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A Wavelet Transform Approach To Texture Analysis And Classification With Linear Regression Model

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Abstract

Texture analysis and classifications are ologybased on multi resolution properties of wavelet transform which is used to extract spectral information of the texture image at different scales and it ignores the structural information of the texture. A special emphasis is that a distinctive correlation exists between the different frequent regions of the sample images, belonging to the same kind of texture. Experimentally, it was shown that different regions of sample image obtained by 2-D wavelet packet transform and observed that this correlation varies from texture to texture. The linear regression model is employed to analyze this correlation and extract texture features that discriminate the samples. We proposed a texture classification algorithm that considers frequency regions and also the correlation between these regions. Experiments show that our method significantly improves the texture classification rate in comparison with other the multiresolution methods, including the Gabor transform, the pyramid-structured wavelet transform (PSWT) and the tree- structured wavelet transform (TSWT) .

1. Introduction

Texture provides vital in order about image Classification tasks. The most conventional approaches included gray level co-occurrence matrices (GLCM) that considers second order statistical texture features, Gauss–Markov random field, which are constrained to the analysis of spatial models and local linear transform considers relations between neighborhood pixels in a small image region[1],[4]. Recently, random set stochastic model is employed to texture classification in which texture can be analyzed by set of structuring windows and extracts structural properties defined by a neighborhood system. A texture image is transformed into a pattern map by a set of templates with principal component analysis (PCA) for characterizing texture information. The Fisher criterion is employed to optimize FIR filters[4] for texture feature extraction. The mutual information of different subbands after the multichannel decomposition is used for the sparse representation of texture image.

The most common multiresolution analysis approach is to transform a texture image into a local spatial/frequency representation by convolving this image with a bank of filters. The Gabor transform is also limited to its filtering area. Consequently, the wavelet transform to obtain the spectral information of the texture image. To make use of the texture primitives, GLCM as commonly popular structural descriptor is recently combined with the traditional multiresolution methods [24], [25]. An image texture is described by the number and types of its primitives and the spatial organization or layout of its primitives. The basic pattern and repetition frequency of a texture sample could be perceptually invisible, although quantitatively present. In the deterministic formulation texture is considered as a basic local pattern that is periodically or quasi-periodically repeated over some area. An image texture may be defined as a local arrangement of image irradiances projected from a surface patch of perceptually homogeneous irradiances. Texture is characterized not only by the grey value at a given pixel, but also by the grey value `pattern' in a neighborhood surrounding the pixel. The unit of texture is texels, and the repetitiveness of the texels determines the type of the texture and decides the texture analysis approach.

2. System design

2.1 Preprocessing algorithm:

1. The original image is decomposed into four subimages, which can be viewed as the parent node and thefour children nodes.
2. Calculate the energy of these subimages and the tree forms four branches from the parent node.
3. Repeat the decomposition of these subimages and the tree branches at the power of four until satisfying the least size of the subimage[5].
4. Repeat the steps for j samples and construct the channel energy matrix M .
5. Figure out the covariance matrix C.
6. Select the top channel pairs with the correlation coefficient $p \geq T$ and order them into a list as p descends.

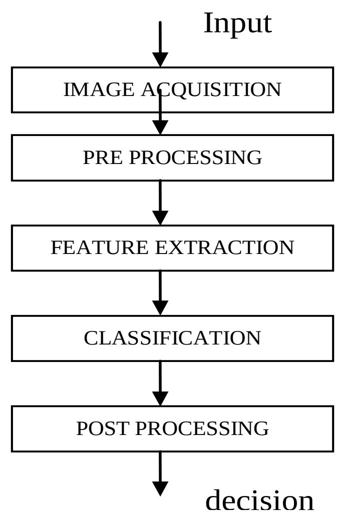
2.2 Learning phase:

Learning phase directly extracts texture features a, b, μ, σ, two frequency channels and correlation coefficient of each top channel pair and index of this texture.Put all such features into a list and insert into a database.

