Texture Classification using Angular and Radial Bins in Transformed Domain

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Abstract—**Texture is generally recognized as fundamental to perceptions. There is no precise definition or characterization available in practice. Texture recognition has many applications in areas such as medical image analysis, remote sensing, and robotic vision. Various approaches such as statistical, structural, and spectral have been suggested in the literature. In this paper we propose a method for texture feature extraction. We transform the image into a two-dimensional Discrete Cosine Transform (DCT) and extract features using the ring and wedge bins in the DCT plane. These features are based on texture properties such as coarseness, smoothness, graininess, and directivity of the texture pattern in the image. We develop a model to classify texture images using extracted features. We use three classifiers: the Decision Tree, Support Vector Machine (SVM), and Logarithmic Regression (LR). To test our approach, we use Brodatz texture image data set consisting of 111 images of different texture patterns. Classification results such as accuracy and F-score obtained from the three classifiers are presented in the paper.**

Keywords—Texture; discrete cosine transform; radial and angular bins; decision tree; support vector machine; logarithmic regression

I. INTRODUCTION

Texture is generally recognized as being fundamental to perception. Texture provides useful information in identifying objects in images. Texture is different from color. Texture is defined as something composed of closely interwoven elements [1]. The description of interwoven elements leads to the idea of texture resolution. Texture primitives may be pixels or aggregate of pixels such as regions. It refers to the spatial organization of basic elements or primitives [2]. Many texture images do not have geometrical regularity of texture primitives in the image, but they can be described by statistical models. Texture recognition has many applications in areas such as medical image analysis, remote sensing, and robotic vision. There is no precise definition of texture available in practice. Texture has been described in a variety of ways. Texture descriptors provide measures of properties such as smoothness, coarseness, and regularity [3]. Gonzalez and Woods [4] describe three principal approaches for texture analysis: statistical, structural, and spectral. Statistical approaches yield texture properties such smoothness, coarseness, or graininess. Structural approaches are based on arrangement of primitive shapes in the image. Spectral properties are found on the Fourier spectrum and they yield global periodicity in the image or a region of the image. In this paper, we propose a new algorithm for extracting texture features from the two-dimensional Discrete Cosine Transform (DCT) of the image. These features capture directional and coarseness properties of the texture. We classify texture images using these features with statistical models. The texture recognition plays an important role in computer vision and has many practical applications such as robotics, reconnaissance, and biometrics. We have used three classifiers Support Vector Machine (SVM), Decision Tree (DT), and Logarithmic Regression (LR). We can also use a neural network with a backpropagation learning algorithm as a classifier. The main advantage of the proposed algorithm is that it can be incorporated in layers of a Convolution Neural Network (CNN).

The outline of the paper is as follows. Section II describes related work and provides historical developments in texture recognition. Section III provides the proposed approach. Section IV illustrates the experimental work and the results, and Section V provides conclusions.

II. RELATED WORK

Picture analysis involves representation, classification, segmentation, and synthesis. Many texture feature extraction algorithms are available in practice. Haralick et al. [5] proposed Gray Level Cooccurrence Matrix (GLCM) for extracting texture features. They suggested twenty-eight features that are best on GLCM. The most frequently used features are energy, entropy, inertia, and local homogeneity. Wilson and Bergen [6] developed a model for texture segmentation using Difference-of-Gaussian (DOG) filters. O'Toole and Stark [7] suggested a method for texture feature extraction using the Hotelling Trace (HT). Many spatial frequency filtering techniques have been used for texture segmentation. Bajesy and Lieberman [8] used spectrograms for texture segmentation. Coggins and Jain [9] used radial and angular bins in the Frequency Domain (FD) for extracting texture features. Daugman [10] used 2-D Gabor filters for texture segmentation. Kulkarni and Byers [11] used radial and angular bins in 2-D frequency domain. They employed the Radon transform to calculate the Fourier coefficients. Tuceryan and Jain [12] identified five major categories of texture features: statistical, geometrical, structural, model based, and filtering based. Lows [13] used local invariant descriptors using Fourier Transform (FT) for texture analysis. Zeng et al. [14] categorized texture representation into three broad types: Bag-of-Words (BoW), Convolution Neural Network (CNN)-based, and attribute based. In the BoW approach a feature vector is obtained from a texture image that represents properties of the texture. In this approach the

texture image is first transformed into a pool of local features. Many CNN-based texture presentation models have been proposed in recent years [15, 16, 17].

