TEXTURE CLASSIFICATION USING TREE-STRUCTURED WAVELET TRANSFORM AND NEURAL NETWORKS

Emir Tufan

Department of Electronic Engineering
University of Istanbul
Avcilar, Istanbul 34850, TURKEY
tufane@istanbul.edu.tr

ABSTRACT

In this paper a new approach for texture classification problem is presented. Tree-structured wavelet transform for the pre-processing task while the neural network is used for the classification task. The energy values obtained at the subbands are used for the input vector of the neural network system. The subbands where the energy values are greater than a threshold are determined and it is tried to establish tthe texture classification problem. The back-propagation algorithm is used to test a performance of the system.

I. INTRODUCTION

The classification is very important application of image proccessing. The texture properties are used for the classification purpose [1]-[3]. The texture is very crucious feature for using to image recognition. An image can be described by the combinations of different textures [4].

The textures can be identified by human eyes easily. Therefore the system for extracting texture feature is designed by considering human eyes. The research for human eyes shows that the system of human eyes is based on the spatial/frequency representation of an image [5]. The Gabor transform, Wigner transform and wavelet transform provides spatial/frequency analysis of an image [6],[7]. Images can be analysed at different frequency bands by using these transforms. Especially wavelet transform provides image analysis at high frequency bands and low frequency bands [7],[8]. Also it is possible to have multiresolution image analysis by wavelet transform [9].

The organization of this paper is as follows: Section II presents wavelet transform. In Section III, the details of subband image decompositionare given. In Section IV tree-structured wavelet transform is presented. Section V presents conclusions.

II. WAVELET TRANSFORM

Several researches have been presented on wavelet tansform and spatial/frequency analysis of images [7]-[9]. Wavalet transform provides analysis of non-stationary signals. It offers a tool for providing fine time resolution for high frequencies as well as fine frequency resolution for low frequencies [7]. The wavelet transform is defined by decomposing the signal into a family of functions which are the shifted and scaled of a unique function which is called the mother wavelet. The wavelet set, $\psi_{ab}(x)$, is obtained from $\psi(x)$, called as mother wavelet, such that [7]

$$\psi_{ab}(x) = \frac{1}{\sqrt{a}}\psi\left[\frac{x-b}{a}\right] \qquad (1)$$

where a and b represent scaling and shifting parameters, respectively. As is obvious from (1), $\psi_{ab}(x)$, is obtained from $\psi(x)$ by shifting and scaling. These functions are short duration, high frequency; and long duration, low frequency functions. The scaling parameter ensures that the width of the wavelet is squeezed for high frequencies and expanded for low frequencies. The wavelet transform of f(x) is defined by [8]

$$W_f(a,b) = \int f(x)\psi_{ab}(x)dx \qquad (2)$$

The inverse wavelet transform is

$$f(x) = \iint_{ab} W_f(a,b)\psi_{ab}(x)\frac{dadb}{a^2} \qquad (3)$$

III. SUBBAND IMAGE DECOMPOSITION

The basic objective of subbad image decomposition is to split an image frequency band into a set of uncorrelated frequency bands by filtering.

A discrete wavelet transform provides a subband image decomposition. The main contribution of a discrete wavelet transform is that it provides an image representation in which some of the coefficients represent long data lags corresponding to a narrow band, low frequency range, and some of the coefficients represent short data lags corresponding to a wide band, high frequency range .

At the beginning an image is divided into four subbands which arise from separable application of vertical and horizontal filters and subsampled by 2. These subbands are labelled as LL_1 , HL_1, LH_1, HH_1 representing the coarse and finest scale wavelet coefficients.

The coarse subband is obtained by low-pass filtering and the finest subbands are obtained by high-pass filtering. The coefficient at the coarse scale is called the parent, and all coefficients corresponding to the same spatial location at the next finer scale of similar orientation are called children. For a given parent, the set of all coefficients at all finer scales of similar orientation corresponding to the same location are called descendants. Similarly, for a given child, the set of coefficients at all coarser scales of similar orientation corresponding to the same location are called ancestors. Fig. 2 illustrates the first stage of subband image decomposition. The low frequencies represent a bandwidth approximately corresponding to $0 < |\omega| < \pi/2$, whereas the high frequencies represent the bandwidth $\pi/2 < |\omega| < \pi$.

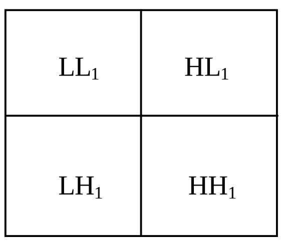

Figure 1. The first stage of four subband image decomposition.

