*MVA2000* IAPR Workshop on Machine Vision Applications, Nov. 28–30, 2000, The University of Tokyo, Japan

# 3—31 Iris Identification System Using Tree-Structured Wavelet Algorithm

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## Abstract

The unique iris structures motivate the development of an automatic identification system based on iris characteristic. Texture analysis with multichannel filtering approach is meant to extract feature from iris texture images and encode them into a compact and unique information for each iris. One of the tools that can analyze texture image in multiresolution approach is wavelet transform. In this research, we propose a multiresolution approach based on a modified wavelet transform called the tree-structured wavelet transform for iris texture analysis and classification. A MATLAB simulation program has tested texture classification algorithm on 12 texture images (taken from Brodatz texture album) and 11 iris images (including real iris image).

*Keywords: biometrics, iris recognition, texture analyzing, tree-structured wavelet*

## Introduction

The human iris has unique features and is complex enough to be used as a biometric signature. This means that the probability of finding two people with identical iris patterns is almost zero. This iris identification system uses the textural information on the iris image. Iris texture is also stable for decades. The unique iris structures motivate the development of an automatic identification system based on iris characteristics.

In this research, we propose a multiresolution approach based on a modified wavelet transform called the tree-structured wavelet transform or wavelet packets for texture analysis and classification. This method can be applied on iris identification system. By optimizing system parameters, this tree-structured wavelet method can recognize an iris image and determine, whether or not it belongs to any of the classes in the database.

This approach will be used to classify 12 texture images taken from Brodatz album and 11 iris images (including real images) by a MATLAB simulation program.

## Texture Analysis with Tree-Structured Wavelet Transform

Texture analysis with multichannel filtering approach is meant to extract feature from iris texture image and encode them into a compact and unique information for each iris. This approach enables us to explore different frequencies and dominant orientation in various textures. The development of this new transform is motivated by the observation that a large class of natural textures can be modeled as quasi-periodic signals whose dominant frequencies are located in the middle frequency channels. With the transformation, we are able to zoom into any desired frequency channels for further decomposition. Textural features are represented on an energy-map that contains its dominant frequency channels in sequence. In contrast, the conventional pyramid-structured wavelet transform performs further decomposition only in low frequency channels.

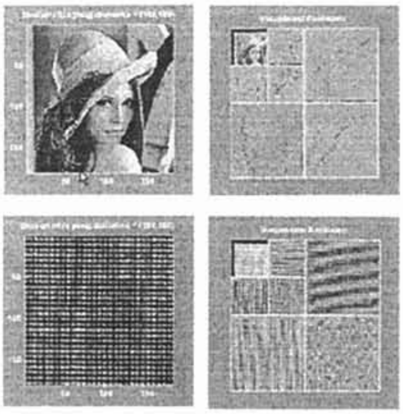

Figure 1. Pyramid-structured wavelet transforms
(a) Lena (b) BrodatzD21

Fig.1 shows that pyramid-structured wavelet transform is applied to two different kinds of images. We use the Lena image as a representative of an ordinary image and the Brodatz D21 image as a texture image. By examining the wavelet-transformed images in Fig. 1. (Right), we recognize the Lena image clearly from its low frequency channel (the upper left corner). In contrast, we are not able to recognize a similar texture pattern in the same low frequency channel for Brodatz21 image. The simple experiment implies that the low frequency region of textures may not necessarily contain significant information. Instead, we observe some horizontal and vertical line patterns clearly in the middle frequency region. Thus, an appropriate way to perform the wavelet transform for textures is to detect the significant frequency channels and then to decompose them further.

The above idea leads to a new type of wavelet transform called the tree-structured wavelet transform. The difference between this algorithm and the traditional pyramid algorithm is that the decomposition is no longer simply applied to the low frequency subsignals recursively. Instead, it can be applied to the output of any filter $h_{LL}$, $h_{LH}$, $h_{HL}$, or $h_{HH}$. Note that it is usually unnecessary and expensive to decompose all subsignals in each scale to achieve a full decomposition. To avoid a full decomposition, we may consider a criterion to decide whether decomposition is needed for a particular output. We use the averaged $l_i$-norm

$$e(\mathbf{x}) = \frac{1}{N}\|\mathbf{x}\|_1 = \frac{1}{N}\sum_{i=1}^{N}|x_i|$$

where $x = (x_i, \ldots, x_N)$, as the energy function to locate dominant frequency channels. The tree-structured wavelet transform is given below.