III. PROPOSED APPROACH

In our proposed approach we use ring and wedge bins to extract texture features in the DCT domain. The DCT coefficients are given by (1).

$$F_{pq} = a_p a_q \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} A_{mn} \cos \frac{\pi(2m+1)p}{2M} \cos \frac{\pi(2n+1)q}{2N}$$

where

$$a_p = \begin{cases} \frac{1}{\sqrt{M}}, p = 0 \\ \sqrt{\frac{2}{M}}, 1 \le p \le M-1 \end{cases} \quad \text{and} \quad a_q = \begin{cases} \frac{1}{\sqrt{N}}, q = 0 \\ \sqrt{\frac{2}{N}}, 1 \le q \le M-1 \end{cases}$$

$$(1)$$

We use the DCT coefficients because FT coefficients have real and imaginary parts. We can achieve data compression with the DCT as most information is stored in a few DCT coefficients at the top left corner in the DCT matrix. As we go away from the origin (0,0) the DCT coefficient values gradually become smaller. Most images in practice exhibit statistical redundancy. Therefore, it is possible to reconstruct the original image with a few DCT coefficients without affecting the visual quality of the images. It can be seen from Fig. 1 that if we rotate the image, the DCT also rotates. In Fig. 1, the texture image is rotated 45 degrees and it can be observed that the corresponding DCT also rotates by 45 degrees. Images with high spatial frequency contents show more spread of the DCT coefficients. In Fig. 2, the image in the second row shows relatively more coarseness. The DCT coefficients are more spread out for that image. Texture images with low spatial frequency contents show DCT coefficients concentration near the origin. The angular and radial bins are shown in Fig. 3. We can extract directional properties of the texture using the angular bins. The radial bins capture coarseness of the texture images. Radial and angular features are given by (2) and (3), respectively.

$$V_{r_1 r_2} = \sum_{u=0}^{n-1} \sum_{v=0}^{n-1} F_{uv}$$
$$r_1^2 \le u^2 + v^2 < r_2^2$$

$$(2)$$

$$V_{\phi_1 \phi_2} = \sum_{u=0}^{n-1} \sum_{v=0}^{n-1} F_{uv}$$
$$\phi_1 \le \tan^{-1}\left(\frac{v}{u}\right) < \phi_2$$

$$(3)$$

We used three classifiers to categorize texture images from extracted feature vectors: a) Decision Tree classifier, b) Support Vector Machine (SVM), and c) Logarithmic Regression model. SVM was proposed by Cortes and Vapnik [18]. In the SVM model, two hyper-planes are selected to maximize the distance between the two classes and not to include any points between them. The SVM algorithm is extended to non-linearly separable classes by mapping samples to a higher dimensional feature space [19]. SVM was

chosen as one of the classification methods because it has been shown to successfully handle small datasets in comparison to other traditional methods [20]. Moreover, it has good theoretical foundations, and generalization capacity as its decision functions are determined directly from the training data so that decision borders' margins are maximized in a highly dimensional feature space leading to less classification errors [21]. Decision Tree implementation using ID3 algorithm was suggested by Quinlan [22]. The algorithm uses information gain to decide as to which attribute is the best for the split at each non-terminal node. It is a recursive algorithm that starts with the root node and the leaf nodes represent the classes. C4.5 algorithm is an extension of ID3 algorithm, and it allows usage of both discrete and continuous variables. Logarithmic Regression can be implemented as shown in (4).

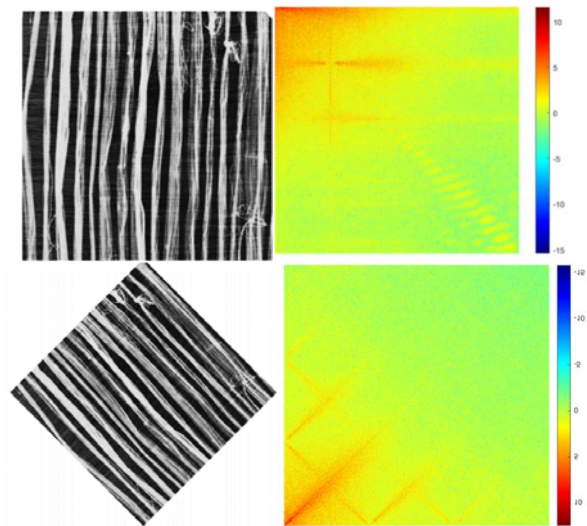$$y = \frac{e^{(b_0 + b_1)}}{1 + e^{(b_0 + b_1)}}$$
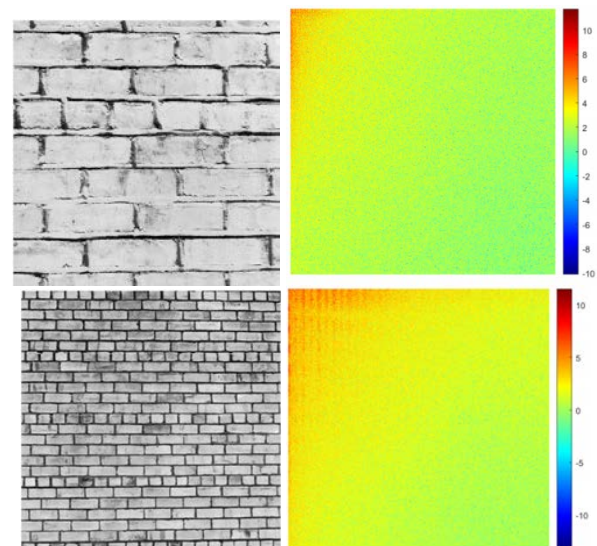
$$(4)$$

