Image Texture Analysis Using Deep Neural Networks

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***Abstract*—Optimal texture feature extraction in multi-class texture classification is a challenging task. The choice of traditional texture features for texture classification and segmentation is subjective and highly application dependent with lower generalization to other textures. The Deep Neural Network (DNN) approach can overcome the problem of selecting a suitable and optimal subset of texture feature extraction method. The hidden layers inside the DNN architecture automatically extract suitable features without user intervention to give the best texture discriminating performances in multi-class texture classification environment. Our results on publicly available texture datasets show that deep learning techniques could be successfully used in image texture classification and segmentation.**

***Keywords*—deep learning; neural networks; texture features; dimensionality reduction; image segmentation**

I. Introduction

Texture analysis is one of the key aspects of image recognition and image processing. Its practical applications are broad in extent from low level image segmentation to high level object recognition. There have been many texture feature extraction methods proposed in the literature, [3,5]. Selecting the correct texture feature extraction technique from numerous existing methods and selecting the optimal texture features out of these extracted features have been always a difficult task. Furthermore, the formulation of traditional texture features loses some degree of information on texture, which could be important for texture discrimination.

Deep Neural Network (DNN) extending from Artificial Neural Networks (ANN) can automate the process of finding optimal texture features in a certain way. As illustrated in *Fig. 1*, DNN, can automatically extract the best texture features spanning from micro to macro scale, without losing useful information which usually happens in the traditional subjective texture feature extraction. In each hidden layer more complex and abstract feature representations are captured in an orderly fashion.

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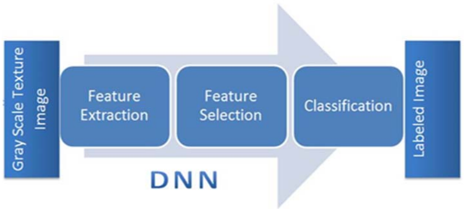

Fig. 1. Basic methodology in texture analysis which fits into DNN

In this paper a DNN comprised of several hidden layers is proposed for multiclass image texture classification and segmentation. To acquire more descriptive features without loss of information, Unwrapped Image Vector (UIV) of input texture image is considered. The normalized distributions of UIV, intensity histogram (IH) and reduced image vectors using Principal Component Analysis (PCA) are also incorporated by the proposed DNN to increase the performance. A regularized cost function for DNN is used to avoid over fitting. Learning plays a central role in identifying the region boundaries. The degree of difficulty of texture segmentation depends on the variability in the feature values of instances in the same class and the difference between feature values of instance in different classes.

This paper is organized as follows. Section II provides a brief literature review on texture analysis and ANN. Section III explains the method and Section IV provides the results. Section V and VI give discussions and conclusions on results obtained.

II. Literature review

A. Image Texture and Texture Feature Extraction

Texture is a coherent property which belongs to a surface of an object or a region. It carries important information on the structural arrangements and distributions of primitive patterns in the formulation of surface appearance. The notion of repeating characteristic contributes to the homogeneity of a texture.

Texture analysis has a rich history in image processing and computer vision. Texture analysis has a wide range of applications in many fields including medical image processing, defect detection, textile industry, image retrieval, object recognition and computer graphics.

Texture feature extraction is concerned with the quantification of texture characteristics in terms of a feature vector. The choice of appropriate descriptive features results in the reliability and effectiveness of the texture analysis system. A good texture feature is required to be invariant with translation, scale, and rotation. In [3] texture feature extraction methods are classified into four sub fields namely statistical methods, structural methods, spectral methods, and model based methods. ANN and DNN can be considered as model based texture analysis techniques.

B. Texture Classification and Segmentation

The texture classification algorithm should categorize an unknown texture image as belonging to one of a known texture class depending on training data. The classical pattern classification techniques such as ANN, k-nearest neighbor algorithm, Bayesian classifiers, and Support Vector Machine are commonly employed in texture classification. Pattern classifiers which generate the class decision boundaries. The discriminative ability of learned class boundaries depends on the quality of feature vectors used in learning process. To cope with the problem of curse of dimensionality, feature dimensionality reduction is usually performed. PCA seeks for the projections that best represent the variance of data.

