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Modified Vehicle identification system using image processing

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Abstract— **Demand for intelligent systems for vehicle control is increasing in the recent years, to ensure safety and convenience. The rapid increase of on road vehicles and also the rise in human needs have paved way for the same. Numerous intelligent systems were developed for the identification of vehicles. This work is dependent on image processing techniques for vehicle identification. It includes two portions, a descriptor and a classifier. Log Gabor filter descriptors are used for the extraction of features and effective edge detection of the vehicles in the captured frame. This overcomes the flaws in the Gabor descriptors that were previously employed. The objects are classified as vehicle or non-vehicle with an SVM classifier. Number plate extraction is appended to vehicle identification, to improve the relevance of the work. A pre-trained neural network is employed to extract the characters in number plates of identified vehicles.**

***Index Terms*— Log Gabor filters, SVM, Neural Networks.**

I.INTRODUCTION

Vehicle identification systems find high importance in the intelligent traffic systems. The increase in the number of vehicles and the increase in the human population and needs justify the same. Thus, as days pass, the complexity of controlling and identifying vehicles is increasing and much difficult to solve. Intelligent transportation systems find wide application at such scenario since they improve mobility, productivity and foremost the safety.

Techniques for vehicle identification implemented with image processing have high demand today. The grounds are the flexibility, reduced cost and the ease of implementation. The complexity increases since the vehicles are of different shapes, colors size etc. A key to this issue covets with a system employing a descriptor and a classifier. The habitual methods employ generation of hypothesis and further verification [2]. In the former stage, the vehicle portions are pointed from the captured frame. The vehicle portions are found using several features like color [3], edges[4], motion[5] etc. At the later stage, the identified feature sets verify the result. Nowadays, learning based methods find wide application since the processor speeds has increased. Such methods usually classify the objects to two classes, where a bunch of samples are trained for desired features that enable classification. These methods involve the need of descriptors and usual descriptors include the HOG [7][8], PCA[6] etc.

Gabor filters forms such a descriptor which typically uses the statistics like mean and variance for classification of the detected objects [10]-[13]. Their relevance is reflected in the work of Daugman [9], which describes the similarity of the Gabor functions to that of visual system in mammals and hence in human. This has aroused its application including image compression [19], segmentation [20], [21], scanning and retrieval of image data [16], [15], object tracking [24], texture classification [18], [22], and [23] and extracting features for further classification [14], [15], and [25]

Other than these merits, several drawbacks exist associated with bandwidth and information redundancy. These are used with various direction and scales for performing feature extraction. Because of limited bandwidth, several filters are required for wide spectrum coverage. Also, a major Gabor response is low frequency.

This work employs Log Gabor filter descriptor introduced by Field [26], to overcome the disadvantages mentioned above. These have 0 DC components and hence the risk of redundant information in the lower frequency range is avoided. Symmetry is an important feature of this descriptor in log axis in place of linear frequency axis. The equation below, gives its frequency response.

$$LG_{m,n}(f,\theta) = \begin{cases} exp\left\{\dfrac{-\left(log\left(\frac{f}{f_m}\right)\right)^2}{2(log\beta)^2}\right\} exp\left\{\dfrac{-(\theta-\theta_n)}{2\sigma_\theta^2}\right\} & \\ 0 & f=0 \end{cases} \quad (1)$$

II.PROPOSED SYSTEM

The functional block diagram of proposed system is shown below.