Tree-Structured Wavelet Transform Algorithm:

1. Decompose a given texture image with 2-D two scale wavelet transform into 4 subimages, which can be viewed as the parent and children nodes in a tree
2. Calculate the energy of each decomposed image (children node). that is, if the decomposed image is x(m,n), with $1 \le m \le M$, and $1 \le n \le N$, the energy is :
$$e = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}|x(m,n)|$$
3. If the energy of a subimage is significantly smaller than other subimages, we stop the decomposition in this region since it contains less information. This step can be achieved by comparing the energy with the largest energy value in the same scale. That is, if $e < Ce_{max}$, stop decomposing this region where C is a constant less than 1.
4. If the energy of a subimage is significantly larger, we apply the above decomposition procedure to the subimage.

The size of the smallest subimages should be used as a stopping criterion for further decomposition. If the decomposed channel has a very narrow size, the location and the energy value of the feature may vary widely from sample to sample so that the feature may not be robust. According to our experience, the size of the smallest subimages should not be less than 16 x 16. Consequently, if the input image size is 256 x 256 (or 64 x 64), a 4-level (or 2-level) tree-structured wavelet transform is appropriate. The tree-structured wavelet transform above provides a non-redundant representation, and it takes no more space to store the wavelet coefficients than it does to store the original image. This algorithm will be used in extracting texture features of the iris image.

## Texture Classification Algorithms

A simple texture classification algorithm with a fixed number of features follows directly from the above decomposition algorithm. The process is described as follows:

1) Learning phase

Given m samples obtained from the same texture, decompose each sample with the tree-structured wavelet transform and calculate the normalized energy at its leaves which defines an energy function on the spatial/frequency domain known as the energy map. Generate a representative energy map for each texture by averaging the energy maps over all m samples. Repeat the process for all textures.

2) Classification phase

Decompose an unknown texture with the tree-structured wavelet transform and construct its energy map. Pick up the first J dominant channels, which are the leaf nodes in the energy map with the largest energy values as features. Denote this feature set by $x = (x_l, \ldots, x_J)$. For texture $i$ in the database pick up the energy values in the same channels and denote the energy value by

$$m_i = (m_{i,l}, \ldots, m_{i,J})$$

Calculate the discrimination function for textures avail-in the candidate list by

$$D_i = \text{distance}(x, m_i)$$

Assign the unknown texture to texture $i$ if

$$\boldsymbol{Di < Dj} \text{ for all } j \ne i$$

Note that if the associated leaf node does not exist in the energy map of texture i in step 3, we may have the following two choices. Since the energy value of the parent node is the averaged energy value of its children nodes with the $l_2$, norm, we may use the energy value of its parent node as an approximation. It also implies that texture $i$ is unlikely to be the unknown texture because the energy value of its corresponding channel is too small. Thus, another alternative is simply to discard texture $i$ from the candidate list and test the next texture in the database.

## Iris Identification System Program

In this paper, there are two simulations for testing texture classification method using tree-structured wavelet transform and its application on iris identification system. The first simulation uses texture image taken from Brodatz texture album, and the second simulation use downloaded and real iris images. The sequence of this experiment is detailed as follows:

1. Image Enhancement

This process can only be applied on iris image. The boundary between the pupil and the iris is detected after the position of the eye in the given image is localized so that the program only analyzes iris image. The process also includes illumination and histogram equalizing.

2. Sampling

To get some samples from a texture or iris image, a window which size smaller than the image will be made. This window will be moved along the horizontal and vertical axis of the image and taking the image within the window as a sample.

3. Decomposition

All samples will be decomposed by tree-structured wavelet transform method. In this stage, we have to set number of decomposition level (N), the type of wavelet transform, and tree structured wavelet constant (C) that determine number of channel frequencies from decomposition process. The result of this process is energy-map that presents texture features for each sample.

4. Calculation of each class energy-map

Energy-map for each class is determined by averaging energy in the same channel from all samples energy-map. The number of class is equal to number of texture (iris) used. This energy-map for each class will be stored in database as a reference for classification process.

5. Identification

This stage will analyze an input image and identify it. The images are taken from sampled image from previous stage and from another sample out of the database.

## Experimental Results

The identification system implementation using a MATLAB simulation program will be carried out to classified 12 texture images taken from Brodatz album and 11 iris images (including real images).

***Brodatz Texture Image***

Original image 640x640 pixel will be sampled to 100 images 256x256 pixel. Each sample image decomposed by using tree-structured wavelet with decomposition parameters:

- decomposition level, N=4
- wavelet type, dB8
- tree-structured wavelet, C=0,095

The result from this process is energy-map for each sample.

