Texture Images: Analysis, Classification and Comparison Study

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Abstract
Texture is an important characteristic for image analysis. This paper contains study and review of most major image texture classification approaches using different wavelet domain feature extraction algorithms, which have been proposed in the recent literature for image-texture classification, and perform a comparative study. The objective of study is to offer a comparison study to help other researchers to find technique or combination of techniques to reduce complexity, while increasing the accuracy at the same time.

Keywords
Image Texture, Discrete Wavelet Transform, Image decomposition.

1. Introduction

Image texture is one way that can be used in image analyzing, specifically in the image segmentation or classification. There are two different perspectives can depend on to define the image texture, structural or statistical. According to the structural perspective, image texture is defined as a set of primitives in some regular or repeated relationship. But from statistical view it is defined as a quantitative measure of the arrangement of intensities in a region [1].

Texture analysis is an important field of image analysis, and it has an essential importance in many tasks, such as machine vision, medical imaging, pattern recognition, and digital geometry. There are numerous methods have been invited for texture analysis, but no one method has proved that it is have a highest results in all tasks. These invited methods depend on different bases, structural, statistical, model, and transform base.

Actually, although the structural approaches[2][3],which represent the texture using both micro texture(well pre-known primitives) and macro texture(hierarchy of spatial arrangements of the primitives) are good in providing a clear symbolic descriptions of the images; these descriptions are more useful for synthesis but not for analysis tasks where the abstract descriptions for natural textures –for example – may be unwell defined because both micro- and macrostructure are changeable and it is hard to distinguish between them.

In contrast to structural methods, statistical approaches represent the texture by the non-deterministic properties in indirect way. These properties govern the distributions of the grey levels of an image and the relationships between them. Many methods which are based on the statistical approaches have been shown to give higher discrimination rates than the structural methods even than transform-based methods. The most noted statistical features which are used in texture analysis are derived from what is called co-occurrence matrix [2]. They showed an effective discrimination for the textures in the biomedical-images [4] [5].The approaches based on multidimensional co-occurrence matrices provided a wavelet packets (a transform-based method) when they are applied to texture classification [6].

According to model based texture analysis methods, they are based on the idea of constructing a model for the image which can be used for both texture description and synthesis. Markov random fields (MRFs) are considered as one of the most popular parameters that are used in images modeling. These parameters determine the spatial contextual information in an image. The model based methods which depend on MRFs assume that the intensity of each pixel in the image relates to the intensities of the around pixels. Actually, MRF models have been shown good results in different image processing fields, such as texture classification and synthesis, image segmentation, restoration, and compression [7].

About transform based methods for texture analysis, such as Fourier, Gabor, and wavelet transforms, they represent the image in a space whose coordinate system has an interpretation that is closely related to the characteristics of a texture (such as frequency or size). In one hand, both Fourier and Gabor are not used widely in natural textures analysis because they do not have a clear spatial localization since they have no single filter resolution. On the other hand, the wavelet transforms represent textures by very professional scales because of the varying in the spatial resolution. Also, wavelet transforms can be used in different texture analysis applications because they have several choices for the wavelet function [8].

Texture analysis includes four domains, texture classification (assigning unknown texture image to one of

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known classes of texture images), segmentation (partitioning a texture image to number of parts that have a likewise texture properties), synthesis (building an image texture model to generate a complete texture image in later stage), and shape from texture (constructing a 2D image for a 3D view by the projection process).

In this paper, we focus on texture classification using the transform based methods, specifically on number of different wavelet transform algorithms.

Texture classification process consists of two phases, learning phase and assigning phase. The goal in the learning phase is to build a vector for the extracted features for each known texture class in the training data using one of the analysis methods mentioned in advance. In assigning phase, firstly, the unknown sample image is analyzed by the same analysis method that was used in the learning phase. Secondly, the extracted features for the sample image are compared with those of the training images with a specific classification algorithm. According to the followed classification algorithm, the sample image will be assigned to the best matched class of the training classes. Some time the best match is not acceptable, in this case the unknown sample is rejected.

