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A Novel Approach in Vehicle Object Classification System with Hybrid of Central and Hu Moment Features using Back Propagation Algorithm

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Abstract

Objectives: To increase the classification accuracy and the performance of the artificial neural network classifier based on hybrid feature extraction. Two different literatures are hybrid together to obtain the better result. **Methods/Analysis:** Identification and classification of vehicle object system are based on a hybrid feature extraction method and neural classifier. Every image is divided in two equal size 10x10 sub-block. From each sub-block of the image, central moment and geometrical moment features are extracted without pre-processing. The extracted feature vector is normalized and combined together. Normalization is done by using ZScore normalization technique. Then the normalized feature vectors are fed to the Artificial Neural Network (ANN) classifier by using Feed Forward Back Propagation Algorithm (FFBPA) for classifying the vehicle object. **Findings**: Illinois at Urbana-Champaign (UICI) standard database is used for vehicle object classification. UIUC Dataset contains 500 car images and 500 non-car images with mixed background. The normalized input feature vectors which have been selected are improving the classification accuracy compared with the previous work. It increases the true categorization ratio and decreases the false categorization ratio. The quantity improved performance result shows 95.3% compared with a similar work of various literature methods. **Applications/Improvements:** This novel method plays a vital role in applications such as vehicle security system, traffic monitoring system etc.

Keywords: Artificial Neural Network, Back Propagation Algorithm, Central Moment Features, Feature Extraction, Geometrical Moment Features, Hybrid Feature, Normalization, Vehicle Classification

1. Introduction

Traffic monitoring system is a necessary component in artificial intelligence. Recognition and categorization of vehicles on the road side traffic are difficult task in the real world. It may correspond to different objects in natural scenes like, different types and classes, humans, and other moving objects such as animals, motorcycles, etc[3]. They also have a Problem with identifying vehicles like, similarity, appearance, viewing conditions, cluttered background and mixed background. Lot of hybrid methods is available for object recognition and classification. Most of the methods are done with the pre-processing stages. The novel work is to make an attempt on a hybrid method without pre-processing. The vehicle of interest is car and non-car image from UIUC standard database for classification.

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This work is based on Invariant Moment Feature extraction method for object classification using artificial neural network classifier[1].The work is done with the central moment feature extraction method for classification using neural classifier[2]. The work is done with neural network classification based noise identification method is presented by isolating some representative noise samples, and extracting their statistical features for noise type identification[3]. The objective of the work is to find and adjust the timing of signals based on the traffic density[4]. This paper presents a forecasting model based on Discrete Wavelet Transform (DWT) and Artificial Neural Network (ANN) for predicting financial time series[5]. The work is classified based on Kohkiloye and Boyer Ahmad province bloggers dataset considering input features of each blogger to the other methods and previously provided algorithms as more optimal[6]. This work overcomes the limitation as the normalized values lie in the same range as the actual range of the attribute[7].

2. Central Moment Features

Let Z_i be a discrete random variable that denotes intensity levels in an image, and let $p(z_i)$, i=0,1,…,L- 1,be the corresponding normalized histogram, where L is the number of possible intensity values[2,3]. A histogram component $p(z_j)$, is an estimate of the probability of occurrence of intensity value z_j, and the histogram may be viewed as an approximation of the intensity probability density function[2,3]. Thus, the central moments are defined in the Equation[2,3].

$$\mu_n = \sum_{i=0}^{L-1} (z_i - m)^n \, p(z_i) \qquad (1)$$

$$m = \sum_{i=0}^{L-1} z_i \; p(z_i) \qquad (2)$$

Since the histogram is assumed to be normalized, the sum of all its components is 1. So, from the preceding.

Equations (1) and (2), $\mu_0 = 1$ and $\mu_1 = 0$ .The second moment defined in Equation (3) is the variance.

$$\mu_2 = \sum_{i=0}^{L-1} (z_i - m)^2 \, p(z_i) \qquad (3)$$

Features extraction is done by computing the mean given in Equation (2) and statistical central moments up to order *n,* of a histogram. The moment of order 0 is always 1, and the order 1 is always 0.