Texture segmentation aims at dividing an image into several sub regions based on the texture. Here also extracted texture features plays a crucial role in achieving better segmentation [3].

C. Artificial Neural Networks (ANNs)

In machine learning ANN is an algorithm which is closely related to the human neural functionality in the brain. ANNs are generally presented as systems of interconnected neurons in a specific manner. The connections have numeric weights that can be learned which provides a weighted sum of inputs to the neuron and fires an activation function to produce the output. ANN is a very useful tool in nonlinear multiclass classification.

The basic steps of learning the network is to start with an untrained ANN architecture, present training patterns to the input layer, pass the signals through the network and determine the estimated output at the output layer. Next the error between estimated output and true labels is minimized to adjust the weights using back propagation technique. A comprehensive and mathematical review of ANN could be find in [1.8].

III. Methodology

A. Deep Neural Network

DNN is a multi-layer neural network which can be used as a technique to learn abstract representations of data. They are more powerful than ANNs. Two hidden layer DNN can sometimes solve problems that would require a huge number of hidden units in an ANN as described in [7]. The ANN can be extended to DNN by adding more hidden layers. A regularized cost function for DNN is used to avoid over fitting according to [7].

B. Proposed DNN approach

For the traditional texture analysis techniques many features must be extracted for better texture discrimination. Feature selection should be carried out afterwards to find most discriminative features. DNN integrates both functions into its hidden layers, therefore cumbersome decision making on which feature extraction scheme and which features to select is easily avoided when a DNN is employed. Here an Artificial Neural Network with a single hidden layer (ANN1), 2 hidden layers (DNN2) and three hidden layers (DNN3) are formulated. Number of hidden units in each layer is adjustable. The sub image UIV which is the vectorized form of an input sub image of size w x w is used as the input. To observe the performance of the designed networks with other transformed inputs, Intensity Histogram of image (IH) and reduced UIV using PCA are also used. For training and testing of the DNN, 10-fold stratified partition cross validation method is used.

C. Dataset

Two commonly used texture databases are employed for classification, namely Brodatz as given in [4] and CURet as given in [2]. The variations in translation, rotation and scale of texture samples further increase the difficulty of texture discrimination. The number of texture classes and the samples associated with each formed dataset is given in *Table 1*. For the Brodatz Generated, images from Brodatz dataset are preprocessed to obtain various texture invariances.

D. Semantic segmentation for scene labelling

In the training phase predetermined number of texture patches of size wxw from a randomly selected area on a known texture is extracted, vectorized and feed in to DNN as input. This is repeated for all texture classes. Once the DNN is trained in this way we moved in to testing phase.

First, we perform texture classification. A test set comprising wxw sub image textures are used. The vectorized sub images are fed in to trained DNN and the misclassification error is recorded.

Next, we perform texture segmentation. Here, a mosaic image is provided. Sliding window technique is used to extract wxw sub images from the mosaic test image. These sub images are labeled using the trained DNN. Error between true label and DNN output label is recorded. *Fig. 2* illustrates the method used here to segment the mosaic image.

TABLE 1. SUMMARY OF TEXTURE DATASETS USED IN CLASSIFICATION

Dataset	No. of Classes	Images per Class	Total Images	UIV Size
Brodatz Generated	10	500	5000	20×20
CURet	10	62	620	32×32

IV. EXPERIMENTAL RESULTS

The experiments are done using an Intel dual core processor with a 4 GB RAM in MATLAB environment operating on a 64 bit Windows operating system.

A. Results for Texture Classification

The training and testing accuracies (%) and standard deviations obtained after cross validation are presented in Table 2. Results for the experiments with UIV features, IH features with 256 bins and features reduced by PCA are presented in *Table 2* ,*Fig. 3* and *Fig. 4*.