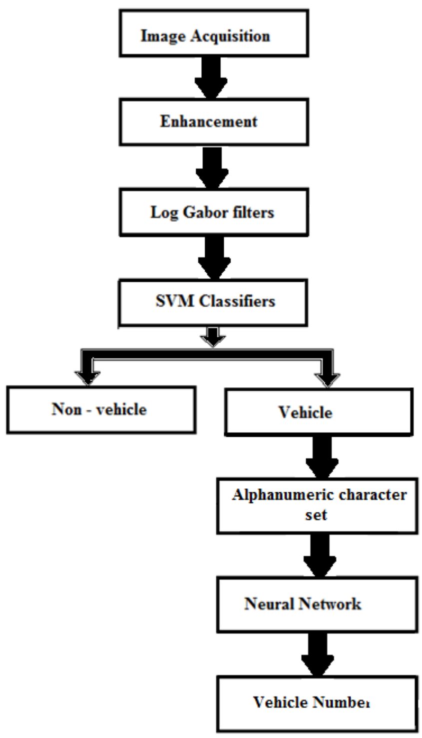

Fig 1.Block Diagram of proposed system

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The method starts with the image collection using a camera on the vehicle dashboard, or on vehicle overhead. The captured images are stored in either .jpeg or .png form. The images were affected with noise as a result of changing illumination, weather factors, vehicle speed etc. Hence, an image enhancement was done prior to the major work. Here I have used the vehicle images taken from the open GTI database. The images include both vehicle and non vehicle images, captured from cameras fixed at front, left, right and farther positions. Fig 2 shows sample images used in this work.

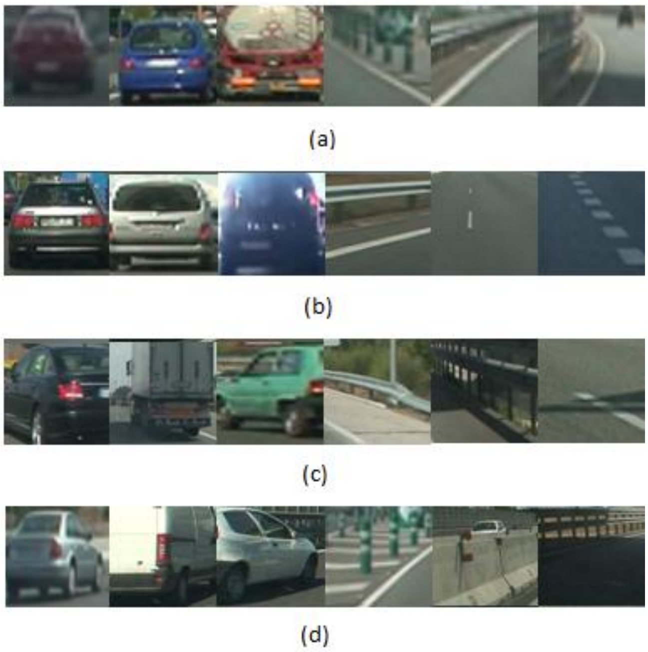

Fig 2: The image samples used for training the descriptor. These images are taken from the open GTI database. Four sets of images (a), (b), (c) and (d) are taken where in the camera position is changed. (a): Far end position, (b): Front end position, (c): Right end position and (d): Left end position

Extracting image features can be made more efficient with the image enhancement. Further the input image in discrete time domain should be converted to frequency domain using DFT. Later it is multiplied with the filter and IDFT. However, the image borders are replicated to bypass artifacts in the processed image.

The statistical moments are calculated from the enhanced image using the equations mentioned below [1].

$$\mu_{(m.n)} = \frac{1}{R.C}\sum_{X}\sum_{Y}\left|J_{(m,n)}(x,y)\right| \qquad (1)$$

$$\sigma_{(m,n)} = \sqrt{\frac{1}{R.C}\sum_{X}\sum_{Y}\left(\left|J_{(m,n)}(x,y)\right| - \mu_{(m,n)}\right)^2} \qquad (2)$$

$$\gamma_{(m,n)} = \frac{1}{R.C}\sum_{X}\sum_{Y}\left(\frac{\left|J_{(m,n)}(x,y)\right| - \mu_{(m,n)}}{\sigma_{m,n}}\right)^3 \qquad (3)$$

This feature set is saved for comparison in the later stage. An SVM is used to perform the grouping. This is a two phase classifier. Here, value 1 and 0 are given to vehicle and non-vehicle groups respectively. The classification to the two groups are done, by analyzing the statistical moments in feature set table values saved earlier. Thus the object in the input image is destined to be vehicle or not.

To read the number plate, this works implements the optical character recognition method. For this, we train the system with a set of characters, including both alphabets and numbers. For the purpose of implementation, only limited numbers of characters were used. This can be enhanced, to localize the output of the system for a particular purpose. The figure below shows the sample set of characters that were used to train the system.