The central moment features[2,3] is described from Equations (4) to (9).

Mean

$$m = \sum_{i=0}^{L-1} z_i \; p(z_i) \qquad (4)$$

Variance

$$\mu_2 = \sum_{i=0}^{L-1} (z_i - m)^2 \, p(z_i) \qquad (5)$$

3rd Central Moment

$$\mu_3 = \sum_{i=0}^{L-1} (z_i - m)^3 \, p(z_i) \qquad (6)$$

4th Central Moment

$$\mu_4 = \sum_{i=0}^{L-1} (z_i - m)^4 \, p(z_i) \qquad (7)$$

5th Central Moment

$$\mu_5 = \sum_{i=0}^{L-1} (z_i - m)^5 \, p(z_i) \qquad (8)$$

6th Central Moment

$$\mu_6 = \sum_{i=0}^{L-1} (z_i - m)^6 \, p(z_i) \qquad (9)$$

Thus six central moment features from Equations from (4) to (9) are calculated for every sub- block size (10x10) of an image.

3. Geometrical/HU Moment Feature

Invariant Moments (IM) are also called Geometric Moment Invariants or Hu Moment Invariants. The Moment invariants[8,9] are useful features of a two-dimensional image as they are invariant to rotation, scaling and to general linear transformations of the image. Moment-based invariants are the region-based image invariant which has been used for pattern features in many applications. The central moments of f(x,y) are defined in Equation[9,10].

$$\mu_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} (x-\bar{x})^p (y-\bar{y})^q f(x,y)\,dxdy \tag{1.1}$$

where, $\bar{x} = m_{10}/m_{00}$ and $\bar{y} = m_{01}/m_{00}$ which are the centroid of the images.m_{01} and m_{10} are moments with respect to x-axis and y-axis respectively. M_{00} is the mass of the object[9,10]. The central moments are computed using the centroid of the image. Based on normalized central moments[11,12], the following seven invariants have been derived (Hu 1962)[13,14].

$$\phi_1 = \eta_{20} + \eta_{02} \tag{1.2}$$

$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \tag{1.3}$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \tag{1.4}$$

$$\phi_4 = (\eta_{30} - \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \tag{1.5}$$

$$\begin{aligned}\phi_5 &= (\eta_{30} - 3\eta_{12})^2(\eta_{30}+\eta_{12})[(\eta_{30}+\eta_{12})^2 - 3(\eta_{21}+\eta_{03})^2] \\ &+ (3\eta_{21}-\eta_{03})(\eta_{21}+\eta_{03})[3(\eta_{30}+\eta_{12})^2 - (\eta_{21}+\eta_{03})^2]\end{aligned} \tag{1.6}$$

$$\begin{aligned}\phi_6 &= (\eta_{20} - \eta_{02})[(\eta_{30} - \eta_{12})^2 - (\eta_{21}+\eta_{03})^2] \\ &+ 4\eta_{11}(\eta_{30}+\eta_{12})(\eta_{21}+\eta_{03})\end{aligned} \tag{1.7}$$

$$\begin{aligned}\phi_7 &= (3\eta_{21} - \eta_{03})(\eta_{30}+\eta_{12})[(\eta_{30}+\eta_{12})^2 - 3(\eta_{21}+\eta_{03})^2] \\ &+ (3\eta_{21}-\eta_{30})(\eta_{21}+\eta_{03})[3(\eta_{30}+\eta_{12})^2 - (\eta_{21}+\mu_{03})^2]\end{aligned} \tag{1.8}$$

From each single sub-block of size (10x10) an image, seven invariant moment measures are calculated. Depending on the size of the sub-block, feature vector varies.

4. Vehicle Classifier using Neural Networks

The feed forward back-propagation algorithm[15,16] is used for training the Artificial Neural Network classifier that learns to classify a vehicle object as a car or non-car image. The extracted feature vectors are fed to the neural classifier. The output of the neural classifier target is fixed at 1(either ON/OFF) and the threshold value is also fixed at 0.7. The output of the classifier is nearer to 1 or greater than the threshold value represents car image and output nearer to 0 and less than the threshold value represents non-car image.

