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Hybrid Features based on Zernike Moments and Single Value Decomposition (SVD) for Vehicle Classification System

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***Abstract* - Vehicle identification and classification in a traffic environment containing mixed background is an important application of machine vision. The goal of this paper is to build a classifier for vehicle identification using hybrid features. The proposed work is to identify a "car" from a "non-car" amidst the mixed background taken from University of Illinois at Urbana-Champaign (UIUC) standard database. UIUC image database contains mixer of car and non-car image database. Every image is divided into equal sized small sub-block images. The Zernike features and Singular Value Decomposition (SVD) features are extracted from each sub-block of the image. The features of the vehicle objects are fed to the artificial neural classifier after normalization. The performance of the classifier is compared with various literature methods of similar work. Quantitative evaluation shows improved results of 95.6% compared with the literature papers. A critical evaluation of this approach under the proposed standards is presented.**

Keywords: Neural Classifier, Zernike Moments, Singular Value Decomposition, Hybrid Feature, Vehicle Classification, Normalization.

I. INTRODUCTION

Vehicle identification and classification are necessary components in an artificially intelligent traffic monitoring system. Vehicle identification plays a major role in applications such as vehicle security system, traffic monitoring system, etc [1-3]. It is expected that these artificially intelligent traffic monitoring system venture onto the street of the world, thus requiring identification and classification of car objects commonly found on the road side. In reality, these vehicle classification systems face two types of problem. (i) Vehicles of same category with large variation in appearance. (ii) Vehicles with different viewing conditions like hidden cars, mixed background containing buildings, people, etc. This article makes an attempt on Hybrid feature based on Zernike and Singular Value Decomposition (SVD) for vehicle classification. The derived Zernike and Singular Value Decomposition (SVD) features from various images are normalized and fed to the artificial neural classifier. The vehicle of interest being a car and non-car images are identified and classified.

Vehicle classification is a major area where researchers design computational systems that can identify and classify vehicles automatically. Vehicle classification has been a focus of investigation over last decades [8-10]. Agarwal et al. [7] proposed a new approach to vehicle classification that makes use of a sparse, part-based representation model. This proposed work gives a promising result in the identification of vehicles from a group of non-vehicle category. Nagarajan and Balasubramanie [8] have proposed their work based on wavelet features towards object identification and classification with mixed background. Nagarajan and Balasubramanie [9]-[11] have presented their work based on moment invariant, statistical and spectral features to identify the vehicles with mixed background respectively. Devendran et. al. [12] proposes an SVD based features for classifying the natural scenes in real world environment. Selvan and Ramakrishnan [13] introduced a new work for image texture classification based on wavelet and singular value decomposition models. Roman W. Swiniarski and Larry Hargis [14] describes an application of rough sets model which includes SVD features used for artificial neural-network-based texture images recognition.

II. ZERNIKE MOMENT FEATURES

Zernike moments are a set of complex polynomials $\{V_{nm}(x,y)\}$ which form a complete orthogonal set over the unit disk of $x^2+y^2 \le 1$, in polar coordinates. These polynomials are of the form given in Equation (1).

$$V_{nm}(x,y) = V_{nm}(r,\theta) = R_{nm}(r)\exp(jm\theta) \quad (1)$$

Where n is positive integer or zero and m is an integer subject to constraints $n-|m|$ is even and $|m| \le n$. $r=\sqrt{x^2+y^2}$ is the length of the vector from the origin to the pixel (x,y). $\theta = \arctan(\frac{y}{x})$ is the angle between the vector r and x axis in counter clockwise direction. $R_{nm}(r)$ is a radial polynomial defined in Equation (2).

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 5 Issue 03, March-2016

$$R_{nm}(r)=\sum_{s=0}^{(n-|m|)/2}\frac{(-1)^s(n-s)!}{s!\left[\frac{n+|m|}{2}-s\right]!\left[\frac{n-|m|}{2}-s\right]!}r^{n-2s} \quad (2)$$

The two-dimensional zernike moment of order n with repetition m for function $f(x,y)$ is defined in Equation (3).

$$Z_{nm}=\frac{n+1}{\pi}\iint_{unitdisk} f(x,y)\,V^*_{nm}(x,y)dxdy \quad (3)$$

Where $V^*_{nm}(x,y)=V_{n-m}(x,y)$

To compute the zernike moment of a digital image, It is required to change the integrals with summations as given in the Equation (4).

$$A_{nm}=\frac{n+1}{\pi}\sum_x\sum_y f(x,y)V^*_{nm}(x,y), \quad (4)$$

Where $x^2+y^2\le 1.$

The defined features of zernike moments are only invariant to rotation (R). To achieve scale(S) and translation(T) invariance, the image needs to be normalized first by using the regular zernike moments.

