid accidents and intimation of road side boards. Arduino based hardware tools installed in vehicles and make assistance for driver safety. The role of MATLAB simulation part is vital role in this application. Many automated companies makes Simulink with this tool and achieved high interfacing process between nature and human activity.

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