2.3. Classification Phase:

Order all textures in the database into a candidate list, Pick out the parameters a, b, μ,σ of the j^{th} channel pair of a texture in the candidate list from its feature list, and select the energy of two frequency channels identical to that of this top channel pair from the channel-energy vector of this unknown texture image. Take one energy of two channels get the residual Remove the texture from the candidate list if the residual is larger than $\mu \pm 3\sigma$ .If there is only one texture is left in the candidate list, assign the unknown texture image to this texture.

2.4 Architecture Of The System:



3. Methodology

3.1 Wavelet Transform

The wavelet transform provides a precise and unifying framework for the analysis and characterization of a signal at different scales. It can be implemented efficiently with the pyramid-structured wavelet transform and the wavelet packet transform. The pyramid-structured wavelet performs further decomposition of a signal only in the low frequency regions. Adversely, the wavelet packet transform decomposes a signal in all low and high frequency regions[7].

3.2 2-D Wavelet Packet Transforms

As the extension of the 1-D wavelet transform, the 2-D wavelet transform can be carried out by the tensor product of two 1-D wavelet base functions along the horizontal and vertical directions, An image can be decomposed into four sub images by convolving the image with these filters. These four sub images characterize the frequency information of the image in the LL, LH, HL, and HH frequency regions.

LL 3	HL 3	LL 3	HL 3	LL 3	HL 3	LL 3	HL 3
L H3	H H3	L H3	H H3	LH 3	H H3	L H3	H H3
LL 3	HL 3	LL 3	HL 3	LL 3	HL 3	LL 3	HL 3
L H3	H H3	L H3	H H3	LH 3	H H3	L H3	H H3
LL 3	HL 3	LL 3	HL 3	LL 3	HL 3	LL 3	HL 3
L H3	H H3	L H3	H H3	LH 3	H H3	L H3	H H3
LL 3	HL 3	LL 3	HL 3	LL 3	HL 3	LL 3	HL 3
L H3	H H3	L H3	LH 3	H H3	H H3	L H3	H H3

Fig 3.1 2-D wavelet packet Decomposition

3.3. Energy Distribution:

The wavelet domain focuses on directly extracting the energy values from the sub images and uses them to characterize the texture image. The energy distribution of a sub image can be calculated by one of the three commonly used functions: the magnitude ,The squaring, and the rectified sigmoid.. The magnitude and squaring functions are similar in the effect of the nonlinearity. The rectified sigmoid function requires appropriate saturation parameter. The mean and the standard deviation of the magnitude of the sub image coefficients is used as its energy. That is, if the sub image is x[m,n] with $1 \le m \le M$ and $1 \le n < N$ its energy can be represented as

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

Where x(i,j) is the pixel value of the sub image.

3.4 Correlation Analysis

The wavelet (packet) transform approximately decorrelates the image using the orthogonal bases. Correlation indicates the spatial correlation between some sample texture images, belonging to the same kind of texture, at different frequency regions obtained by 2-D wavelet transform. The most common approach is to calculate all frequency regions' energy values of every image with the energy function and to characterize this texture by the statistics of these energy values. This approach ignores the spatial relation of these sample texture images. From a statistical perspective, a frequency region of a sample texture image can be viewed as a random variable and the energy values of this frequency region can be treated as the random values of this variable.

3.5 Linear Regression Model

The simple linear regression model to analyze the correlation. Suppose that we have a set of the random data for two numerical variables X and Y. From the simple linear regression analysis, the distribution of the random data approximately appears a straight line in space.. This line function (also called the simple linear regression equation) can be given as follows:

$$Y = a \times x + b$$

exploit the simple linear regression model to extract the texture features from the correlation in the frequency channel pairs. The channel-pair list includes all channel pairs with $\beta \ge T$. For two frequency channels of one channel pair in the list, we take out their energy values from the channel-energy matrix The parameters a and b of the line can be figured out through the least square method.

3.6 Texture Feature Set

The feature lists of the textures are needed to store into the database. In the feature lists, every texture feature contains the a,b,μ, and σ , two frequency channels and the correlation coefficient β of one channel pair and the index of a texture. The parameters a,b and two frequency channels are used to compute the residual of an unknown texture image at a top channel pair of a texture, and the parameters ,μ and σ are used to get the threshold $\mu \pm 3\sigma$ in order to determine whether this image satisfies the correlation at this top channel pair of this texture.

