Vehicle Classification with Time-Frequency Domain Features using Artificial Neural Networks

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Abstract - *Vehicle classification in a traffic environment with natural background is an important application of machine vision. The goal of this paper is to build a vehicle classifier for vehicle identification with Time and Frequency domain features. The proposed work is to identify a "car" vehicle from "non-car" amidst natural background taken from university of Illinois at Urbana-Champaign (UIUC) standard database. UIUC image database contains images with natural background of car and non-car image database. Every image is divided into equal sized small sub-block images. The Time and Frequency domains 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 93.5% compared with the literature papers. A critical evaluation of this approach under the proposed standards is presented.*

Key Words: Time Domain, Frequency Domain, Vehicle Classification, Artificial Neural Networks, Feature Extraction, Sub-Block Images.

1. INTRODUCTION

Vehicle classification is a necessary component in an intelligent traffic monitoring system. Vehicle classification plays a major role in applications such as vehicle security system for Ambulance, VIP vehicles, Toll gate monitoring system, etc [1-3]. It is expected that the traffic monitoring system venture onto the street of the world, thus requiring classification of car objects found on the road side. In reality, these vehicle classifications face two types of problem. (i) Vehicles of same class with large variation in appearance. (ii) Vehicles with different pose conditions like hidden cars, natural background containing buildings, people, etc. This article makes an attempt on Time and Frequency domain Features for vehicle classification. The derived Time and Frequency domain 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. Vehicles classification has been a focus of investigation over last decades [4-7][10]. Agarwal et al. [8] 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 [9] have proposed their work based on wavelet features towards object identification and classification with natural background. Nagarajan and Balasubramanie [1][2] & [4] have presented their work based on moment invariant, statistical and spectral features to identify the vehicles with natural background respectively. Devendran et. al. [11] proposes an SVD based features for classifying the natural scenes in real world environment. Selvan and Ramakrishnan [12] introduced a new work for image texture classification based on wavelet and singular value decomposition models. Roman W. Swiniarski and Larry Hargis [13] describes an application of rough sets model which includes SVD features used for artificial neural-network-based texture images recognition.

2. TIME DOMAIN (TD) FEATURES

The time domain feature is the feature extracted from the image signal in time representation [18]. Time domain features such as Mean Absolute Value (MAV), Root Mean Square (RMS) and Wavelength (WL) were most popular in pattern recognition due processing speed in classification. MAV is defined as the average of total absolute value of signal [18][19]. It can be calculated as:

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \quad (1)$$

Mean Square is the amplitude modulated Gaussian random process. It can be defines as:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2} \quad (2)$$

Wave Length is an improvement of integrated feature. It is defined as the cumulative length of waveform over the segment. It can be represented as:

$$WL = \sum_{i=1}^{N-1}|x_{i+1} - x_i| \quad (3)$$

3. FREQUENCY DOMAIN (FD) FEATURES

Frequency domain feature illustrates the signal Power Spectrum Density (PSD) in frequency representation [18]. Frequency domain features such as the Mean Frequency (MNF), Median Frequency (MDF) were required more computed time as compared to Time Domain features.

The Mean Frequency is the average frequency at which the sum of product of the power spectrum and the frequency divided by total, it can be expressed as:

$$MNP = \sum_{j=1}^{M} P_j / M \quad \textbf{(4)}$$

Where Pj is the power spectrum and M is the length of PSD. The Median Frequency is defined as follows:

$$MDF = \frac{1}{2}\sum_{j=1}^{M} P_j \quad \textbf{(5)}$$

4. 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 of TD & FD 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 Fig. 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 (6) will be representing the existence of a particular class of object.

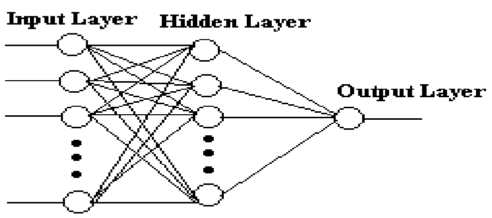

Fig 1. The Three Layered Neural Architecture

$$O_j^l(k) = f\left(\sum_{m=0}^{N\,l-1} w_{jm}^{l} O_m^{l-1}\right) \quad \textbf{(6)}$$

5. PROPOSED WORK

This paper addresses the issues to classify vehicles containing side views of cars amidst natural background. The vehicle 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.

TD and FD features are extracted from each block as mentioned in the previous section using Equation (1) to Equation (5). The TD and FD features are calculated from each squared single block of the sub-image. A total of 50 (5 features x 10 blocks) features are extracted from a single image.

TD and FD features put together 50 data are normalization using equation (7). 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 (7). This process improves the performance of the neural classifier. The overall flow of the framework is shown in Fig 2.

$$Z = (V - \text{mean}(V)) / \text{std}(V) \quad \textbf{(7)}$$

6. IMPLEMENTATION

The proposed method was trained with different kinds of "cars vehicle" against a variety of natural 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].