Classification accuracies for the test set usig DNN are better than that of ANN accuracies. Also features reduced by PCA achieve a higher accuracy.

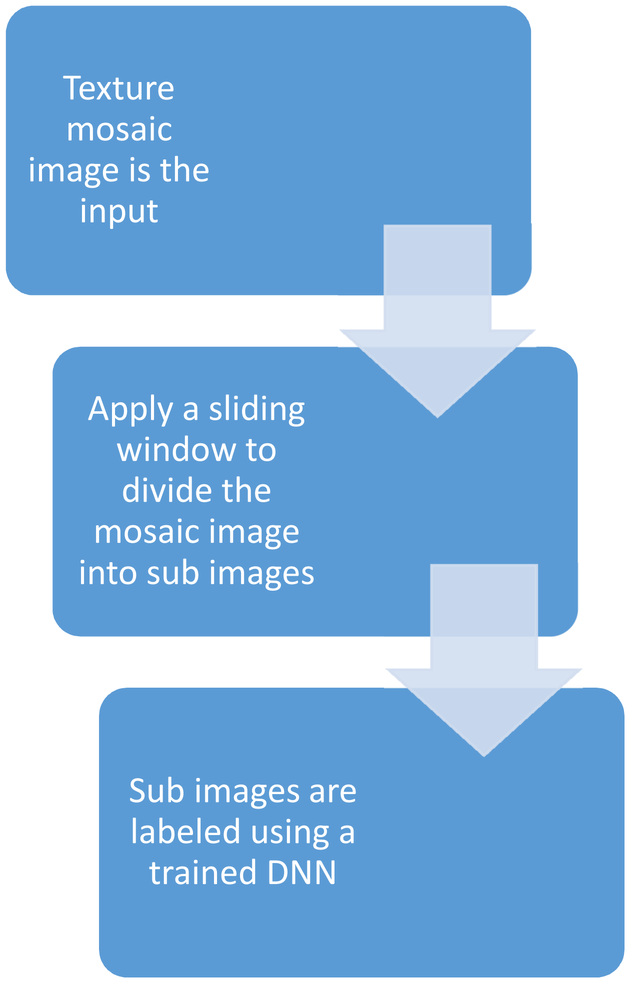

Fig. 2. Proposed method of texture segmentation

TABLE 2. TEXTURE CLASSIFICATION ACCURACIES

Method	**Brodatz Generated**		**CURet**	
	Train accuracy (%)	***Test accuracy (%)***	***Train accuracy (%)***	***Test Accuracy (%)***
ANN1	83.40±1.14	70.66±8.45	99.99±0.02	85.40±1.90
DNN2	88.72±1.27	90.12±8.36	99.78±0.09	86.26±10.6
DNN3	74.84±2.31	79.22±9.69	99.81±0.26	92.80± 3.62
ANN1 with IH	98.70±0.29	86.30± 5.64	97.76±0.34	56.31±5.62
DNN2 with IH	99.96±0.01	94.14±3.00	99.86±0.14	91.43± 3.00
ANN1 with PCA	99.96±0.01	87.22±8.02	99.96±0.04	77.41±3.24
DNN2 with PCA	99.95±1.01	**98.70±0.97**	99.89±0.29	**97.6.±3.51**

