Texture Analysis with Linear Regression Model Based on wavelet transform

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Abstract—Wavelet based preprocessing is a very successful method providing proper Image Enhancement and Denoising without a considerable change in overall intensity level. They are usually artifact free, so mostly used for contrast enhancement in noisy environments. In this paper a texture analysis approach is proposed with the linear regression model based on the wavelet transform. This method is motivated by the observation that there exists a distinctive correlation between the sample images, belonging to the same kind of texture, at different frequency regions obtained by 2-D wavelet packet transform.

Experimentally, it was observed that this correlation varies from texture to texture. The linear regression model is employed to analyze this correlation and extract texture features that characterize the samples. Therefore, this method considers not only the frequency regions but also the correlation between these regions. In contrast, the pyramid structured wavelet transform (PSWT) and the tree structured wavelet transform (TSWT) do not consider the correlation between different frequency regions. Experiments show that this method significantly improves the texture classification rate in comparison with the multiresolution methods, including PSWT, TSWT, the Gabor transform, and some recently proposed methods derived from these.

Keywords—Linear regression, texture analysis, wavelet transform.

I. INTRODUCTION

Texture provides essential information for many image classification tasks. Extensive research has been done on texture classification during the last three decades[1]-[4]. In the 1980s, most traditional approaches included gray level co-occurrence matrices (GLCM) [5], second-order statistic method[6], Gauss–Markov random field[7], and local linear transform[8], which are restricted to the analysis of spatial relations between neighbourhood pixels in a small image region. As a consequence, their performance is the best for the class of so called microtextures[9]. With a study on human vision system, researchers begin to develop the multiresolution texture analysis models, such as the wavelet transform and the Gabor transform. Extensive research has demonstrated that these approaches based on the multiresolution analysis could achieve reasonably good performance, so they have already been widely applied to texture analysis and classification. The most common multiresolution analysis approach is to transform a texture image into a local wrapping this image with a bank of filters with some tuned parameters. This property coincides with the study that the human visual system can be modelled as a set of channels. This clearly motivate researchers to study how to extract more discriminable texture feature based on the multiresolution techniques. Currently, the wavelet and the Gabor transform are the most popular multiresolution methods. Compared to the wavelet transform[10]-[12], the Gabor transform needs to select the filter parameters according to different texture. There is a trade-off between redundancy and completeness in the design of the Gabor filters because of non orthogonality. The Gabor transform is also limited to its filtering area Consequently, the wavelet transform has been chosen to obtain the spectral information of the texture image. While the traditional multiresolution methods keep eye on the spectral information of the texture image at different scales and
use the statistics of the spectral information as the texture
descriptor. Adversely, the wavelet packet transform
decomposes a signal in all low and high. As the extension of
the 1D wavelet transform, the 2D wavelet transform can be
carried orthogonally by the tensor product of two 1D wavelet
base functions along the horizontal and vertical directions, and
the corresponding filters can be expressed as texture structural
information. In this paper, it is found that there exists a
distinctive correlation between some sample texture images,
belonging to the same kind of texture, at different frequency
regions obtained by 2D wavelet packet transform. Experimentally it is demonstrated that this correlation varies
from texture to texture. A new texture analysis method, in
which the simple linear regression model is employed into
analyzing this rate in comparison with the multiresolution
methods including PSWT, TSWT, the Gabor transform, and
some recently proposed methods. This paper is organized as
follows. The brief review about 2-D wavelet transform and an
application of the correlation between different frequency
regions to texture analysis are described in section II. Several
traditional multiresolution techniques, such as PSWT, TSWT,
and the Gabor transform, and our method are compared.
Finally, the conclusions are summarized in Section III.

II. TEXTURE ANALYSIS WITH LINEAR REGRESSION
MODEL

A. Two-Dimensional Wavelet Packet Transform:
The wavelet transform provides a precise and unifying
framework for the analysis and characterization of a signal at
different scales. It is described as a multiresolution analysis
tool for the finite energy function. 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. 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, and the corresponding filters can be expressed as h

\[
L(k, l) = h(k)h(l), \quad H(k, l) = h(k)h(l), \quad L(k, l) = g(k)h(l)
\]

and \( H(k, l) = g(k)h(l) \). An image can be decomposed into
four subimages by convolving the image with these filters.
These four subimages characterize the frequency information
of the image in the LL, LH, HL, and HH frequency regions
respectively. The 2-D PSWT can be constructed by the whole
process of repeating decomposition in the LL regions, whereas
the 2-D wavelet packet transform decomposes all frequency
regions to achieve a full decomposition, as shown in Fig. 1.
Therefore, the 2-D PSWT depicts the characteristics of the
image in the LL regions and the 2-D wavelet packet transform
describes the properties of the image in all regions. Most of the
research in the multiresolution analysis based on the wavelet
domain focuses on directly extracting the energy values from
the subimages and uses them to characterize the texture image.
In this paper, the mean of the magnitude of the sub-image
coefficients is used as its energy. That is, if the sub image is
\( x(m, n) \) with \( 1 \leq m \leq M \) and \( 1 \leq n \leq N \) its energy can be represented
as;

\[
E = \left( \frac{1}{MN} \right) \sum_{i=1}^{M} \sum_{j=1}^{N} x(i, j)
\]

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

Fig.1 Two-Dimensional Wavelet Packet Transform

B. Analysis of Correlation between Frequency Channels.
Given that there are some sample texture images from the same
kind of texture, these images should have the same spatial
relation between neighbourhood pixels as this texture. These images are all decomposed to obtain the same frequency regions 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. In this study, we capture this inherent texture property by learning a number of 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. Experimentally it is found that there exists a distinctive correlation between different variables (frequency regions).

