Automated Vehicle Identification System based on Discrete Curvelet Transform for Visual Surveillance and Traffic Monitoring System

N.G.Chitaliya
E & C Engg. Department
S.V.I.T, VASAD
Gujarat, India.

A.I.Trivedi
Electrical Engg. Department
M.S.U, VADODARA
Gujarat, India

ABSTRACT

For identification of vehicles, Classifier is designed. Designing of vehicle classifier using the discrete Curvelet transform via wrapping is proposed in this paper. To increase the efficiency of classifier, 3 class structures designed with respect to the ratio of length and width of the vehicle or person on the road. Each Image is preprocessed with Unsharp filtering which provides edge details. Each sharpen Image is converted into binary image by applying global threshold using otsu's method . Binary images are decomposed using fast discrete Curvelet transform. The Curvelet coefficients from low frequency and high frequency component at different scale and orientations are obtained. The frequency coefficients used to create the feature vector matrix for all images. The Eigen value of the feature matrix is used for dimensionality reduction. The Experiments carried out on different types of vehicle images. The results of the classifier show the efficiency to handle the real time dataset.

Keywords

Discrete Curvelet Transform; Vehicle Classifier, Euclidean Distance; Principal Component Analysis; Feature Extraction; Neural Network

1. INTRODUCTION

Vehicle detection and classification has received a great attention by researchers concerned with visual surveillance and Machine Intelligent application. Vehicle detection task is a complicated due to the interference of illumination and blurriness. These characteristics make some readily available approaches unsuitable.

In surveillance, categorical recognition of road vehicles is of great interest. However vehicles are generally visible with low texure. Surveillance videos are having limited resolution and with degraded quality as it is stored in compressed file. shape-relevant models are enough capable to discriminate between classes. Based on this, an edge-based feature extraction and recognition is designed which is highly repeatable within one class and discriminative enough to separate different classes. Experiments on different dataset shows that the approach outperforms than some state-of-the-art approaches which achieves high recognition rates.

Object detection and classification have been done in different ways. Gupte etc al. [1] uses a background subtraction and tracking updates to identify the vehicle positions in different scene. Kirby and Sirovhich [2] proposed the use of the Principal Component analysis in reducing dimensions and extract featured parts of objects. A concept of Eigen picture was defined to indicate the Eigen functions of the covariance matrix of a set of face images. Turk and Pentland [3] have developed an automated system using Eigen faces with a similar concept to classify images in four different categories, which help to recognize true/false of positive of faces and build new set of image models. Use of Eigen spaces and Support Vector Machine for nighttime detection and classification of vehicles has been mentioned by Thi et al. [4]. S.Zehang, G.Bebis, and R.Miller [6] used PCA based vehicle classification framework. Harkirat S.Sahambi [7] and K.Khorasani used a neural network appearance based 3-D object recognition using Independent component analysis. N.G.Chitaliya and A.I.Trivedi [19] used Wavelet-PCA based feature extraction face recognition.

Several multiscale geometric analysis (MGA) tools were proposed such as Curvelet [9, 10], bandlet and Contourlet [8, 11, 12, 14, 15] etc. Nonsubsampled Contourlet was pioneered by Do and Zhou as the latest MGA tool [11, 12], in 2005. Contourlet transform can effectively represent information than wavelet transform for the images having more directional information with smooth contour [18] due to its properties, viz. directionality and anisotropy. Yan et al. [16] proposed a faced recognition approach based on Contourlet transform. Yang et al. [13] proposed a multisensor image fusion method based on nonsubsampled Contourlet transform. N.G.Chitaliya and A.I.Trivedi [23, 24] used facial feature extraction using discrete Contourlet transform with Euclidean distance classifier and neural network.

1.1 Our Approach

Feature extraction and feature selection are important part for object detection. It should be robust and speedy to deal with the real time system. Performance of the proposed algorithm is increased by performing Unsharp filtering to enhance the edge details. Thresholding is applied to enhanced images to get edge details. Discrete Curvelet Transforms are applied to the training images from the vehicle dataset. Dimensionality reduction can be done by Principal Component Analysis. Finally the created training Feature matrix is matched with the testing image using the Euclidean distance Classifier. This framework can be used for classification of different types like traffic surveillance system, Automated guided Vehicles, Mobile Robotics also.