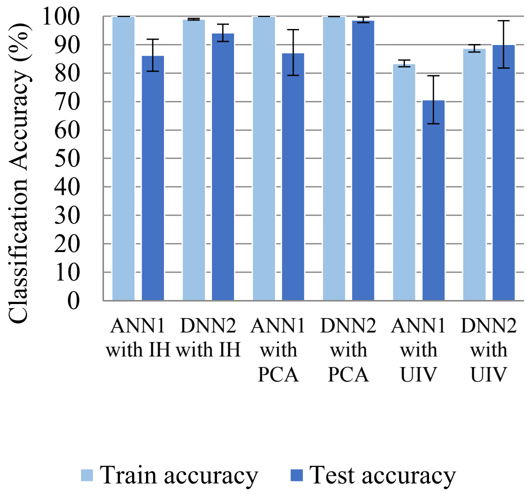

Fig. 3. Accuracies for Brodatz Generated dataset

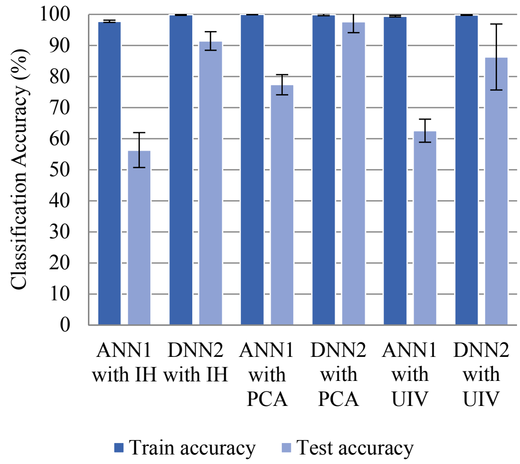

Fig 4. Accuracies for CURet dataset

B. Segmentation Results from Deep Neural Networks

As the texture mosaic have different number of textures to be classified the patch size should be able to represent largest texture pattern. Here 35 bin IH of the UIV is used. Segmentation results for UIV features are given in *Fig. 5, Fig. 6, and Fig. 7. Fig. 8* presents the segmented result for IH features. It can be observed that IH features perform better.

Segmentation error for a mosaic of ten textures is considerably reduced when DNN is used instead of ANN as given in *Fig. 9*.

Furthermore, the segmentation accuracy for a ten texture mosaic using UIV features is 71.32% and for IH features is 87.20%. Clearly patch size, w should be adjusted to get better results.

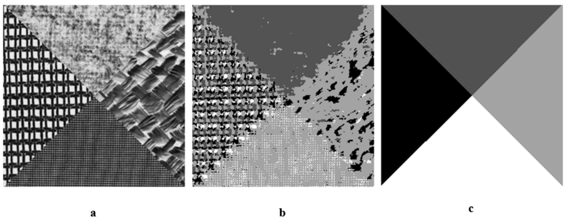

Fig. 5. Mosaic image from CURet, (a) original (b) segmented image using UIV features (c) ground truth

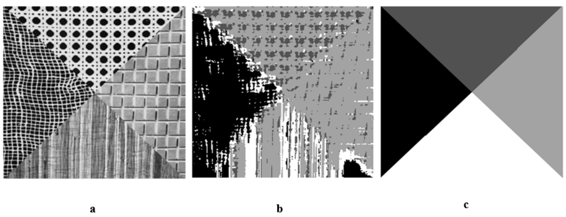

Fig. 6. Mosaic image from Brodatz Generated, (a) original (b) segmented image using UIV features (c) ground truth

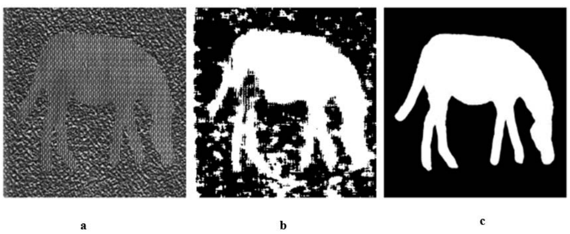

Fig. 7. Mosaic image from CURet textures, (a) original (b) segmented image using UIV features (c) ground truth