2. Discrete Wavelet Transform (DWT)

The discrete wavelet transform (DWT) for a signal is calculated usually by cascade filtering followed by sub sampling. First step: the signal is passed through a low pass filter (L), then through a high pass filter (H). The results of these filtering are approximation (a_j) and detail (d_j) coefficients, respectively. Second step: the filters outputs are sub sampled by 2 (↓2) [9]. The approximation coefficients are always used only in the next scale as shown in figure (1).

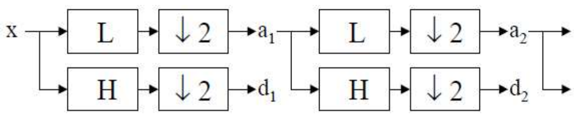

Figure (1): DWT tree.

A. Two-Dimensions Discrete Wavelet Transform (2DDWT)

DWT algorithm is used for two-dimensional pictures in similar way as for a signal. The DWT is computed for all image rows at the first, and then for all columns as shown in figure (2). The resultant sub-bands images for one level wavelet decomposition for two-dimensional pictures are illustrated in figure (3)

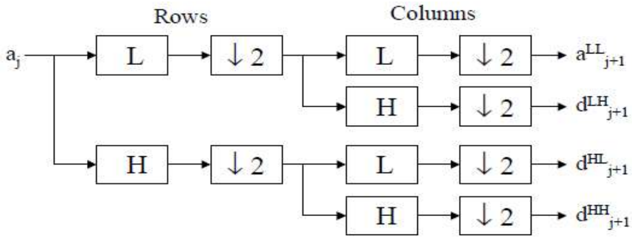

Figure (2): One level wavelet decomposition for two-dimensional pictures.

LL	LH
HL	HH

Figure (3): The resultant sub-band images for process of figure (2).

Image decomposition: In an experiment for Kociołek and Materka [10], they use 2-DDWT where the cascaded decomposition was performed for LL sub-bands image. Figure (4) illustrates the result sub-bands images for three levels of decomposition.

<table>
<tr><td></td><td></td><td rowspan="2">dHL2</td><td rowspan="3">dHL1</td></tr>
<tr><td></td><td></td></tr>
<tr><td colspan="2">dLH2</td><td>dHH2</td></tr>
<tr><td colspan="3">dLH1</td><td>dHH1</td></tr>
</table>

Figure (4): Sub-band images for three decomposition levels.

Texture Features Vector: To build the feature vector, the energy of sub-band images dLH, dHLand dHHis calculated according to the next equation at any selected scale in marked ROIs (Region of Interest).

$$E_{subband\ ,scale} = \frac{\sum_{x,y \in ROI} \left(d_{x,y}^{subband} \right)^2}{N}$$

Where N is the number of pixels in ROI, at given scale and sub-band. The output of these steps is a vector of features containing energies of wavelet coefficients calculated in sub-bands at successive scales.

Classification Methodology: By using 13 images as Brodatz's research [11] catalogue with size 512×512 pixels, the wavelet-derived features were calculated for 32 different ROIs with sizes of 64×64. By using convert program, for each pair of textures, Fisher coefficient was calculated according to next equation.

$$F = \frac{D}{V}$$

Where D is the mean between class separations and V is the mean within-class variance. The highest ten F values were used by the nearest neighbor classification test (1-NN) [2].

Results: Most of examined pairs of textures can be separated by means of these features with classification error equal to zero. Only in two cases, the observed classification error was greater than 0, but of a small value (3%).

B. Discrete Multi-Wavelet Transform (DMWT)

Multiwavelets are considered as extensions of scalar wavelets. They have numerous advantages over the scalar wavelets in terms of features as short support and symmetry. Moreover, they treat the vanishing moments which are important issue in signals processing. Multiwavelet transforms have proven their worth in many applications such as signal compression and denoising.