This paper is organized as follows. Section 2 provides mathematical model implemented on the Vehicle Dataset. Section 3 describes proposed methodology for feature extraction and recognition for the dataset. Section 4 describes Experiment results and discussion for the proposed technique. Finally section 5 concludes with informative remarks and future directions of work.

2. BACKGROUND WORK

2.1 Unsharp Filter, Thresholding and Morphological Operations

The Unsharp filter is a simple sharpening operator that enhances edges and amplifies high frequency components in an image via a procedure which subtracts smoothed version of an image from the original image. Let S is the vehicle dataset having p images for training and q images for testing. Color image $f1(m,n)$ of size $m \times n$ is converted into the gray scale image. Unsharp masking produces an edge image $g(m,n)$ from input image $f1(m,n)$ by performing negative of Laplacian filter $f_{smooth}(m,n)$ as shown in the Figure 1. [26].

$$g(m,n) = f1(m,n) - f_{smooth}(m,n) \quad (1)$$

Convolution has been performed with unsharp mask U and the image $f1(m,n)$ to get the edge image $g(m,n)$.

$$U = \frac{1}{(\alpha+1)}\begin{bmatrix} -\alpha & \alpha-1 & -\alpha \\ \alpha-1 & \alpha+5 & \alpha-1 \\ -\alpha & \alpha-1 & -\alpha \end{bmatrix} \quad (2)$$

The value of α controls the shape of Laplacian function. The range of α is from 0 to 1. Figure 1. (c) shows the result after applying unsharp mask.

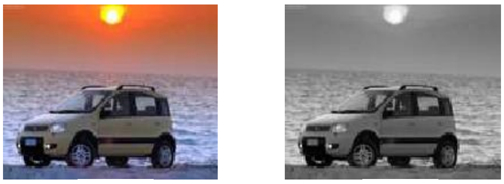
Thresholding has been applied on the Image after applying the unsharp filter. Global Thresholding has been applied using Otsu's method [26]. Otsu's method is one of the better threshold selection methods with respect to uniformity and shape measures. The Otsu method is optimal for thresholding large objects from the background [26].

If the original image is considered as a mask, the marker image

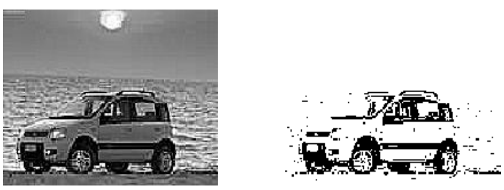
$$f_{mask}(m,n) = \begin{cases} g(m,n) & \text{if (x, y) is on the border of image} \\ & 0 \end{cases} \quad (3)$$

The clear border image can be constructed by

$$f\ (m,n) = g - f_{mask} \quad (4)$$



(a) (b)

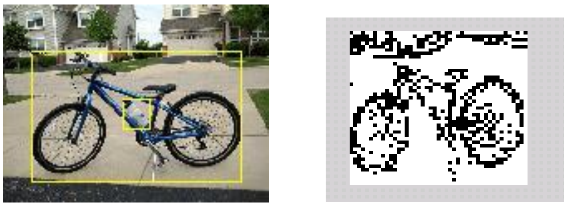


(c) (d)

Figure 1: Preprocessing Stage (a) Original Image (b) Gray Image

(c) Unsharp Filtered Image (d) Image with Preprocessing

Figure 2 shows the preprocessing steps performed on the image. The original image and the resultant image have been shown in the Figure 2. The preprocessed image has been used for the feature extraction purpose. For Feature extraction fast discrete Curvelet Transform via wrapping is used.



(a) (b)

Figure 2: (a) Original image (b) Preprocessed Image

2.2 Discrete Curvelet Transform via Wrapping

Candes and Donoho introduced a new multiscale transform named Curvelet transform which was designed to represent edges and other singularities along curves much more efficiently than traditional transforms. There are two separate Discrete Curvelet Transform (DCT) algorithms introduced by Candes, Donoho and Demanet [9]. The first algorithm is the unequispaced FFT transform (FDCT via USFFT), where the Curvelet coefficients are found by irregularly sampling the Fourier coefficients of an image. The second algorithm is the wrapping transform, which uses a series of translation and a wrap around techniques. The wrapping FDCT is more intuitive and has less computation time. Curvelet transform based on wrapping of Fourier samples takes a 2-D image as input in the form of a Cartesian array f [m, n] such that $0 \le m < M$, $0 \le n < N$ and generated a number of Curvelet coefficients indexed by a scale j, an orientation and two spatial location parameters (k_1, k_2) as output. Discrete Curvelet coefficients can be defined by [9]:

$$cc^D(j,l,k_1,k_2) = \sum_{\substack{0 \le m \le M \\ 0 \le n \le N}} f[m,n]\phi^D_{j,l,k1,k2}[m,n] \quad (5)$$

