Wavelet - Based Classification of Outdoor Natural Scenes by Resilient Neural Network

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***Abstract*—**Natural outdoor scene classification is active and promising research area around the globe. In this study, the classification is carried out in two phases. In the first phase, the features are extracted from the images by wavelet decomposition method and stored in a database as feature vectors. In the second phase, the neural classifiers such as back-propagation neural network (BPNN) and resilient back-propagation neural network (RPNN) are employed for the classification of scenes. Four hundred color images are considered from MIT database of two classes as forest and street. A comparative study has been carried out on the performance of the two neural classifiers BPNN and RPNN on the increasing number of test samples. RPNN showed better classification results compared to BPNN on the large test samples.

***Keywords*—**BPNN, Classification, Feature extraction, RPNN, Wavelet.

I. Introduction

THE classification of outdoor natural images is an important area of research in the field of computer vision. The problem is that each scene image differs from others in content of same class such as mountain, forest, coast, street etc. The illumination differences are more in the scene and hence to model is difficult. The researchers have proposed methods in the past with varying degree of success depending on the choice of classifiers, features, type of training and test data and semantic knowledge for automatic classification of scenes as indoor or outdoor [2]. The classification of scene has applications in content based image video retrieval from archives [9], [11], [22], robot navigation [24], digital photography [13] etc. The wavelet transforms [4], [6], [12], [17] are popular and attracted the scientists to apply effectively in the pattern recognition tasks. Natural outdoor scene classification is solved by extraction of information from the images using wavelets and decision by the neural networks [10]. Artificial neural networks techniques are very popular, robust and well-known used to approximate real, discrete and vector-valued functions from examples [15]. The networks are powerful methods that can predict for not only the data presented to it during the training phase but also the unseen data not present in the training phase.

In this study, the back-propagation neural network (BPNN) [10], [25], [26] and resilient back-propagation neural network (RPNN) based networks are employed as classifiers to classify the images feature vectors [21]. The BPNN usually converges slowly and tends to get trapped in local minima easily compared to resilient back-propagation (neural network RPNN) for the present work. The RPNN performance is measured in terms of accuracy and convergence speed with respect to training parameters and applied in many applications [3], [14], [16], [18]-[20]. A single image can be considered as two-class classification problem such that the classifier must decide it if it belongs to the forest or street class. The scene recognition problem consists in matching the test image against a database. Despite the work done by the researchers [4], [6], [10], [12], [23], [24], the natural outdoor scene classification is still a challenging problem. The primary concern in the problem is the selection of appropriate feature detection methods used for classification purpose.

The natural outdoor image is set to be a collection of arbitrary shape, texture and colors and each image differ from one another in this respect. The feature set is extracted from the images and the length of each feature vector is kept constant in this work. The aim of this paper is to make a comparative study on neural classifiers trained on simple methods of feature extraction from images and classify the test images by feedforward neural networks trained with back propagation and resilient propagation algorithms. The recognition system consists of five modules: feature extraction, data preparation, experiments: training on different neural classifiers and performance evaluation on test dataset and conclusion. The feature extraction process is described in Section II. Methodology adopted is mentioned in Sections III. Section IV describes the experiments conducted and results obtained for the given dataset. The conclusion is given in Section V.

II. Feature Extraction

The extraction of meaningful information from the image is taken into account by using wavelet decomposition method. In order to extract the features of the scene, 2-D wavelet transforms db1 is used to decompose the image of size P x Q into four sub-bands, namely the low-low, low-high, high-low and high-high (LL, LH, HL, HH) sub-bands respectively. The wavelet decomposition process can be recursively applied to the sub-band (LL) only to get decomposition values at the next level. The process of decomposition was repeated n times to an image and the decomposed coefficients of all four sub-bands are horizontally concatenated to form a k-dimensions data. We use these wavelet coefficients as features for the classification purpose. The feature vector is normalized by

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zero mean method. The method was applied to rest of the images to obtain feature vectors. The flowchart diagram of the process is shown in Fig. 1. The features represent the important characteristics of each image for a particular class.