As a powerful multiresolution analysis tool, the 2-D wavelet transform has proved useful in texture analysis, classification, and segmentation. The 2-D PSWT performs further decomposition of a texture image only in the low frequency regions. Consequently it is not suitable for images whose dominant frequency information is located in the middle or high frequency regions. Although the 2-D wavelet packet transform characterizes the information in all frequency regions, this representation is redundant. On the other hand, in order to generate a sparse representation, the 2-D TSWT decomposes the image dynamically in the low and high frequency regions whose energies are higher than a predetermined threshold. However, it ignores the correlation between different frequency regions. We use 2D wavelet packet transform to obtain all frequency information of a texture image in this paper. The detail is described as follows:

First, the original image is decomposed into four sub-images, which can be viewed as the parent node and the four children nodes in a tree and named as O, A, B, C, and D respectively, as shown in Fig. 2.

![Fig. 2 Tree Representation](image)

They symbolize the original image, LL, LH, HL, and HH frequency regions.

**C) Linear Regression Model:**

The correlation between different frequency regions has been validated as a sort of effective texture characteristic. In this section, we employ the simple linear regression model to analyze the correlation. Suppose that we have a set of the random data \((x_1 \ y_1) \ T, \ldots, (x_n \ y_n) \ T\), for two numerical variables \(X\) and \(Y\) and suppose that we regard \(X\) as a cause of \(Y\). From the simple linear regression analysis, the distribution of the random data approximately appears a straight line in \(X, Y\) space when \(X\) and \(Y\) are perfectly related linearly. There is a linear function that captures the systematic relationship between two variables. This line function (also called the simple linear regression equation) can be given as follows:

\[
y^\prime = a * x + b
\]

where \(y^\prime\) is called a fitted value of \(y\).

We 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 \(= T\). For two frequency channels of one channel pair in the list, we take out their energy values from the channel-energy matrix \(M\) and then consider these energy values as the random data \((x_1 \ y_1) \ T, \ldots, (x_n \ y_n) \ T\) for two variables \(X\) and \(Y\). The distribution of these energy values should also represent a straight line in \(X,Y\) space. In general, the wavelet packet transform generates a multiresolution texture representation including all frequency channels of a texture image with the complete and orthogonal wavelet basis functions which have a “reasonably well controlled” spatial/ frequency localization.
property. Our method absorbs this advantage of the wavelet packet transform. The difference between our method and other multiresolution based texture analysis methods are PSWT loses the middle and high frequency information. TSWT does not take into account the correlation between different frequency channels. The Gabor transform uses a fixed number of filter masks with predetermined frequency and bandwidth parameters. In contrast, this method not only thinks about all frequency channels but also analyzes the correlation between them with the simple linear regression model. So, it can be viewed as a very useful multiresolution method.

III. PREPROCESSING ALGORITHM

- Input: All j samples of a given Texture
- Output: The channel-pair list and the channel-energy matrix M.

Algorithm Process
1. Decompose a sample of a given texture with 2-D wavelet packet transform into an output of k frequency channels
2. Calculate the energy of channels k and get a channel-energy vector v of length k
3. Repeat the first and second steps for all j sample images of this texture and then take j channel-energy vectors to construct j×k channel-energy matrix M.
4. Figure out the k×k covariance matrix C from M.
5. Select the top channel pairs with the correlation coefficient ρ ≥ T and order them into a list as ρ descends, and, finally, output this list and the channel-energy matrix M.

In the fifth step of Algorithm 1, the constant T is a controllable parameter which serves as a threshold for selecting the top channel pairs with enough correlation. According to the statistics T is the critical value that separates the acceptance and rejection regions of the correlation. The correct decision of T is related to the significance level α and the sample number of texture.

IV. EXPERIMENTAL RESULT

In this section, the performance is verified. 20 textures has been used. Every original image is of size 640 x 640 pixels with 256 grey levels. 81 sample images of size 128 with an overlap 32 pixels between vertically and horizontally adjacent images are extracted from each original colour image and used in the experiments and mean of every image is removed before processing. In this, Energy is calculated of each image.
V. CONCLUSION

In this paper, a new modified approach to texture analysis with the simple linear regression model based on the wavelet
transform is presented. Although the traditional multiresolution methods, like PSWT, TSWT, the Gabor transform are suitable for some textures, this method is natural and effective for much more textures.

Next, the correlation of different frequent channels can be applied in this method through the simple linear regression model and this method employs the correlation between different frequency regions to the construct the texture feature. So, it employs threshold comparison in one dimension space rather than some distance measures in the multidimension space. Therefore, it is very easy and fast to examine the change of different frequent channels for texture image.

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REFERENCES

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