3.7 Threshold Comparison

The statistics implies that a normally distributed (or Gaussian) random variable X has probability density function

$P(x)=(1)/(\sigma\sqrt{2\pi})\exp[-((x-\mu)^2)/2\pi^2)]$

Where the parameters μ and σ of the distribution are the mean and Variance of X, respectively. It can be known that a texture always have many top channel pairs and the combination of these channel pairs is the characteristic of this texture. If a sample image meets the correlation of all top channel pairs of a texture, it can be inferred that it belongs to this texture. Therefore, the value of $\mu \pm 3\sigma$ can be considered as an appropriate way to assign an unknown texture image to a texture. The estimation of mean and variance can be carried out by

$$\mu = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n-2}}.$$

The average retrieval rate defined is different from that of other methods because our classifier is threshold based comparison in one dimension. All query samples are processed by our method and respectively assigned to the corresponding texture. We count the samples of this texture, which are assigned to the right texture, and get the average percentage number as the average retrieval rate of this texture. Moreover, our method takes simply the threshold comparison in 1-D space in the classification phase owing to taking advantage of the texture inherent correlation characteristic in the learning phase.

4. EXPERIMENTAL RESULTS

Every original image is of size 640×640 pixels with 256gray levels. 81 sample images of size 128 ×128 with an overlap of 32 pixels between vertically and horizontally adjacent images are extracted from each original image and used in the experiments, and the mean of every image is removed before the processing.

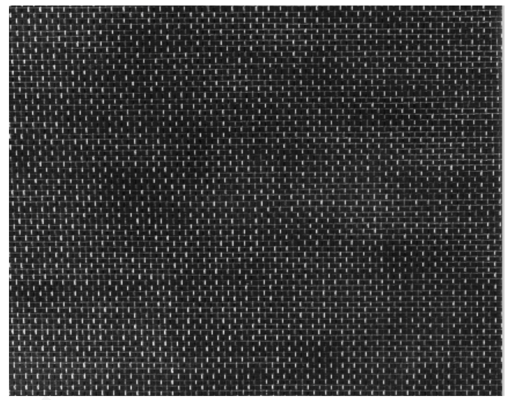


Fig 4.1 Texture Image

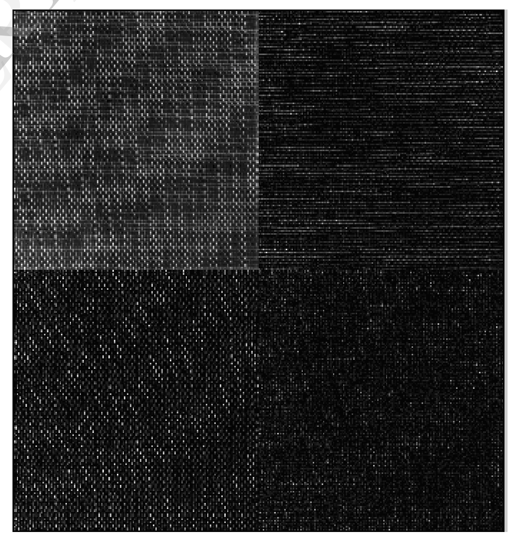


Fig 4.2 First level Decomposition

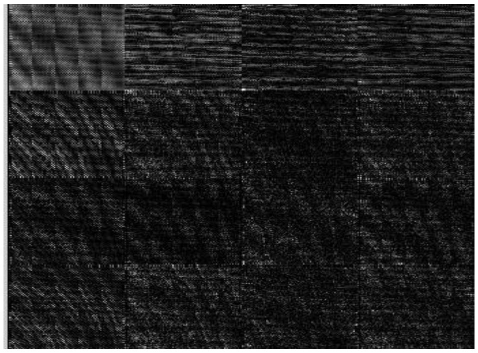


Fig 4.3 Second Level Decomposition

This table illustrates the classification accuracy of different textures obtained from Brodatz's Texture album[2]. I used 40 textures and verify the performance of the classification algorithm. Each texture with its classification rate is shown in Table 4.1 and Figure 4.4