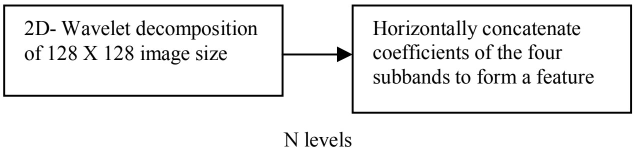

Fig. 1 The feature vector obtained by 2d-wavelet decomposition

III. Methodology Adopted

The proposed methodology consists of classifying the outdoor scenes of forest and street into respective classes. The features are extracted from the images by wavelet decomposition method. In our study, a multilevel (n-level) 2D-DWT is considered for decomposition of the image of size P x Q. After five levels of decomposition, we obtain 2x2 sized approximations from P x Q size input image. Two different neural network training algorithms, back-propagation and resilient back-propagation are considered for the present study. The extracted features are randomly selected without overlapping to form the training and test datasets for the neural classifiers. Once the networks are trained properly on the predefined goal, the unseen test datasets are presented to them to view which algorithm produces better classification results and has faster training for the application under consideration. The goal is set to 0.001 for the convergence of the networks. The complete procedure is demonstrated in the flow diagram in Fig. 2. The test datasets are divided into four subgroups with increasing number of test samples. The performance of the classifiers is evaluated on correctly classifying the test sets into respective classes.

IV. Experimental Results

The proposed classification method is tested on benchmark MIT [5] natural scene classification database using Matlab [7] software on INTEL XEON E5506 QUAD 2.13 GHZ core processor machine with Windows XP. Some of the sample images of the forest and street classes were shown in Figs. 3 (a) and (b). It was considered that the images were free from noises hence no noise removal method was adopted.

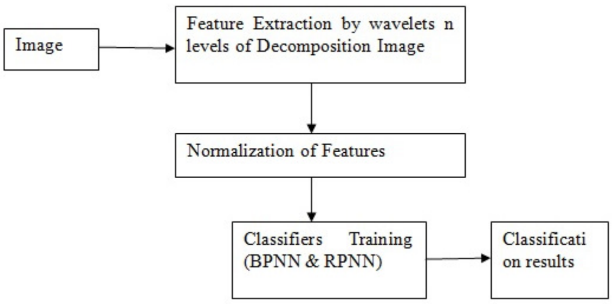

Fig. 2 The complete flowchart of the proposed method

Fig. 3 (a) Sample Forest Images

Fig. 3 (b) Sample Street Images

The four hundred images of two classes (forest and street) were considered for the simulation work. Two hundred images of each class were downloaded from the benchmark dataset as mentioned above. The images were resized to 128x128. The wavelet decomposition was applied to the given image. The recursive level (n) was set to 5 to obtain the coefficients of four sub-bands of wavelet transform. These coefficients of four sub-bands were horizontally concatenated to form feature vectors of 16 dimensions in length. The same procedure is applied to the rest of the images to obtain feature vectors. The extracted features were normalized across the dataset.

The dataset was divided into two groups: training and testing. In the training set, two hundred feature vectors from the entire data set were selected for training the two neural classifiers: BPNN and RPNN. BPNN and RPNN used for the classification have two hidden layers apart from one input and an output layer each as shown in the Fig. 4. The hidden layer and output layer neurons are nonlinear functions neurons. The networks are feedforward in architecture. Two different networks were trained and tested as mentioned in [1]. Classification accuracy is evaluated by accurately finding the number of correctly classified test images divided by the total number of test images presented as discussed in [8].

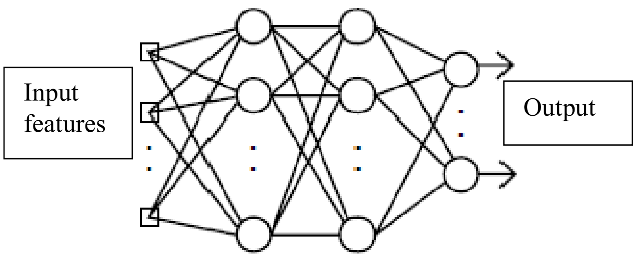

Fig. 4 The diagram of feedforward neural classifier having two hidden layer

The test set was divided into four sets having 50, 100, 150 and 200 feature vectors (25, 50, 75 and 100 images from each class) respectively. After the successful training of BPNN and RPNN at one time on 200 feature vectors from two classes for once, the neural networks were tested with test datasets. Four experiments were carried out to investigate the performances of classifiers on proposed feature extraction method. The test dataset was divided into four sets. The datasets consist of 50, 100, 150 and 200 feature vectors (25, 50, 75 and 100 images from each class) respectively. The experiments were listed below.