Image decomposition: The process of image decomposition using multi-wavelet is shown in figure (5). At first, the pre-filter is applied to all image rows, before the first level decomposition is applied to every resultant row. The first half of each row of the decomposition results contains coefficients corresponding to the first scaling function and the second half contains coefficients corresponding to the second scaling function. At second, the pre-filter and decomposition processes are repeated to the columns, such that the first half of each column contains coefficients corresponding to the first scaling function and the second half of each column corresponding to the second scaling function. At the end of the first 2-D multi-wavelet decomposition, 16-subband intermediate image will be as shown in figure (5).The next decomposition will be in the "low-low pass" sub-matrix, the shaded part in figure (6). According to advance process, an L-level decomposition of a 2-D image will produce 4(3L+1) sub-bands [12].

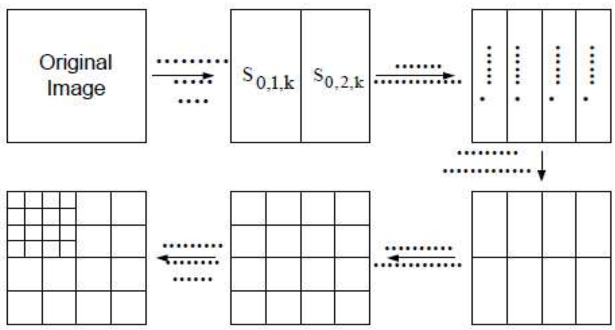

Figure (5): One level of 2-D multi wavelet decomposition of a 2-D image

L1L1	L2 L1	H1 L1	H2 L1
L1 L2	L2L2	H1 L2	H2 L2
L1 H1	L2 H1	H1H1	H2 H1
L1 H2	L2 H2	H1 H2	H2H2

Figure (6): the resultant 16-subband intermediate images for first 2-D multi wavelet decomposition

Texture Features Vector: A 2-D DMWT with depth L typically produces J=4(3*L+1) sub-bands images. The normalized energy was computed on each sub-bands image and defined as in the next equation.

$$E = \frac{1}{N} \sum_{i,j} x_{i,j}^{2}$$

The energy features vector will consist of the energies of the decomposed sub-bands images except of the low-low pass sub-bands images

Classification Methodology: By using 20 texture images from Brodatz album, a testing database was created with size of 1280 region images by constructing a 64 random region images with size of 128×128 from each original texture image. For classification, four distance functions (Euclidean Distance, Bayes Distance, Mahalanobis Distance, and Simplified Mahalanobis Distance) were calculated between the texture feature vector of the 1280 region images and that of the original texture images. Each test image was assigned to the texture which had the minimum distance for all four distance functions [13].

Results: By taking the average of the results over the 20 selected partitions of the data set into sample and test sets, the classification performance was 100% where all test sample were classified correctly.

C. Tree-Structured Wavelet Transform (TSWT)

In broad class of natural textures, the dominant frequencies concentrate in the middle frequency channels. Since the pyramid structured wavelet transform continues the decomposition in the low frequency channel, it cannot be used for natural textures. Tree-structured wavelet transform is developed to deal with natural texture where the cascading decompositions can be in different frequencies channels depending on the most dominant one.

Image decomposition: Using 2-DDWT the texture image was decomposed into 4 sub-band images, which was represented as tree (parent and children nodes). The cascading decomposition continued in the sub-band images which had significant energy value which was calculated by the next equation. The sub-band image which had energy significantly smaller than others, the decomposition was stopped [14].

$$e = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}|x(m,n)|$$

The result of this procedure is called Energy Map. Figure (7) shows an example for sub-band images of cascading decomposition using Tree-Structured Wavelet Transform, and figure (8) illustrates the resultant Energy Map.

<table>
<tr><td rowspan="2">A3</td><td rowspan="2">B3</td><td rowspan="2">E3</td><td>A4</td><td>B4</td><td rowspan="4">B1</td></tr>
<tr><td>D4</td><td>C4</td></tr>
<tr><td>D3</td><td>C3</td><td>H3</td><td colspan="2">G3</td></tr>
<tr><td colspan="2">D2</td><td colspan="3">C2</td></tr>
<tr><td colspan="5">D1</td><td>C1</td></tr>
</table>

Figure (7): Example of cascading decomposition using Tree-structured wavelet transform.