In Artificial Neural Network, there are three layers of 1. Input Layer 2. Hidden Layer 3. Output Layer. The 130 feature vectors are fed to the input layer. The given input features are multiplied with the weights which are associated with them and produce the output. These outputs are taken as an input for the next layer called hidden layer. The input of the hidden layers is multiplied with the weights which are associated with them and produce the output. Same process continued with the number of hidden layers used for the work. Then hidden layer produces the output. This output is depending on the activation function, which will classify the vehicle object as car or non-car. The weights of the hidden units will change till the target output is achieved. This process will be repeated up to the number of images is given for the testing. The existence of a particular class will be reflected of the given output unit in equation (1.9). The optimal structure (Figure 1) of the neural network classifier is 130-2-1.

$$O_j^l(k) = f\left(\sum_{m=0}^{Nl-1} w_{jn}^l O_m^{l-1}\right) \tag{1.9}$$

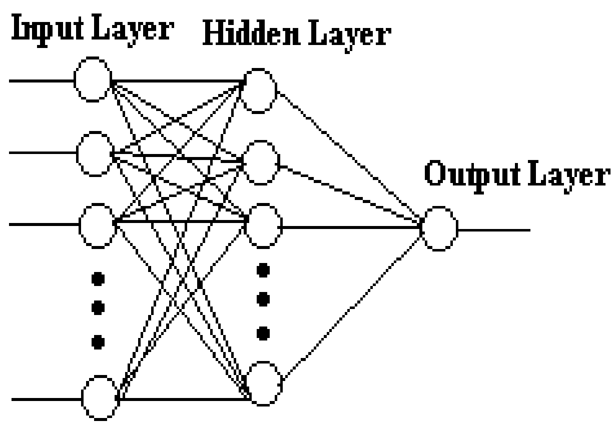

Figure 1. The optimal structure of artificial neural network.

5. Proposed Work

The proposed method is to combine the two different literatures to increase the performance of the neural classifier and increase the classification accuracy. The idea is to classify side views of car or non-car images with a mixed background. The work uses UIUC standard car database. Every image is divided in to10 sub-blocks with equal size. Hybrid feature extraction is done by using central and geometrical moment features without pre-processing. The extracted feature vector is fed to the neural classifier for classification. The feed forward Back Propagation algorithm [FFBPA] is used to train ANN for classification.

Six Central Moment features are extracted from each block from Equation (4) to Equation (9). The central moment features are calculated from each squared single block of the sub-image. A total of 60 (6 features x 10 blocks) features are extracted from a single image.

Seven invariant geometrical moment features are extracted from each block from Equation (1.2) to Equation (1.8). The geometrical moment features are calculated from each squared single block of the sub-image. A total of 70 (7 features x 10 blocks) features are extracted from a single image.

Central moment features and Geometrical moment features are combined together to form 130 features (60 Central Moment Features + 70 Geometrical moment features). These data are normalized using ZScore normalization technique Equation (2.0) in order to improve the process performance of the neural classifier.

The proposed work of the hybrid method (Central and Geometric Moment) framework is in Figure 2.