Experiment I: The trained networks were tested with 50 feature vectors (25 from each class). BPNN classified 90% correctly compared to 76% by RPNN.

Experiment II: 100 feature vectors were used to test the performance of the classifiers. The correct classification results of 80% and & 75% were reported by BPNN and RPNN respectively.

Experiment III: In this experiment, 150 feature vectors were used to test the performance of the classifiers. 72% and 74.67% correctly classified the samples by BPNN and RPNN respectively.

Experiment IV: For this experiment, 200 feature vectors were used to test the efficiency of classifiers. It is found out that 66% and 73% samples were classified correctly by BPNN and RPNN.

Tables I and II predicted the parameters and performance of the proposed method with different combinations of test datasets. The BPNN performed better with the small test data but fails to give good results in large test data whereas RPNN showed better performance on large test data compared to small one. It is observed that classification rate by BPNN was high compared to RPNN on the least number of test data samples. With the increase of test samples, the RPNN classification performance was better compared to BPNN. The performance of BPNN degraded by 26% from experiments I to IV whereas RPNN came down to 3% from experiments I to IV. RPNN classification performance was consistent compared to BPNN and it took less time to train the network compared to BPNN. A comparative result of two classifiers was shown in Fig. 5.

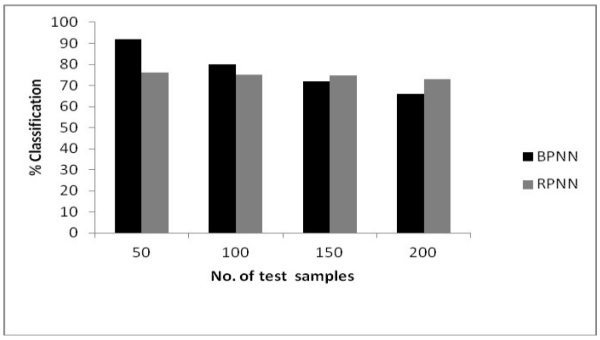

Fig. 5 A Classification comparision in between BPNN and RPNN

TABLE I
THE PARAMETERS AND NET ARCHITECTURES CONSIDERED DURING THE EXPERIMENTS

No. of Features	Goal	Net Architecture	CPU time taken to train the network
16	0.001	BPNN 16:2118:2	73 secs
		RPNN 16:32:28:2	01secs

TABLE II
CLASSIFICATION PERFORMANCES OF NEURAL CLASSIFIERS IN % ON VARYING TEST SAMPLES

Training Images	200			
Testing Images	50	100	150	200
BPNN	92	80	72	66
RPNN	76	75	74.67	73

V. CONCLUSION

A method for outdoor natural scene classification is presented here. The image is represented by using a feature set with varying number of feature vectors each describing the properties of the image. The two neural classifiers BPNN and RPNN are used for the performance evaluation on varying number of feature vectors of the feature-set corresponding to scene images. The proposed method has tested on scene classification MIT database [5]. It is observed the performance of the classifiers started going down as the number of test samples is increased. The performance of RPNN is better than BPNN on number of test patterns whereas BPNN performance is better than RPNN classification rate of less number of test samples. It can be inferred from that our feature extraction method yield good performance results. Future work incorporates exploring the use of other features such as moments, edge ratio, texture etc. and the performance of Radial Basis Function Neural Network (RBFNN); Probabilistic Neural Network (PNN) etc. may be evaluated. The proposed method may be used with or without alteration to other areas also.

REFERENCES

[1] Ajay Kumar, "Neural Network Based Detection of Local Textile Defects," Pattern Recognition 36, pp. 1645-1659, 2003.
[2] Andrew and Sameer Singh, "Indoor vs. outdoor scene classification in digital photographs," Pattern Recognition 38, pp. 1533-1545, 2005.
[3] Chien-Sheng Chen and Jium-Ming Lin, " ApplyingRprop Neural Network for the Prediction of the Mobile Station Location," Sensors (Open Access), pp.4207-4230, 2011.