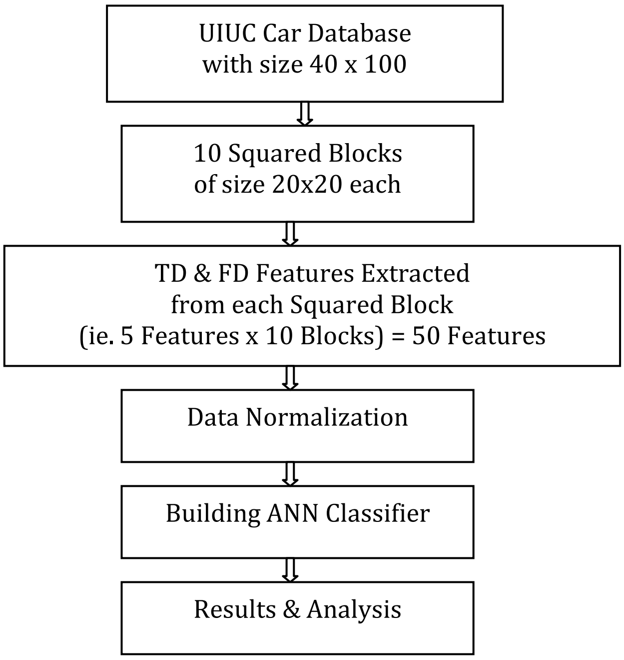

Fig 2. Proposed TD & FD Feature based vehicle classification Framework

The feed-forward network for learning is done for 10 blocks of size 20x20. The input nodes is a TD & FD feature extracted from each block of size 50. 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 50-2-1. The Performance graph of the neural classifier is shown in Fig 3.

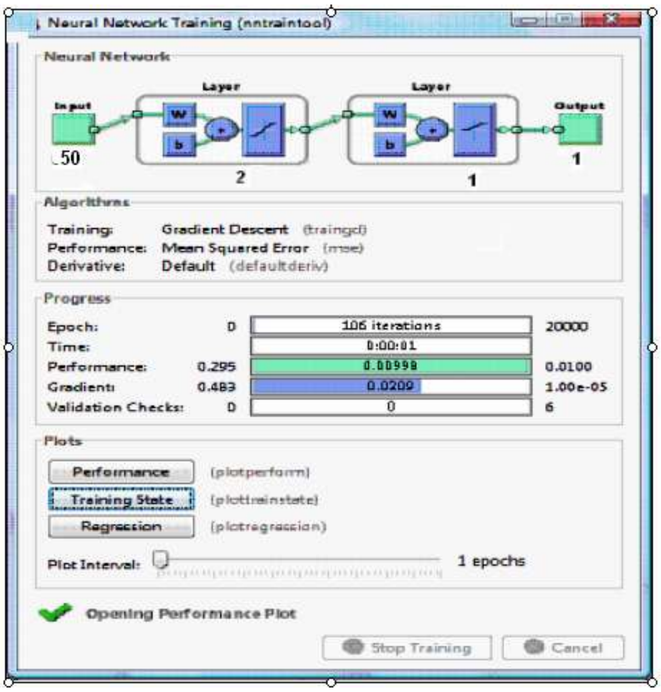

Fig 3. The performance of neural network training for 10 Blocks of size 20x20 each.

7. RESULTS AND 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).

$$TPR = \frac{Number\ of\ true\ positive\ (TP)}{Total\ no.of\ positive\ in\ data\ set\ (nP)} \quad \textbf{(8)}$$

$$TNR = \frac{Number\ of\ true\ negative\ (TN)}{Total\ no.of\ negative\ in\ data\ set\ (nN)} \quad \textbf{(9)}$$

$$FPR = \frac{Number\ of\ false\ positive\ (FP)}{Total\ no.of\ positive\ in\ data\ set\ (nP)} \quad \textbf{(10)}$$

$$FNR = \frac{Number\ of\ \ false\,negative\ \left(FN\right)}{Total\,no.of\ negative\ in\ data\,set\ \left(nF\right)} \quad \textbf{(11)}$$

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 Fig 4 and Fig 5 respectively.

Fig 4. Sample results of the vehicle classifier of the category car images with natural background.

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

It is evident from Table 1 that the proposed method has the highest overall classification accuracy of 93.5% compared to the literature methods [9-11]. The proposed work is compared with the work in the literature shown in Fig 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 natural backgrounds are not removed using background removal method as found in the literature [10-12].

Table 1. Comparison of Experimental Methods

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	**92.4%**	7.6%	**94.6%**	5.4%
	Overall Classification Accuracy (TPR+FPR)/2 is **93.5%**			

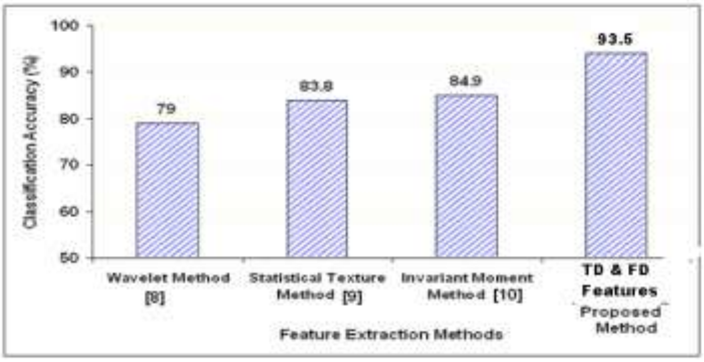

Fig 6. Comparison of proposed work with the previous Literature

8. CONCLUSION

Thus an attempt is made to build a system that classifies the vehicle amidst natural background is achieved to certain extent. The novelty of this paper is that the input features are the hybrid of two different literature namely TD feature and FD features. Thus the goal is to classify vehicle objects of real-world images containing side views of "cars" images with natural 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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