Wrapping based Curvelet transform is a Multiscale transforms with a pyramid structure consisting of many orientations at each scale. This pyramid structure consists of several sub bands at different scales in the frequency domain. Subbands at high and low frequency levels have different orientations and positions. The Curvelet is non-directional at the coarsest scale and becomes fine like a needle shape element at high scale.

To achieve higher level of efficiency, Curvelet transform is usually implemented in the frequency domain. In the Fourier frequency domain both the Curvelet and the image are transformed and then multiplied. Combination of the frequency response of Curvelet at different scales and orientations gives the frequency tilting that covers whole image in Fourier frequency domain as shown in the Figure 3. The product of multiplication is called a wedge. The product is then inverse Fourier transformed to obtain the Curvelet coefficient.

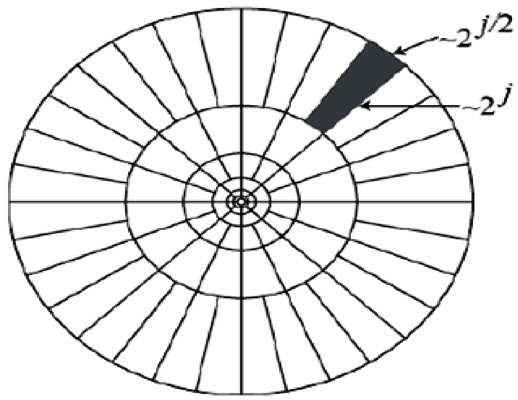


Figure 2 : Curvelet in the Fourier Frequency Domain [9]

Let S is the dataset having P images. Let f (m, n) is a gray level image of size N x N . The Curvelet transform of 1 coarsest level and 8 angles are applied on the face images. In the proposed method, the images are decomposed into single scales using real-valued Curvelet. The number of second coarsest level angles used is 8. This results in 1subbands at finest level (L=1), 8 subbands at second coarsest level (L=2) and again 1 subbands corresponding to last coarsest level (L=3).These resultant Curvelet Coefficients are used to reorder the column vector I_i of the images.

Figure 4: (a) Curvelet without Pre processing. (b) Curvelet with Pre processing

Curvelet images with pre processing and without pre processing are shown in the Figure 4. Image Vector I_i is constructed by converting coefficients to a column vector and then concatenation of all coefficient vectors. Let I = [I_1, I_2, I_3….I_P] is the Feature Image Matrix constructed by Discrete Curvelet Coefficient. Eigen value and Eigen vectors are calculated for I using principal component analysis.

2.3 Principal Component Analysis

All Eigenvectors ν_i and Eigenvalues λ_i of this covariance matrix are derived from the relationship:

$$\lambda_i = \frac{1}{P}\sum_{i=1}^{P}(\nu_i^T \phi_i^T)^2 \qquad (6)$$

Where $\phi_i = I_i - \psi$ and Ψ is the mean value of matrix I.

This set of eigenvectors will have a corresponding Eigenvalues associated with it, with indicates the distribution of this eigenvector in representing whole dataset. Many papers have shown that, only a small set of eigenvectors with top Eigenvalues is enough to build up the whole image characteristic. In our system, we keep Q top eigenvectors where Q represents the number of important features from the vehicle Eigenspace. The value of Eigenspace is represented by

$$\lambda_i = \frac{1}{P}\sum_{i=1}^{P}(\nu_i^T \phi_i^T)^2 \qquad (7)$$

The weight ω_i of each input image vector I_i is calculated from the matrix multiplication of the different ϕ_i with the Eigenspace matrix ε.

$$\omega_i = \phi_i \times \varepsilon \qquad (8)$$

The image weight calculated from the (8), is the projection of an image on the Eigenspace, which indicates relative "weight" of the certainty that whether such image is an image of a Dataset or not.

This transformation has showed how PCA has been used to reduce the original dimension of the dataset (P × m × n) to T^w (Size (P × P)) where generally P << m × n. Thus the dimensions are greatly reduced and the most representative features of the whole dataset still remain within P Eigen features only.

