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Soft Computing Tool Approach for Texture Classification Using Discrete Cosine Transform

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Abstract - Texture can be considered as a repeating pattern of local variation of pixel intensities. Cosine Transform (DCT) coefficients of texture images. As DCT works on gray level images, the color scheme of each image is transformed into gray levels. For classifying the images using DCT, two popular soft computing techniques namely neurocomputing and neuro-fuzzy computing are used. A feedforward neural network is used to train the backpropagation learning algorithm and an evolving fuzzy neural network to classify the textures. The soft computing models were trained using 80% of the texture data and the remaining was used for testing and validation purposes. A performance comparison was made among the soft computing models for the texture classification problem. In texture classification the goal is to assign an unknown sample image to a set of known texture classes. It is observed that the proposed neuro-fuzzy model performed better than the neural network.

Keywords— *Texture classification, DCT, Neurocomputing, Neuro-Fuzzy, Soft Computing*

I. INTRODUCTION

Texture is defined as something consisting of mutually related elements. Texture as a primitive visual cue has been studied for a long time. An important and emerging application where texture analysis can make a significant contribution is the area of content-based retrieval in large image and video databases. Texture classification and segmentation schemes are very important in answering such queries.

The neighbouring pixels within an image tend to be highly correlated. The DCT technique is used for a large class of images with energy concentration and de-correlated parameters. The DCT decomposes the signal into underlying spatial frequencies, which then allows further processing techniques without sacrificing the precision of DCT coefficients. The DCT coefficients of an image tend themselves as a new feature, which have the ability to represent the regularity, complexity and some texture features of an image, which can be directly applied to image data in the compressed domain.

Hybrid systems consisting of neural networks, fuzzy inference system, approximate reasoning and derivative free optimization techniques, which can provide human like expertise such as domain knowledge, uncertainty reasoning, and adaptation to a noisy and time varying environment.

The proposed prediction models based on soft computing are easy to implement and produce desirable mapping functions by training on the given data set.

II. DISCRETE COSINE TRANSFORM

For the DCT transform to work, firstly the RGB image is converted into Gray-image. This image is divided into 8x8 sized sub-blocks.

Fig.1. Spatial compression with DCT

Each of the 64 DCT coefficients is uniformly quantized. Quantization is defined as division of each DCT coefficient by its corresponding quantizer step size, followed by rounding to the nearest integer. The quantized DC coefficient is treated separately from the 63 AC coefficients. The DC coefficient is a measure of

the average value of the 64 image samples. Since there is strong correlation between the DC coefficient of adjacent 8x8 block. This special treatment is used because DC coefficients frequently contain a significant fraction of the total image energy. This is illustrated in Fig. 2.

Fig.2. (a) DCT basic pattern (b) Vector element from frequency components (c) Vector element from directional information.

As shown in Fig.2, the coefficients of the most upper region and those of the most left region in a DCT transform domain represent some vertical and horizontal edge information.

III. TEXTURE FEATURE EXTRACTION

Texture feature extraction use statistical methods. Analysis of texture image requires large storage space and a lot of computation time to calculate the matrix of feature such as SGLDM (Spatial Gray Level Dependence Matrix) and NGLDM (Neighbouring Gray Level Dependence Matrix). A set of scalar feature calculated from the matrix is not efficient to represent the characteristics of image contents. So a new texture extraction method based on Discrete Cosine Transform (DCT) is implemented. Fig 3. shows such approach.

Firstly a query image is provided and converted into a gray level version. The texture feature vector is obtained from some DCT coefficients. It is computed directly from the DCT coefficients and the spatial localization using sub blocks. Thus, it does not require additional complex computation as well as it overcome some problems such as computational complexity and storage space.

Fig. 3. Block diagram of the texture feature extraction.

IV. ARTIFICIAL NEURAL NETWORK

One efficient way of solving complex problems is following the lemma “divide and conquer”. Neural networks are computer algorithms inspired by the way information is processed in the nervous system. An artificial neuron is a computational model inspired in the natural neurons. One type of network sees the nodes as ‘artificial neurons’. These are called artificial neural networks (ANNs).

An important difference between neural networks and other AI techniques is their ability to learn. The network “learns” by adjusting the interconnections between layers. A valuable property of neural networks is that of generalization, whereby a trained neural network is able to provide a correct matching in the form of output data for a set of previously unseen input data.

Learning typically occurs by example through training, where the training algorithm iteratively adjusts the connection weights (synapses). Backpropagation (BP) is one of the most famous training algorithms for multilayer perceptrons. BP is a gradient descent technique to minimize the error E for a particular training pattern.

V. NEURO-FUZZY SYSTEMS

ANN learns from scratch by adjusting the interconnections between layers. FIS is a popular computing framework based on the concept of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. The advantages of a combination of ANN and FIS are obvious. We broadly classify the integration of ANN and FIS into three categories namely concurrent model, cooperative model and fully fused model. Neuro Fuzzy (NF) computing is a popular framework for solving complex problems.