Fig. 1. DCT Visualization on Rotated Images.
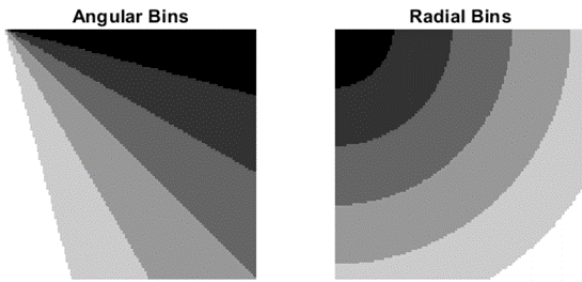

Fig. 2. DCT Visualization of Coarse Features.

Fig. 3. Angular and Radial Bins.

where, y is the predicted output and b0 and b1 are coefficients that are estimated using training set data. The model predicts the probability of a default class [23].

IV. EXPERIMENT AND RESULTS

To test our approach, we used Brodatz texture image data set consisting of 111 images of different texture patterns [24]. In the pre-processing stage, we grouped texture images in the Brodaz data set into five categories using K-means clustering algorithm. Sample images from each cluster are shown in Fig. 4. All the images were first resized to the dimension of 256×256 pixels. The Discrete Cosine Transform (DCT) has been widely used to convert an image from its spatial domain to its frequency domain where we can reduce digital image storage size, expedite data transmission, and remove redundant information [25]. We used the DCT coefficients of each image to extract information from its frequency domain. Most of the information in the image is concentrated in a few coefficients that are in the top left corner of the DCT matrix. We used the top left 128×128 region of the DCT matrix for feature extraction. The values of DCT coefficients were normalized. Furthermore, all the DCT coefficients that were less than zero were made zero as those values were very small. We normalized feature values between 0 and 5 so that all features are treated equally [26]. We extracted 34 features from the DCT coefficients. These features represent 6 wedge features, 4 ring features, and 24 features from the top left-hand corner. We have chosen 24 features from the top left corner as they showed the maximum variance and contained most information. The DCT coefficient at (0,0) was dropped because its normalized values were the same for all images. The 3-D scatter plot for five categories is shown in Fig. 5. Mean values of features are shown in Fig. 6 and Fig. 7 shows the decision tree. The results are shown in Table I.
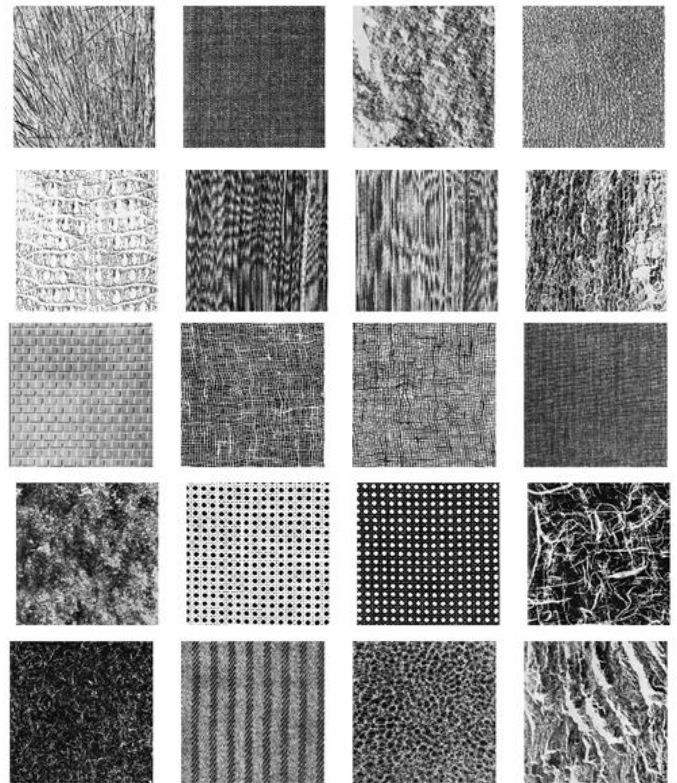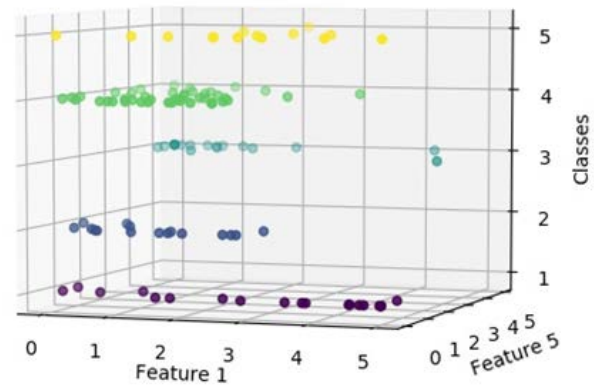