3. METHODOLOGY

The objective of the proposed work is to extract the texture features of an image used for object Identification. Figure 5 illustrates overall process of calculating Curvelet transform and PCA applied to the training images and recognition of testing dataset.

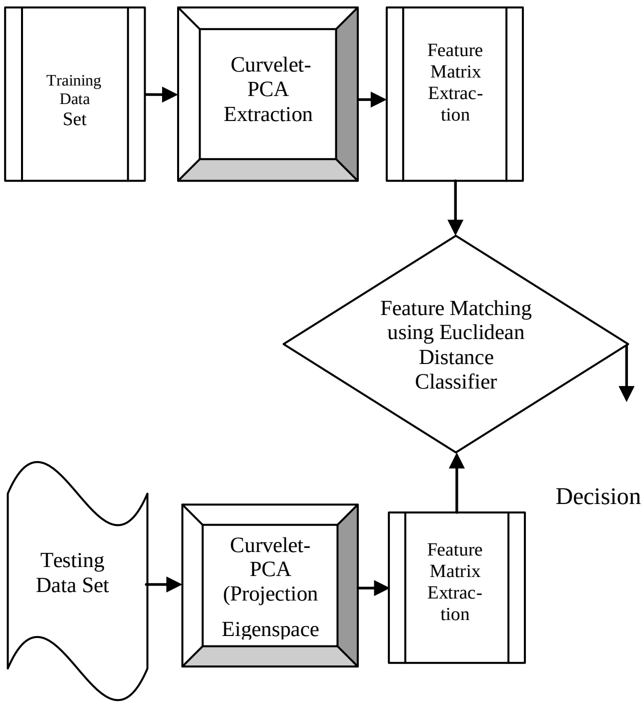


Figure 5: Vehicle Classifier System

3.1 Feature Extraction

Let X_Vehicle and Y_Vehicle represent the training and testing dataset. For gaining the best feature vector from the training dataset, at first, all images are normalized. The novel approach using three Class structures has been proposed to improve the efficiency of vehicle identification. Three classes have been classified according to the length and width ratio. For example as classification of vehicle has been categorized in bus, truck, cycle, scooter, rickshaw etc. If bus or truck is considered from side view, the length to width ratio becomes less than one. These types of vehicles which are rectangular in shapes are considered as class one. Class one vehicles are stored separately as a training set one. The second class of vehicles is considered having length to width ratio greater than one. Pedestrians are considered in this class. Vehicles having equal length and width where ratio is close to one is considered to be class 3. Different feature vectors are calculated for each class.

The following steps are performed for feature extraction.

- According to the ratio of the height and width of the bounding box images extracted from the real time video frames, vehicle images are stored in any of the three class structure.
- RGB images of each class are converted into grey scale image and resize to 64 ×64.
- Filtering is applied to remove noise and sharpening the image. Unsharp filter mask is applied on each image. The result of preprocessing is shown as Figure 2 and Figure 3.
- **Curvelet Transform**: Decompose each image into the Curvelet transform. As a result of performing Curvelet Transform, coefficients of low frequency and high frequency in different scales and angles are obtained. Decomposed coefficients of different sizes are obtained as C_1, $C_{2\text{-}1}$, $C_{2\text{-}2}$…..$C_{n\text{-}1}$….$C_{n\text{-}v}$ where v is the number of angles. These Coefficients are used to reorder the column vector Ii of the images. In our method we use 1 level and 8 angles of decomposition coefficients to construct the feature matrix. All the coefficients are arranged to make a column vector .
- The Feature image matrix I_{class} = [I_1, I_2, I_3 ….. I_P] is constructed from the coefficients column vector Ii. Where i represent the number of image. Three feature image matrix I_{class1} , $I_{class\ 2}$,$I_{class\ 3}$ created for three different cl
- Feature matrix I is transformed to lower dimension subspace Tw using PCA.
- Tw consists of Weight calculated for each image of the respective Dataset.
- Euclidean Classifier is used to measure the distance between the images.

3.2 Feature Matching

Each image transformed to a lower order subspace using Curvelet –PCA using the above steps. Upon observing an unknown test image X according to the ratio of the length and width , the weights are calculated and stored in the vector W_X which is compared with the weights of training set T^w using the Euclidean distance using equation (9). The unknow image X is identified as a label of matching image.

$$De(p,q) = \sqrt[2]{[T^w - w_x]} \tag{9}$$

Weight vector of the unknown image W_X is matched with the training dataset by performing threshold value using the predefine threshold value.