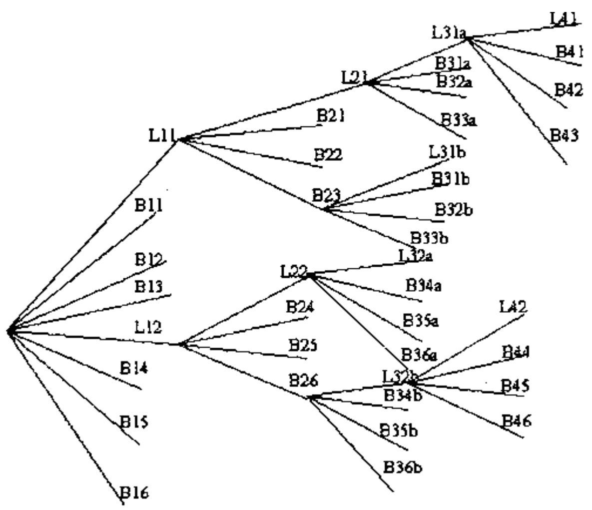

Figure (8): Energy Map of figure (7).

Texture Features Vector: The first 5 largest energy values of leaf nodes in the energy map were selected as features.

Classification Methodology: By using 30 texture images from Brodatz with size 512×512, a 100 sample images were created by randomly selecting 256×256 sized images. For each sample image in the database, the distance between each sample image feature vector and that for the original images was calculated using Euclidean, Bayes, Mahalanobis, and Simplified Mahalanobis Distance functions. The sample image was assigned to the texture which had the minimum distance for all four distance functions [14].

Results: On average over the four distance functions, the correctness was 97.85%.

D. Dual Tree Complex Wavelet Transform (DTCWT)

Many wavelet transforms failed in the directional selectivity for the decomposition of subbands. Also, the results were poor when the texture patterns have similar spatial/frequency where different directional properties cannot be differentiated. Dual Tree Complex Wavelet Transform has a worthy directional selectivity over the others. In addition, it has good approximate shift, invariance, and computational efficiency properties. DTCWT has satisfactory results in several image applications like restoration and enhancement.

Image decomposition: As in TSWT, DTCWT depends on calculating the energy in the sub-bands images to continue the cascading decomposition. But, DTCWT instead of decomposing the image to 4 sub-band images, each texture image was decomposed to 8 sub images (2 low pass, and 6 band pass). The next level of decomposition was to that sub-images which had a significant value of energy -using same equation (3) - for extra 8 sub images. Figure (9) illustrates an example for one texture image [15].

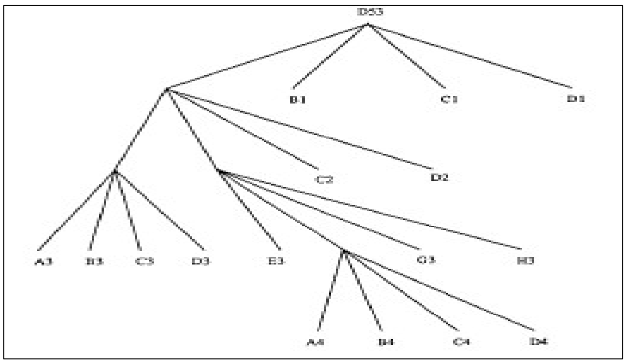

Figure (9): Decomposition example for a texture image using DTCWT.

Texture Features Vector: The features vector was created with size of 32 by calculating the mean and the standard deviation for the largest 16 energy values for sub-images.

Classification Methodology: By using 116 texture images from Brodatz album, a training database was created with size 1856by dividing each image to 16 parts with size 128×128. Normalized Euclidian distance function was used to assign each image in the training database to its original texture image with minimum distance [15].

Results: In Hatipoglu's research [15] the same training database was used by four different methods, DTCWT, Gabor filter, PSWT (Pyramid –Structured Wavelet Transform), and TSWT. The retrieval rates were 79.73%, 75.37%, 68.82%, and 69.64% respectively.

3. Conclusion

Four methods of texture classification have been analyzed in this paper, we hope that the introduced classification will speed up the decision process and assist researchers to focus their attention on the method that meets specific requirements. Since the feature extraction method is computationally efficient. Although, prefect reconstruction is not necessary in texture analysis, this property can be used in further applications.

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