The translation(T) invariance is achieved by translating the original image $f(x,y)$ to $f(x+\bar{x},y+\bar{y})$, where $\bar{x}=\frac{m_{10}}{m_{00}}$ and $\bar{y}=\frac{m_{01}}{m_{00}}$.

In other words, the original image's center is moved to the centroid before the zernike moment's calculation. Scale invariant is achieved by enlarging or reducing each shape so that the 0th regular moment m'_{00} equals to the total number of shape pixels in the image, for a scaled image $f(\alpha x,\alpha y)$, its regular moments $m'_{pq}=\alpha^{p+q+2}m_{pq}$, m_{pq} is the moments of $f(x,y)$.

Being objective is to make $m'_{00}=\beta$, let $\alpha=\sqrt{\frac{\beta}{m_{00}}}$.

Substituting $\alpha=\sqrt{\frac{\beta}{m_{00}}}$ into m'_{00}, $m'_{00}=\alpha^2$, $m_{00}=\beta$ is obtained.

The features of the zernike moments is rotational invariance. If $f(x,y)$ is rotated by an angle α, then the zernike moment Z_{nm} of the rotated image is obtained by Equation (5).

$$Z'_{nm}=Z_{nm}e(-jm\alpha) \quad (5)$$

Thus, the magnitudes of the moments of zernike can be used as RST (Rotation, Scaling & Transformation) invariant image features. 36 zernike features are extracted for every block of an image.

III. SINGULAR VALUE DECOMPOSITION (SVD)

SVD and PCA are the two of the major tools for data analysis, reduction in dimensionality, data processing and compression. SVD works with the principle of data matrix. The m x n data matrix X is decomposed as given in Equation (6).

$$X=USV^T \quad (6)$$

Where U is m x n, V is n x n and S is m x n. The diagonal entries of S are known as singular values. While Eigen decomposition is defined only for square matrices. SVD is defined for rectangular matrices too. SVD is a generalization of Eigen decomposition. The column of U corresponding to the singular values form a basis for the column space of X and those of V form the basis for the row space of X. If the input images form the rows of X, then the columns of V form a basis of that space. These basis vectors can also be ordered according to their "importance" as given by the singular values. If the images are of size (20x20), the feature set is of size (1x20). Hence, 20 features are extracted from every samples using SVD.

IV VEHICLE CLASSIFIER USING NEURAL NETWORKS

Artificial Neural Network (ANN) classifier is built with back-propagation algorithm [10]-[11] that learns to classify a vehicle image as a "car" or "non-car" image. The number of input nodes to the ANN is equal to the dimension of the feature space obtained from the hybrid features. The number of output nodes is usually determined by the application [15] which is 1 (either "Yes/No") where, a threshold value nearer to 1 represents "Car Image" and a value nearer to 0 represents "Non Car Image". The neural classifier is trained with different choices for the number of hidden layer. The final architecture is chosen with single hidden layer shown in Figure 1 that results with better performance.

The connections carry the outputs of a layer to the input of the next layer have a weight associated with them. The node outputs are multiplied by these weights before reaching the inputs of the next layer. The output neuron (7) will be representing the existence of a particular class of object.

International Journal of Engineering Research & Technology (IJERT)
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Vol. 5 Issue 03, March-2016

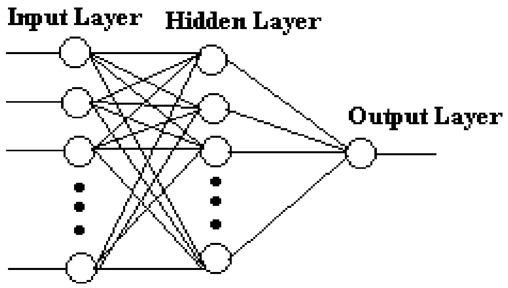

Figure 1. The Three Layered Neural Architecture

$$O^{l}_{j}(k) = f\left(\sum_{m=0}^{N_{l-1}} w^{l}_{jm} O^{l-1}_{m} \right) \qquad (7)$$

V. PROPOSED WORK

This paper addresses the issues to classify vehicles containing side views of cars amidst mixed background. The vehicles of interest to be classified are “car images” and “non-car images” taken from University of Illinois at Urbana-Champaign (UIUC) database. The image data set consists of 1000 real images for training and testing having 500 in each class. The sizes of the images are uniform with the dimension 100x40 pixels. The proposed framework consists of 10 Squared Blocks of size 20x20 each.