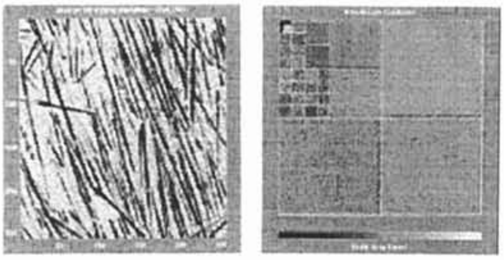

Figure 2. Decomposition of D15 Brodatz texture

Energy-map for each sample is arranged by their channel energy value, in ascending sequence. One texture with 100 samples can produce energy-map with various channel sequences. The result of sequence combination of 5 dominant channels from decomposition process for D18 texture is shown on the table below:

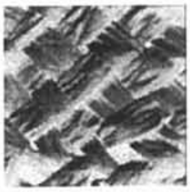

Figure 3. D18 – Brodatz Texture

Table 1. The first 5 dominant channels of D18

| D18 Texture, Dominant Frequency Channel | | | | | | |
|---|---|---|---|---|---|---|
| Type | 1st | 2nd | 3rd | 4$^{th}$ | 5th | % of appearance |
| 1 | 85 | 86 | 87 | 88 | 90 | 85 % |
| 2 | 85 | 86 | 87 | 88 | 92 | 14 % |
| 3 | 85 | 86 | 88 | 87 | 92 | 1 % |

Based on dominant channel sequence which most often occur in the decomposition process, energy-map for each texture can be made. The energy value is the average of energy value from all samples in the same channel. Tested texture is classified to each texture by the closest energy-map (shown by the shortest Euclidean distance). Tested texture is taken from sampled texture image. Classification of one texture image is tested 100 times (number of samples).

### *Iris Image*

Iris images used in this experiment are taken from http://www.cl.cam.uk/users/jdg1000/ and real iris image (scanned from a photograph of iris images). Original image 480x412 pixel will be sampled to 12 images 440x382 pixel. 12 sample is considered to be enough because of the limited iris-analyzing zone. Each sample image decomposed by using tree-structured wavelet with decomposition parameters:

- decomposition level, N=4
- wavelet type, dB8
- tree-structured wavelet, C=0,04

Example of the decomposition sampled iris image is shown on the figure below.

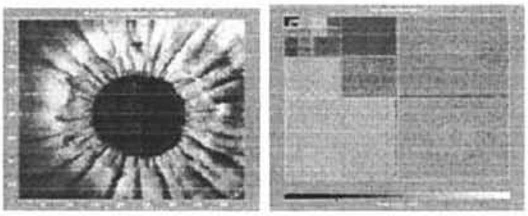

Figure 4. Decomposition of an iris image

In order to test the system precision in classifying and identifying an iris, all sampled iris images in the database and one iris image outside the database are used as a tested iris. The number of analyzed channels is changed between 1 and 12 channels. The result is shown on Figure 5.

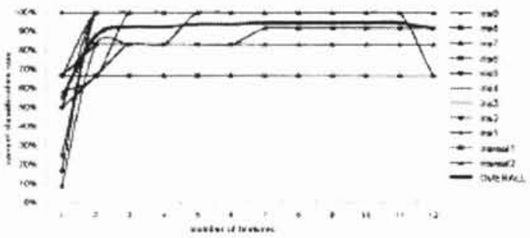


Figure 5. Iris Classification Correction Rates

Simulating the existing of undefined iris, we use an iris image outside the database. The result is that the iris will be defined as the iris image outside the database. The Euclidean distance to the closest class is far enough comparing to the distances in precise classification.

## Conclusions

1. The results of texture classification that analyzed 5 dominant channels show that the average precise level is 99,2 %. It means that the FRR (False Rejection Ratio) is very small. Analyzed channel addition in the D15 and D9 texture classification can reduce each FRR.
2. The iris identification process can be tested by changing the number of analyzed-channel. The graphic of the iris classification correction rates shows that the number of channels can affect the classification precision. Generally, adding the number of analyzed channels can increase the classification precision level. In order to get the best result, the optimal number of analyzed channel is different on each iris. Above the optimal number, the addition of analyzed channel will not give a better precision. The experiment above shows that 7 analyzed channels give the optimal result, with precision level 94.7%.
3. The test on iris images, which is not included in the database, can be defined as an unknown iris. However, that result can't be considered as a small FAR value, because of limited number of the tested iris images.

## References

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