Fig. 4. Sample Images from Five Categories.
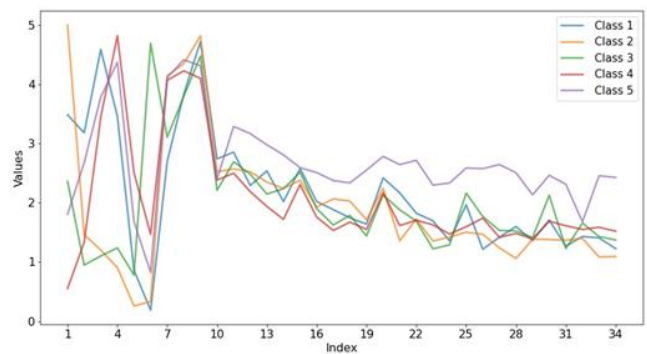

Fig. 5. 3-D Scatter Plot.

Fig. 6. Class Signatures.
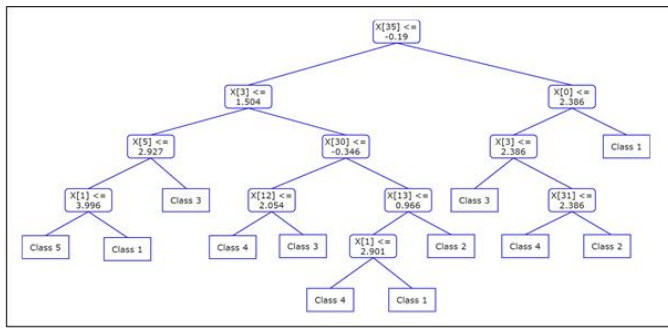
Fig. 7.   Decision Tree.

TABLE I.   ACCURACY AND F-SCORE

Classifier	Accuracy Score Percentage	F1 Score
Support Vector Machine	82.3	0.798
Decision Tree	79.4	0.753
Logarithmic Regression	91.1	0.919

V.   CONCLUSIONS

In this paper we have proposed a method for feature extraction using properties such as coarseness, smoothness, graininess, and directivity of the texture pattern in the image using DCT coefficients. These features can be used for texture image classification and analysis. We considered 34 features. We trained three classifiers using extracted features: a Decision Tree, Support Vector Machine, and a Logarithmic Regression classifier. It can be seen from Table I that the Logarithmic Regression classifier performed very well for this data set compared to the decision tree and support vector machine. The classification accuracy obtained with Logarithmic Regression classifier was 91.1 percent. Decision trees usually perform better with discrete features. The results obtained with our approach suggest that it is a valuable method for feature extraction and classification of texture images. The results may be further improved by using a greater number of radial and angular bin features. Also, we considered five categories of clusters. By using the optimized number clusters in pre-processing and proper grouping of images classification results may be improved.

In the future, we would like to evaluate the method with large datasets containing many images with a greater number of ring and wedge bin features. Furthermore, the feature extraction algorithm with angular and radial bins combining with a multi-layer perceptron model for classification, we plan to develop an architecture for a convolution neural network (CNN) model for classification of texture images.

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