Texture ID	Classification Rate	Texture ID	Classification Rate
D3	84.42	D78	100
D4	99.65	D79	99.30
D6	99.65	D82	100
D9	99.65	D83	100
D11	99.65	D84	99.65
D16	100	D92	100
D19	92.733	D95	100
D21	99.65	D102	99.65
D24	99.65	D103	99.65
D29	100	D105	100
D34	100	D13	97.92
D36	100	D44	100
D52	100	D15	100
D53	95.15	D25	100
D55	100	D28	100
D57	100	D43	100
D65	100	D45	100
D68	100	D62	92.04
D74	100	D60	100
D77	100	D81	100

Table 4.1 Classification Rate of Different Textures without noise

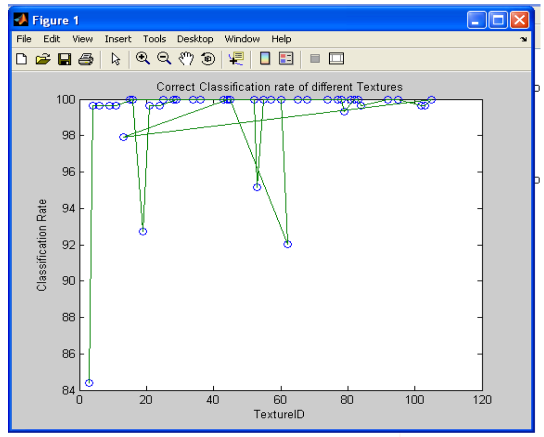


Fig 4.4 Classification Rate of Different Textures without noise

This table illustrates the classification accuracy of different textures obtained from Brodatz's Texture album[2]. I used 40 textures and verify the performance of the classification algorithm by adding guassian noise with the sample image. Each texture and its classification rate with noise is shown in Table 4.2. and Figure 4.5.

TexturelD	Classification Rate with Guassian noise	TexturelD	Classification Rate with Guassian noise
D3	87.54	D4	100
D6	98.96	D9	100
D11	100	D16	98.26
D19	98.26	D21	100
D24	100	D29	100
D34	100	D36	100
D52	100	D53	96.88
D55	100	D57	100
D65	100	D68	100
D74	100	D77	99.30
D78	100	D79	99.3
D82	100	D83	99.6
D84	100	D92	99.6
D95	99.65	D102	99.6

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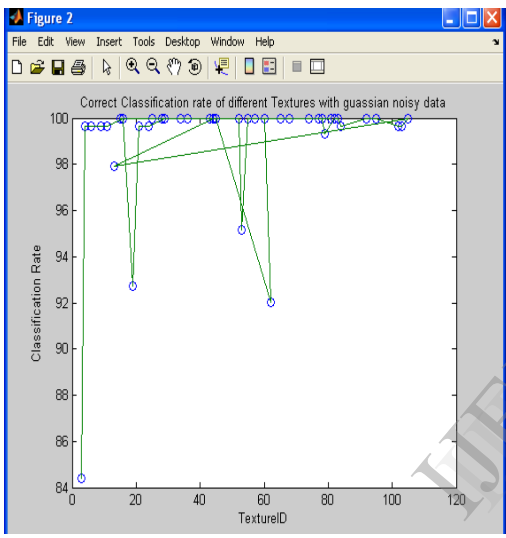
D103	99.65	D105	99.65
D13	98.96	D44	99.65
D15	100	D25	100
D28	100	D43	100
D45	100	D62	89.27
D60	100	D81	100

Table 4.2 Classification Rate of Different Textures with Guassian noisy data



Fige 4.5 Classification Rate of Different Textures with Guassian noisy data

5. CONCLUSION

This wavelet based approach is Effective and its Classification accuracy is good for much more Textures. It provides entire frequent channels in comparison with traditional approaches and it is capable to characterize much more spectral information of the texture at different multi resolution levels. Multiresolution analysis directly computes the energy values from the sub images and extracts the features to characterize the texture image at multidimensional space. Our method employs threshold comparison in one dimension space rather than the multidimensional space. It uses linear regression model to analyse correlation of different frequency channels. It is very easy and fast to examine the change of different frequent channels for texture image.

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