Here knowledge expressed in linguistic rules so, FIS can be build, and if we have data, or can learn from a simulation (training) then we can use ANNs. For building a FIS, we have to specify the fuzzy sets, fuzzy operators and the knowledge base. Similarly for

constructing an ANN for an application the user needs to specify the architecture and learning algorithm. An analysis reveals that the drawbacks pertaining to these approaches seem complementary and therefore it is natural to consider building an integrated system combining the concepts. While the learning capability is an advantage from the viewpoint of FIS, the formation of linguistic rule base will be advantage from the viewpoint of ANN.

A cooperative model can be considered as a preprocessor wherein ANN learning mechanism determines the FIS membership functions or fuzzy rules from the training data. Once the FIS parameters are determined, ANN goes to the background. The rule based is usually determined by a clustering approach (self organizing maps) or fuzzy clustering algorithms. Membership functions are usually approximated by neural network from the training data.

In a concurrent model, ANN helps the FIS continuously to determine the required parameters. In some cases the FIS outputs might not be directly applicable to the process. In that case ANN can act as a postprocessor of FIS outputs.

In a fused NF architecture, ANN learning algorithms are used to determine the parameters of FIS. Fused NF systems share data structures and knowledge representations. A common way to apply a learning algorithm to a fuzzy system is to represent it in a special ANN like architecture. However the conventional ANN learning algorithms (gradient descent) cannot be applied directly to such a system as the functions used in the inference process are usually non differentiable. This problem can be tackled by using differentiable functions in the inference system or by not using the standard neural learning algorithm.

(a) "Rural" texture

(b) "Metal" texture

(c) "Brick" texture

Fig.4. SOME TEXTURE IMAGES

VI. EVOLVING FUZZY NEURAL NETWORK (EFUNN)

In EFuNN all nodes are created during learning. The input layer passes the data to the second layer, which calculates the fuzzy membership degrees to which the input values belong to predefined fuzzy membership functions. The third layer contains fuzzy rule nodes representing prototypes of input-output data as an association of hyper-spheres from the fuzzy input and fuzzy output spaces. Each rule node is defined by 2 vectors of connection weights, which are adjusted through the hybrid learning technique.

The fourth layer calculates the degrees to which output membership functions are matched by the input data, and the fifth layer does defuzzification and calculates exact values for the output variables. Dynamic Evolving Fuzzy Neural Network (dmEFuNN) is a modified version of EFuNN with the idea that not just the winning rule node's activation is propagated but a group of rule nodes is dynamically selected for every new input vector and their activation values are used to calculate the dynamical parameters of the output function. While EFuNN implements fuzzy rules of Mamdani type, dmEFuNN estimates the Takagi-Sugeno fuzzy rules based on a least squares algorithm.

Fig.5. Architecture of EFuNN

VII EXPERIMENTAL SETUP AND RESULT

This paper attempted to classify 3 different types of textures using soft computing techniques. We used DCT coefficients to represent the different textures. Each texture image was represented by 327 DCT coefficients. Our texture database consisted of 240 different textures and they were manually classified into three different classes (brick, metal and rural). A set of sample texture images representing each class is illustrated in Figure 4. For training the soft computing models, we used 192 datasets and remaining 48 texture datasets were used for testing purposes. While the proposed neuro-fuzzy model was capable of determining the architecture automatically, we had to do some initial experiments to determine the architecture (number of hidden neurons and number of layers) of the neural network. After a trial and error approach we found that the neural network was giving good generalization performance when we had 2 hidden layers with 90 neurons each. In the following sections we report the details of our experimentations with neural networks and neuro-fuzzy models. Experiments were repeated three times and the worst errors were reported.

Classes		EFuNN	ANN (20000 ep)
Rural (16 Nos.)	X1	15	12
	X2	01	04
Metal (16 Nos.)	Y1	16	15
	Y2	00	01
Brick (16 Nos.)	Z1	11	14
	Z2	05	02
Total (48 Nos.)	A=X1+Y1+Z1	42	41
	A=X2+Y2+Z2	06	07
Reliability of Classification (%)		88	85.4

Table 1. Test result for texture classification.

VIII. RESULT

The best classification was obtained using EFuNN (88%) followed by neural networks (85.4%).

IX. CONCLUSION

This paper attempted to classify 3 different types of textures using artificial neural networks and Evolving Fuzzy Neural Network (EFuNN). For a texture feature DCT coefficient, does not require additional complex computation for feature extraction. As the high

frequency coefficient is less sensitive to human visual systems, so a feature matrix is constructed which consisting of the first few coefficients of each block. EFuNN outperformed the neural network with the best classification (88%). EFuNN is less computationally expensive as compared to neural networks. EFuNN adopts a one-pass (one epoch) training technique, which is highly suitable for online learning. Hence online training can incorporate further knowledge very easily. When the number of epochs were increased, it was interesting to note the continuous reduction of the training error (RMSE) but the generalisation error (classification accuracy) however tends to settle after 20,000 epochs. Compared to ANN, an important advantage of neuro-fuzzy models is their reasoning ability (if-then rules) of any particular state.

The proposed prediction models based on soft computing on the other hand are easy to implement and produce desirable mapping functions by training on the given data set. Choosing suitable parameters for the soft computing models is more or less a trial and error approach. Optimal results will depend on the selection of parameters. Selection of optimal parameters may be formulated as an evolutionary search to make SC models fully adaptable and optimal according to the requirements.

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