$$Z = (V - \text{mean}\ (V)) / \text{STD}\ (V) \tag{2.0}$$

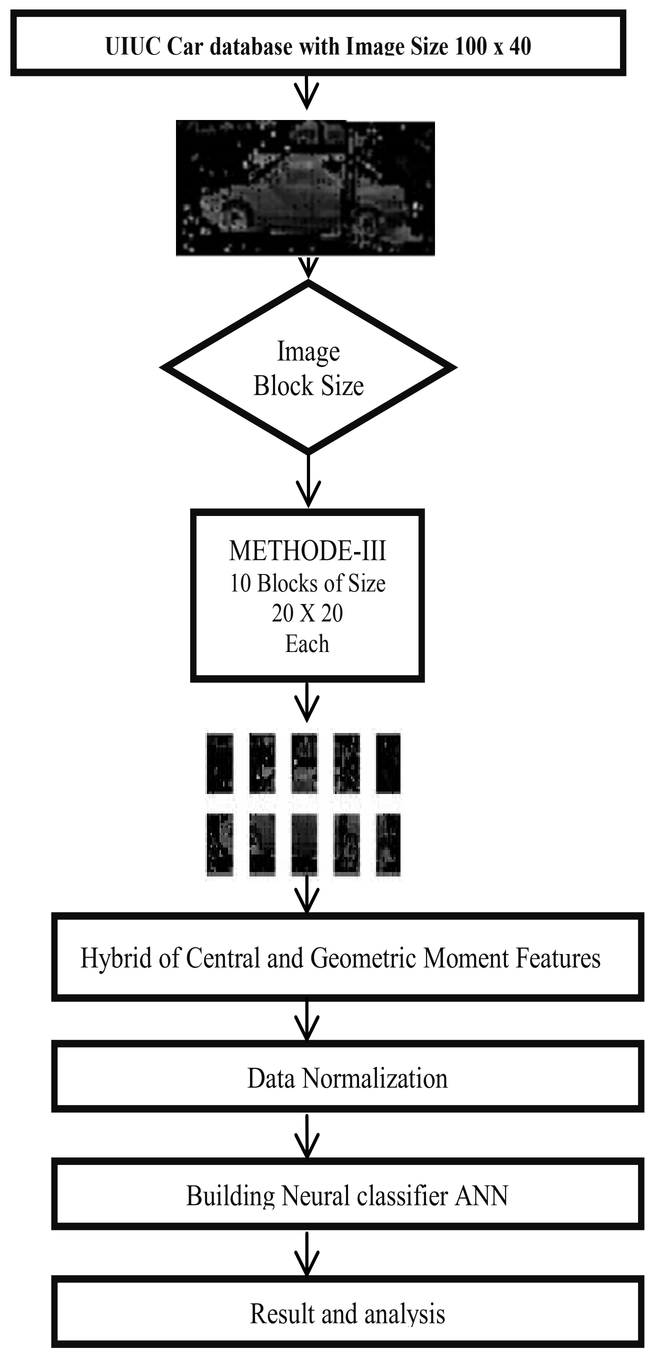

Figure 2. The proposed hybrid (Central and Geometric Moment) framework.

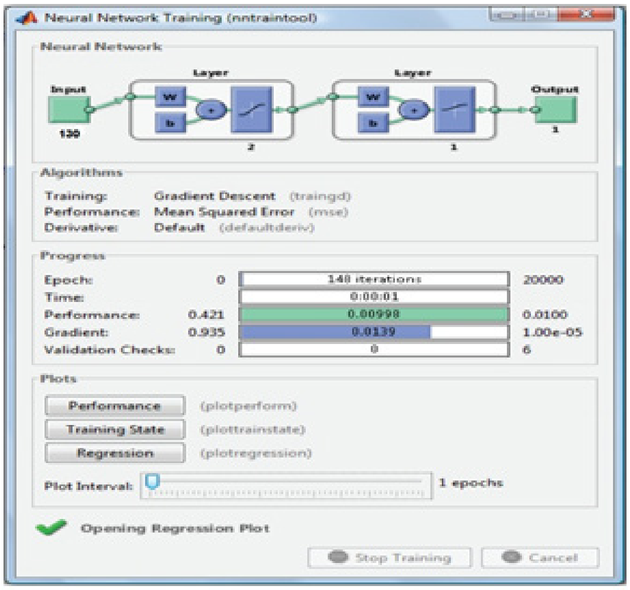

Figure 3. The performance of neural network training.

The feed-forward network for learning is done for 10 blocks of size 20x20. Input values 130 are derived from the central and geometrical moment feature of image size(100x40). Several repeated experiments have been done to achieve the better result. The 130-2-1 is the optimal structure of the ANN classifier. The ANN classifier of performance graph is shown in Figure 3.