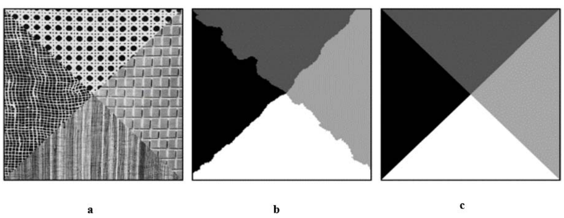

Fig. 8. (a) Mosaic image (b) segmented image using IH features (c) ground truth

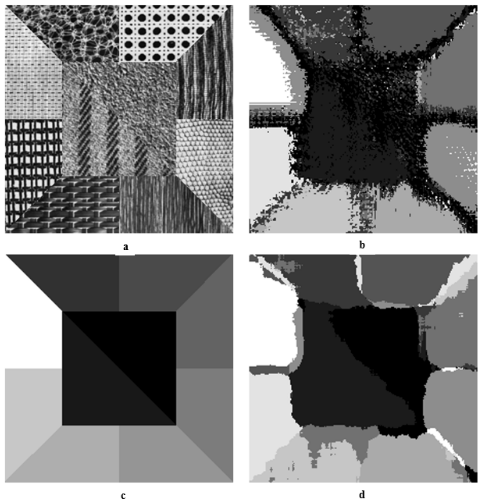

Fig. 9. Segmentation result for mosaic image of ten textures from Brodatz Generated (a) original (b) ground truth (c) using ANN (d) using DNN along with their ground truth

Analysis on RGB image segmentation for varying patch sizes is given in the *Fig. 10*.

To emphasis that the research outcomes are useful in many real world applications of image recognition and image processing, a simple computer program is written. Snapshots of its user interface are given in *Fig. 11*.

Fig. 10. Results for the analysis on patch size for color image segmentation using texture feature

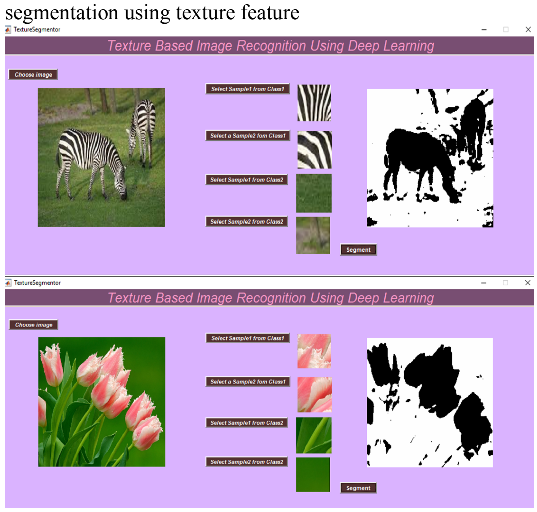

Fig. 11. Snapshots of the user interface for the MATLAB program written to detect objects in an image by its textural behavior

V. DISCUSSION AND FUTURE WORK

The classification results on Brodatz dataset show that with a DNN of two hidden layers, an average accuracy of 98.70±0.97% can be achieved while the ANN only gives 87.22±8.02% for the same dataset. The classification results on CURet dataset show that DNN obtains an average accuracy of 97.60±3.51% while the ANN only achieves 77.41±3.24% test accuracy. DNN achieves superior classification results than the ANN. Moreover, the best classification accuracies and efficiency are acquired when the dataset is preprocessed using PCA.

For UIV features the segmentation accuracy is 71.32%. 35 bin IH increases segmentation accuracy of 87.20%.

An important observation is that with different input features DNN has performed differently. Our initial assumption was even with UIV or raw data DNN should perform well due to its ability to extract abstract representations. This could be the case that we have limited our DNN to two layers. Further experiments should be carried out to evaluate deeper networks with more than two hidden layers. Also accuracy with patch size w should be evaluated in future. Here we have limited our w to 20 and 32 pixels. Even with two hidden layers DNN has perform better than ANN as predicted.

VI. CONCLUSION

Texture carries important information on surface appearance. Optimal texture feature extraction to discriminate many texture classes artificially is a challenging problem in computer vision. Therefore, DNN based approaches are suitable for texture analysis. Here, with limited 2 layer DNN based texture classification and segmentation improved performance compared to ANN is achieved.

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