Thirty six zernike features are extracted from each block as mentioned in the previous section using Equation (1) to Equation (5). The zernike features are calculated from each squared single block of the sub-image. A total of 360 (36 features x 10 blocks) features are extracted from a single image.

Twenty SVD features are calculated from each single squared block of the sub-image. A total of 200 (20 features x 10 blocks) SVD features are extracted from a single image Equation (6).

Zernike and SVD features put together 560 (360 Zernike + 200 SVD) data are normalization using equation (8). Data normalization returns the deviation of each column of D from its mean normalized by its standard deviation. This is known as the Zscore of D. For a column vector V, Z score is calculated from equation (8). This process improves the performance of the neural classifier. The overall flow of the framework is shown in Figure 2.

$$Z=(V-\text{mean}(V))/\text{std}(V) \qquad (8)$$

VI .IMPLEMENTATION

The proposed method was trained with different kinds of “cars vehicle” against a variety of mixed background of positive class. The negative images with natural scenes, buildings, and road views are also used for training. The training is done with 400 images (200 positive and 200 negative) against all the three methods. The testing of images are done with 1000 images (500 positive and 500 negative) taken from the UIUC image database [17].

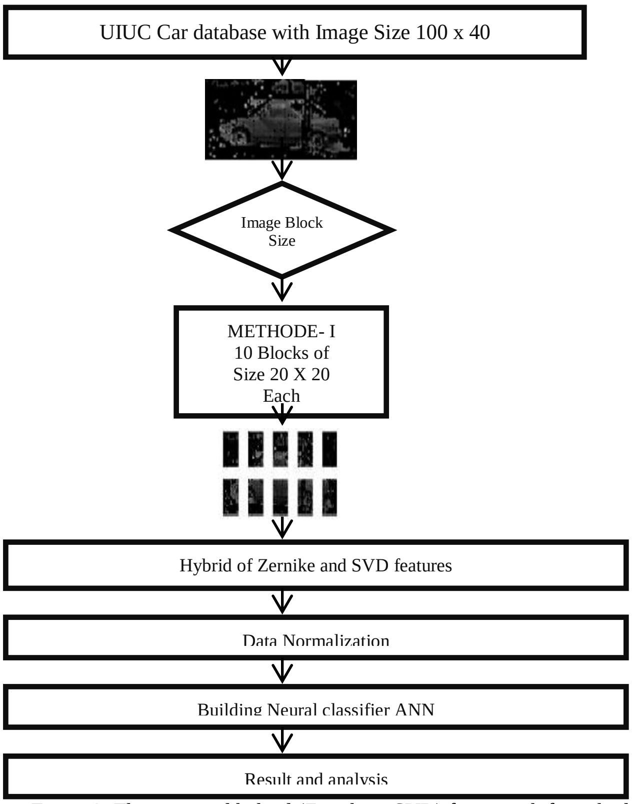

Figure 2. The proposed hybrid (Zernike + SVD) framework for vehicle classification

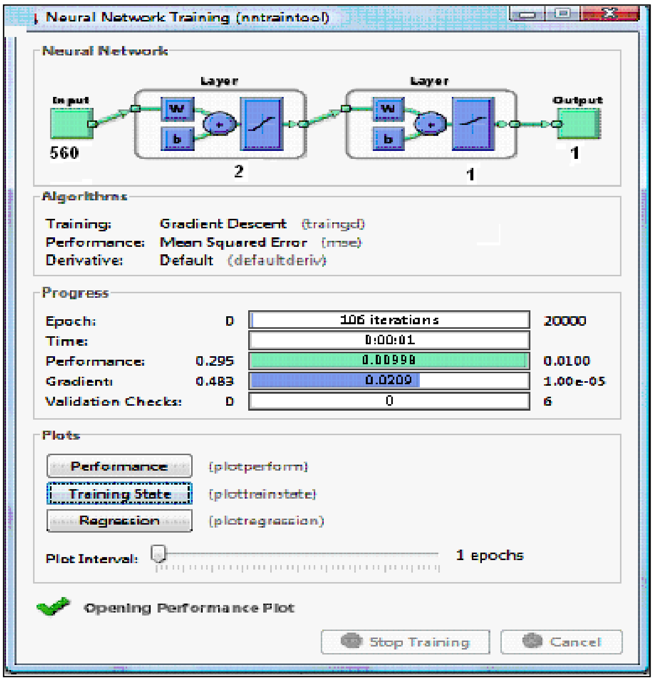

Figure 3. The performance of neural network training for 10 Blocks of size 20x20 each.