[4] C. K. Chui, Wavelets-A Mathematical tool for Signal Processing, SIAM, Philadelphia, 1997.
[5] http://cvcl.mit.edu/database.htm
[6] I. Daubechies, “Ten Lectures on Wavelets ,” SIAM CBMS-NSF, Series on Applied Mathematics, no. 61, pp. 53-166, SIAM, 1992.
[7] H. Demuth and H. Mark eds. 2002, The Matlab version 7.0 : User Guide, The Math Works Inc., USA.
[8] GeethaSrikantan, Stephen W. Lam and Sargur N. Srihari, “Gradient-Based Contour Encoding For Character Recognition,” Pattern Recognition, Vol. 79, No. 7, pp. 1147-1160, 1996.
[9] A. Guerin-Dugue, A. Olivia, “Classification of scene photographs from local orientations features,” Pattern Recognition Lett. 21, pp. 1135-1140, 2000.
[10] S. Haykin, Neural Networks: a Comprehensive Foundation, Macmillan, New York, USA, 2010.
[11] Lalit Gupta, V. Pathangay, A. Patra A. Dyana and Sukhendu Das, “Indoor Vs. Outdoor Scene Classification using Probabilistic Neural Network,” EURASIP Journal on Advances in Signal Processing Special Issueon Image Perceptions, Vol. 2007, pp. 1-10, 2007.
[12] S. G. Mallat, “A Theory of Multiresolution Signal Decomposition : The Wavelet Representation,” IEEE Transactions on Pattern Recognition and Machine Intelligence 11, pp.674-693, 1989a.
[13] Matthew Traherne and Sameer Singh, “An Integrated Approach to Automatics Indoor Outdoor Scene Classification In Digital Images,” Proceedings of 5th International Conference on Intelligent Data engineering Automated Learning (IDEAL), Exeter, UK, 2004.
[14] D. Micˇusˇi´k, V. Stopjakova´ and L. Benˇusˇkova, “Application of Feed-forward Artificial Neural Networks to the Identification of Defective Analog Integrated Circuits,” Neural Computation and Applications, pp. 71-79, 2002.
[15] T. Mitchell, Machine Learning, McGraw Hill, 1997.
[16] Mohammed A. Ayoub, Birol M. Demiral, “Application of Resilient Back-Propagation Neural Networks for Generating a Universal Pressure Drop Model in Pipelines,” University of Khartoum Engineering Journal, Vol. 1, Issue 2 pp. 9-21, October 2011.
[17]]G. Nathalie, L.B. Herve, H. Jeanny, G.D. Anne, “Towards the Introduction of Human Perception in a Natural Scene Classification System, IEEE Conference NNSP, Switzerland, September 4–6, 2002.
[18] OzgurKisi and ErdalUncuoglu, “Comparison of three-backpropogation training algorithms,” Indian Journal of engineering and Material Sciences, Vol. 12, pp. 434-442, October 2005.
[19] L. M. Patnaik and K. Rajan, “Target detection through image processing and resilient propagation algorithms,” Neurocomputing, pp. 123–135, 2000.
[20] Reyadh Shaker Naoum and ZainabNamh Al-Sultani, “ Hybrid System Of Learning Vector Quantization And Enhanced Resilient Backpropagation Artificial Neural Network For Intrusion Classification,” IJRRAS 14 (2), pp. 333-339, February 2013.
[21] M. Riedmiller and H. Braun, “A direct adaptive method for faster backpropagation learning: The RPROP algorithm,” Proc. IEEE Int. Conf. On Neural Network, pp. 586-591, 1993.
[22] E. Saber and A. M. Tekalp, “Integration of color, edge, shape and texture features for automatic region-based image annotation and retrieval,” Electronics Imaging, vol. 7, pp. 684-700, 1998.
[23] Son Lam Phung and A. Bouzerdoum, “A Pyramidal Neural Network For Visual Pattern Recognition,” IEEE Transactions On Neural Networks, Vol. 18, No. 2, pp.329-343, March 2007.
[24] S. Srinivasan, L. Kanal, “ Qualitative Landmark Recognition and using Visual cues,” Pattern Recognition Lett. 18, pp. 1405-1414, 1997.
[25] G. SubramanyaNayak and DayanandaNayak, “Classification of ECG Signals using ANN with Resilient Back Propagation Algorithm,” International Journal of Computer Applications Volume 54, No.6, pp. 20-24, September 2012.
[26] B. Yegnanarayana, Artificial Neural Networks, PHI Learning Pvt. Ltd., 2009.