6. Discussion

Based on, these four quantities the vehicle classification problem results are categories[17]

(i)True Positive Image Ratio (TPIR) : Classify a vehicle car image into vehicle car class.

(ii)True Negative Image Ratio (TNIR) : Misclassify a vehicle car image into non-vehicle car class.

(iii)False Positive Image Ratio (FPIR) : Classify a non-vehicle car image into non-vehicle car class.

(iv)False Negative Image Ratio (FNIR) : Misclassify a non-vehicle car image into vehicle car class.

The goal of Vehicle classification problem is to maximize the number of correct classification denoted by True Positive Image Ratio (TPIR) and False Positive Image Ratio (FPIR) by where minimizing the wrong classification denoted by True Negative Image Ratio (TNIR) and False Negative Image Ratio (FNIR).

$$TPIR = \frac{Number\ of\ true\ positive\ (TP)}{Total\ \ no.of\ \ positive\ in\ data\ set\ \ (nP)} \tag{1.1}$$

$$TNIR = \frac{Number\ of\ true\ negative\ (TN)}{Total\ no.of\ \ negative\ \ in\ \ data\ set\ \ (nN)} \tag{1.2}$$

$$FPIR = \frac{Number\ of\ \ false\ positive\ (FP)}{Total\ no.of\ \ positive\ \ in\ \ data\ set\ \ (nP)} \tag{1.3}$$

$$FNIR = \frac{Number\ of\ \ false\ negative\ (FN)}{Total\ no.of\ \ negative\ \ in\ \ data\ set\ \ (nF)} \tag{1.4}$$

For the experiment, totally 1000 images are taken, from that 500 positive car images and 500 negative non-car images from UIUC standard database[18]. Based on the feed forward Back propagation algorithm[15,16], a threshold parameter is fixed and used for identifying correct and wrong classification. The result is achieved with an active threshold value of 0.7.

It is evident from Table 1 that the proposed method has improved overall classification accuracy of **95.3%** compared to the literature methods. The work proposed is compared with the work in the literature shown in Figure 4. 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.

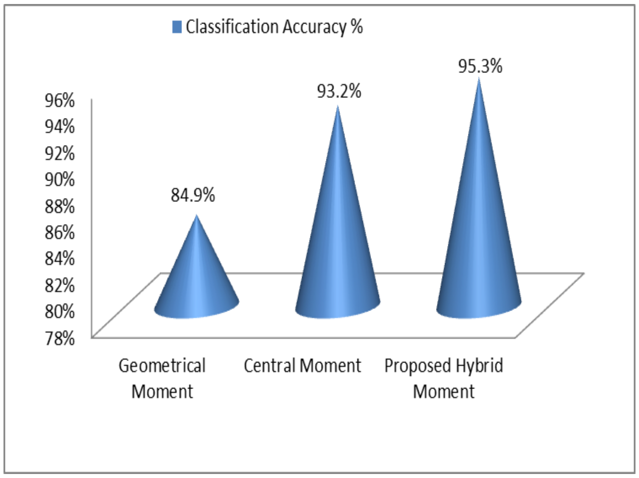

Figure 4. Comparison of proposed work with the literature.

Table 1. Results of experimental methods

Threshold for classification : 0.7	Classifying Positive Images (Car Images)		Classifying Negative Images (Non-Car Images)	
	TPIR	TNIR	**FPIR**	FNIR
10 Blocks of size 20x20 each	**96.2%**	3.8%	**94.4%**	5.6%
	Overall Classification Accuracy (TPR+FPR)/2 is **95.3%**			

7. Conclusion

To achieve the desired result, attempt is made in this research is to build a best classifier that classifies the vehicle image with a mixed background. The novelty of this work is that the normalized input feature vectors are the hybrid of two different literatures namely central and geometrical moment is combined together without pre-processing. The goal of this research is to increase the classification accuracy and the performance of the classifier based on the hybrid feature extraction method. Further work can be done to improve the performance of the classifier and classification accuracy with various hybrid feature extraction methods.

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