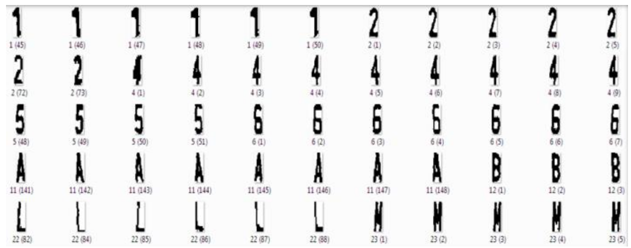

Fig3: Sample character image.

III.EXPERIMENTAL RESULTS

Here the testing is done with the images from the open GTI database set. A group of images were given to the trained system and the objects were identified to be vehicle or not and the result is shown in a tabulated form. The following figure gives the output of a single image that is filtered with Log Gabor filter and the edges are detected.

Fig4: Sample input image.

Fig5: Input image after gray scale conversion

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Fig6: Log Gabor filtered output image.

This step is repeated over multiple images and the features are extracted and tabulated for each. The figures below shows a portion of the feature set table obtained.

Category	Camera Pose	Mean	Sigma	Skewness
Vehicle	Front Pose	3.1662	1.1810	1.3537
Vehicle	Front Pose	3.1866	1.3027	1.3028
Vehicle	Front Pose	3.3965	1.3572	1.3859
Vehicle	Front Pose	3.5473	2.0150	1.2627
Vehicle	Front Pose	3.3567	1.9342	1.7281
Vehicle	Front Pose	3.3748	1.8074	1.3494
Vehicle	Front Pose	3.3544	1.4802	1.8172
Vehicle	Front Pose	3.3881	1.8395	2.4515

Fig7: The feature set for vehicle sample with camera in front position

Category	Camera Pose	Mean	Sigma	Skewness
Non Vehicle	Front Pose	3.6052	0.3045	0.0269
Non Vehicle	Front Pose	2.9086	0.7459	1.3743
Non Vehicle	Front Pose	2.5876	0.7443	0.8422
Non Vehicle	Front Pose	3.0948	0.5401	-0.4850
Non Vehicle	Front Pose	3.8125	1.3459	2.4179
Non Vehicle	Front Pose	3.7975	0.4246	7.1077
Non Vehicle	Front Pose	4.0487	0.9756	2.8729
Non Vehicle	Front Pose	4.3227	1.3092	2.5698

Fig8: The feature set for vehicle sample with camera in front position

After completing the vehicle identification stage, character training is done with neural networks. Black colored alphabets and characters, of different fonts samples are scanned and trained. This step helps to read dark letters in lighter background, similar to that appearing in vehicles. The images in the database are read one by one and saved as a matrix. The training is performed with nntraining tool in MatLab2012. A total of 22 characters, including alphabets and numbers are taken for system training. We have considered 50 samples for each of the characters taken. These are read and stored in a matrix form by repeating a single 50x22 matrix, 50 times. This helps in extracting each features of every single character sample, one after other. In this manner, the images are saved and further, trained with the neural network.

In the verification stage, we read the video sample, which is a sequence of still images. This has been chosen to check the speed of performance of the system. Convert it into frames and each frame image to grey. Further the statistical moments are calculated and saved to data. These images are classified into vehicle and non vehicle groups, using SVM. If the detected frame has a vehicle object, then number extraction is done. The region of interest is selected and the dimensions are stored. The captured frame is cropped and resized to exact dimensions as that of the scanned image patterns. We convert this image to rectangle matrix. Further, scanning is performed in the matrix, to extract the digit and character patterns, using the pre-trained patterns. The patterns are recognized and displayed. The whole process is repeated for each frame captured.

Above 70% of numbers were recognized with this method from the images given. The obtained outputs are shown in the figures below.

Fig9: Detected Number: KL05J8798

Fig10: Detected Number: SAP 729

Fig11: Detected Number: 5RLS

Fig12: Detected Number: No number

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IV.CONCLUSION

This work proposes an advanced vehicle identification system using image processing techniques. This system identifies a vehicle in the captured frame and further reads the number plate. Rather than being simpler, this work offers wide application in areas like automatic parking assistance.

V. FUTURE SCOPE

The system is currently developed considering a limited set of alphanumeric characters for training. This can be enhanced with more font varieties or can be applied in localized vehicle plate identification applications. The system can also be implemented into real time systems.

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