4. EXPERIMENTAL RESULTS

All the algorithms are implemented all the algorithms are implemented in MATLAB 7.0.1, Contourlet Toolbox, Curvelet Toolbox and executed on the Pentium–IV, 3.00GHz CPU with 1 GB RAM. To validate the accuracy of the Vehicle Classifier system, different images of the vehicles from Pascal VOC 2006 dataset have been used [25]. Training dataset consists of 300 images of different subjects. VOC dataset contains 10 different classes of dataset they are bicycle, bus, car, motorbike, cat, cow, dog, horse, sheep and person. Only vehicle dataset from the VOC dataset is used. Some of the vehicle images are downloaded from different commercial websites. Testing dataset consists of 100 real world images. Figure 6 shows the images used for testing purpose. The testing dataset is implemented with unsupervised data not used for training. The results of the recognition of vehicle using discrete Curvelet transforms with Unsharp filtering and without filtering are compared . Figure 7 shows the images used after performing image enhancement step on testing dataset. The testing dataset is considered unsupervised data not used for training.

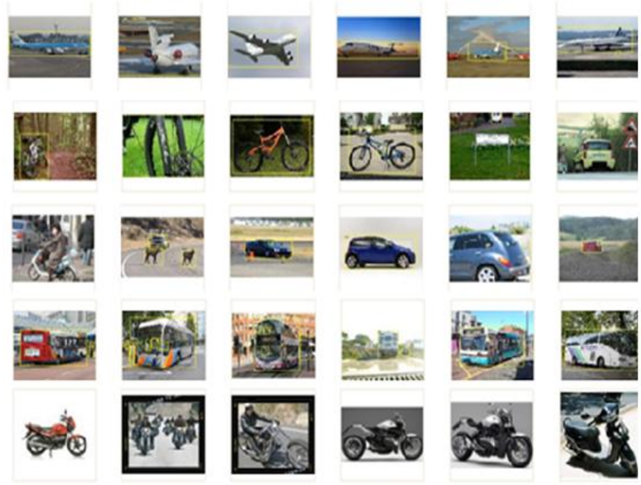


Figure 6 : Vehicle Images from the VOC 2006 Dataset

Figure 7 : Enhanced Image from the VOC 2006 Dataset

Table 1 reports the performance result of Curvelet without applying preprocessing and Curvelet after applying preprocessing steps Table 1 shows different recognition rate of Vehicles and person considering individual training set and combine training set. Table 2 reports the execution time required for pre processing to train the dataset. It does not make much difference in testing time once the features of training set are extracted and stored.

Table 1: Recognition rate of different Vehicle images (in %)

Dataset (JPEG Image)	Original Size of the Image	Feature matrix Created for training	Recogni-tion Rate Curvelet and PCA (in %)	Recogni-tion Rate Preprocessing with Curvelet and PCA (in %)
Vehicle Image	160 x 120	7225 x 300	15	36
Car	160 x 120	7225 x50	20	42
Truck	160 x 120	7225 x30	40	65
Bicycle	160 x 120	7225 x30	22	38
Person	160 x 120	7225 x30	35	40
Vehicle Image (Supervise Learning)	160 x 120	7225 x 300	82	95

Table 2: Comparisions of time required to execute the methods (in second)

Dataset (JPEG Image)	Original Size of the Image	Training Time for Dataset Pre-processing with Curvelet and PCA (second)	Training Time for Dataset with Curvelet and PCA (second)	Testing Time / Image (second)
Vehicle Image	160 x 120	75.80	60.35	1.21

5. CONCLUSIONS

Vehicle Identification system using the Curvelet transform with preprocessing steps applied by the proposed method gives the recognition result almost double than the Curvelet Transform. Feature extraction with PCA is very fast as well as accuracy is very high on recognition rate though it is unsuperviced learning method. For supervision learning set this method gives high recognition rate almost up to 95-97%.The Curvelet transform with preprocessing is very fast and suitable for real time application for visual surveillance and robotics systems. Different run of vehicle images have proved classification using the discrete Curvelet transform as robust method for both in accuracy as well as processing speed. Vehicle classifier is embedded with the tracking system for real time application to traffic monitoring and visual surveillance application.

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