The feed-forward network for learning is done for 10 blocks of size 20x20. The input nodes is a hybrid based on Zernike and SVD features of size 560. Optimal structure validation is done with several repeated experiments and the structure given below leads to better results. Thus the optimal structure (Figure 1) of the neural classifier is 560-

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2-1. The Performance graph of the neural classifier is shown in Figure 3.

VII DISCUSSION

In object classification problem, the four quantities of results category are given below.

(i)True Positive (TP): Classify a car image into class of cars.

(ii)True Negative (TN): Misclassify a car image into class of Non-cars.

(iii)False Positive (FP): Classify a non-car image into class of non-cars.

(iv)False Negative (FN): Misclassify a non-car image into class of cars.

The objective of any classification is to maximize the number of correct classification denoted by True Positive Rate (TPR) and False Positive Rate (FPR) where by minimizing the wrong classification denoted by True Negative Rate (TNR) and False Negative Rate (FNR).

$$TPR = \frac{Number\ of\ true\ positive\ (TP)}{Total\ no.of\ positive\ in\ data\ set\ (nP)} \qquad (9)$$

$$TNR = \frac{Number\ of\ true\ negative\ (TN)}{Total\ no.of\ negative\ in\ data\ set\ (nN)} \qquad (10)$$

$$FPR = \frac{Number\ of\ false\ positive\ (FP)}{Total\ no.of\ positive\ in\ data\ set\ (nP)} \qquad (11)$$

$$FNR = \frac{Number\ of\ false\ negative\ (FN)}{Total\ no.of\ negative\ in\ data\ set\ (nF)} \qquad (12)$$

The testing samples are 500 for positive (nP) and 500 for negative (nN) respectively. Most classification algorithm includes a threshold parameter for classification accuracy which can be varied to lie at different trade-off points between correct and false classification. The comparison of experimental methods for the proposed methods is shown in Table I which is obtained with an activation threshold value of 0.7. Classified images of category "car" and "non-car" objects as resultant sample images are shown below in the Figure 4 and Figure 5 respectively.

Figure 4. Sample results of the vehicle classifier of the category car images with mixed background.

It is evident from Table 1 that the proposed method has the highest overall classification accuracy of 95.6% compared to the literature methods [9-11]. The proposed work is compared with the work in the literature shown in Figure 6. The proposed work gives a significant improvement in classification accuracy. The novelty of the proposed work is that the input images are not pre-processed. The mixed backgrounds are not removed using background removal method as found in the literature [10-12].

Figure 5. Sample results of the vehicle classifier of the category non-car images containing trees, road view, bike, wall, buildings and persons.

Threshold for classification : 0.7	Classifying Positive Images (Car Images)		Classifying Negative Images (Non-Car Images)	
	TPR	TNR	**FPR**	FNR
10 Blocks of size 20x20 each	**93.6%**	6.4%	**97.6%**	2.4%
	Overall Classification Accuracy (TPR+FPR)/2 is **95.6%**			

Table 1. Comparison of Experimental Methods

International Journal of Engineering Research & Technology (IJERT)
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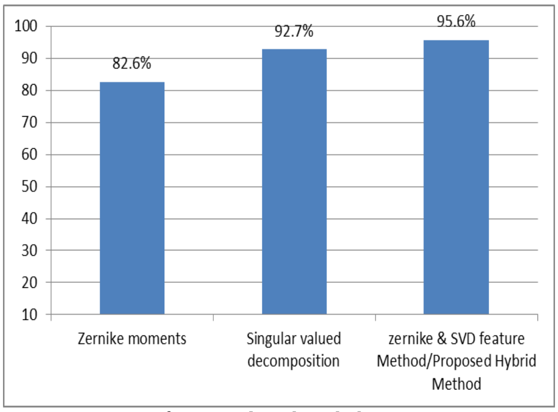

Figure 6. Comparison of proposed work with the previous Literature.

VIII CONCLUSION

Thus an attempt is made to build a system that classifies the vehicle amidst mixed background is achieved to a certain extent. The novelty of this paper is that the input features are the hybrid of two different literatures namely Zernike feature and SVD features. Thus the goal is to classify vehicle objects of real-world images containing side views of "cars" images with mixed background with that of "non-car" images with natural scenes is presented. Further work extension can be made to improve the performance of the classifier system with various hybrid feature extraction methods.

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