The same procedure can be applied to the coarse subband image, LL_1. Thus LL_2, HL_2, LH_2, HH_2 representing a spatial area corresponding to approximately a 4x4 area of the original picture. The low frequencies at this scale represent a bandwidth approximately coresponding to $0 < |\omega| < \pi/4$, whereas the high frequencies represent bandwidth corresponding to $\pi/4 < |\omega| < \pi/2$. Fig. 2 shows the spatial seperation of a two scale four subband image decomposition.

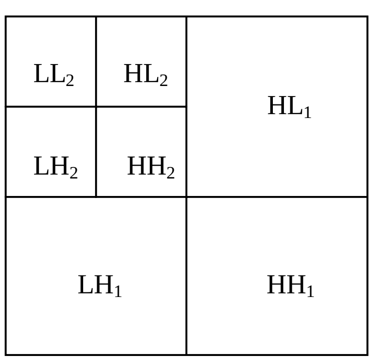

Figure 2. A two scale four subband image decomposition.

The process continues until some final scale is reached.

IV. TREE-STRUCTURED WAVELET TRANSFORM

The traditional wavelet transform is very convinient for low-frequency images since this transform recursively decomposes subsimages in the low frequency channels. However, the wavelet transform does not help very much for images whose most significant appears in the middle frequency channels. To this end the tree-structred wavelet transform is proposed for image decomposition by considering frequency channels where the significant information is obtained. The subband image decomposition is applied for frequency channel where the energy is significant. Therefore it is avoided from analysis of subband images whose energy is not significant which means the corresponding frequency channels have less information. The algorithm for tree-structured wavelet transform is given as follows [6]:

- A given textured image is decomposed into 4 subband images using 2D two-scle wavelet transform.
- The energy of each subband image is calculated as

$$e = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}| f(i,j)| \qquad (4)$$

where $f(i,j)$ is the subband image and MxN is the size of $f(i,j)$.

- If the energy of subband image is significantly smaller than others, the decomposition is stopped.
- If the energy of subband image is significantly larger, the above decomposition procedure is continued.

V. CONCLUSION

Textured images are split into 4 subband images represented in Fig. 1. The Daubechies coefficients are used as low-pass and high-pass filter coefficients.

The energy for each subband image is calculated using (4). The wavelet transform is applied to subband images whose energy is greater than %15 of maximum energy. This procedure is repeated by 4 to extract significant feature for each textured images. The energy map which represents dominat frequency channles where the energy is significant is obatined for these images using above procedure. Fig. 3 illustrates the determination of energy map.

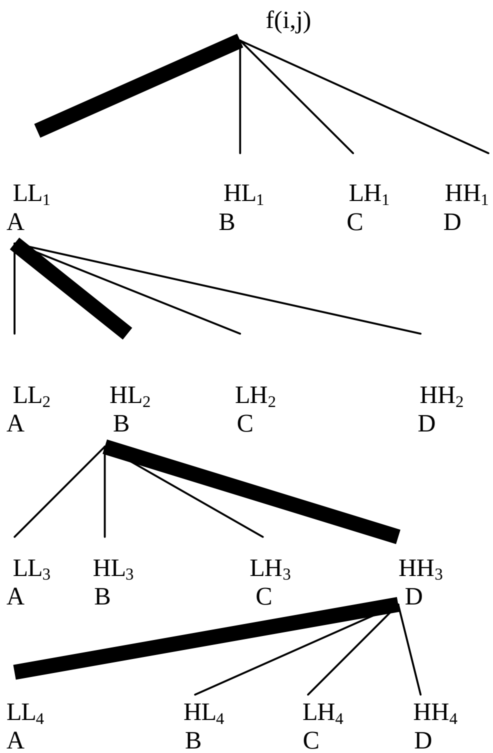

Figure 3. Energy map representation for an image (ABDA).

In the example illustratd in Fig. 3, the dominant frequency channel is obtained as LL_1 denoted as "A" after first subband decomposition. The further dominant frequency channels are obtained as HL_2, HH_3, LL_4 denoted as B, D, A, respectively. This energy map, ABDA, is considered as feature to be extracted for an textured image.

We use 160 textured images whose size is 512x512. The energy map is determined using tree-structured wavelet transform for each image. These energy maps are fed into neural network input. The back-propagation algorithm is used for the classification part.

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