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Fingerprint enhancement using polyphase filterbank

*Shiny John, M. Mathurakani

Department of Electronics & Communication Engineering
TocH Institute of Science & Technology, Ernakulam, India
*Corresponding Author: email: maryevitta@gmail.com

Abstract: Fingerprint as biometric is considered as one of the best way for personal identification. In this paper an efficient method for fingerprint enhancement using non-separable wavelet is introduced, and using polyphase filters the input finger print image is decomposed. This is an efficient method and improves the speed of computation. After performing decomposition on the input image wavelet coefficients will be obtained. These coefficients are then modified and later output image is obtained after reconstruction. This will produce an output image with reduced noise, high contrast between ridges and valleys. This method reduce the time for computation when compared with direct implementation using non-separable wavelet. A good quality fingerprint image has high contrast and well defined ridges and valleys, where as a poor quality fingerprint is marked by low contrast and ill-defined boundaries between the ridges.

Keywords: biometric technology, non separable filter, polyphase filter, fingerprint image

1 Introduction

Biometric technologies are widely used in forensic as well as civilian applications. When compared with other biometric technologies it can be seen that fingerprints are more commonly used. Each individual will have unique fingerprints defined by distinct minutiae. Feature extractor will extract these minutiae. The purpose of fingerprint enhancement is to improve the clarity of ridge and valley structure, to avoid generating pseudo-features, and to guarantee the accuracy and reliability of feature extraction. Fingerprint enhancement needs to perform the following tasks [1]:

- Increase the contrast between the ridges and valleys.
- Enhance ridges along the ridge orientation.

- Complete the broken ridges in cuts and creases and should not change the local ridge shape in the high curvature regions
- Facilitate feature points detection and the number of genuine minutiae should be the same as before enhancement.
- Should not change the ridge and valley structure and not flip minutiae.

There are several methods for fingerprint enhancement and here a new method based on non-separable wavelet is introduced. In this method fingerprint images are first decomposed using non separable filter banks which are polyphase filters. The image is decomposed using polyphase technique and it is a tool that rearrange the computations of filtering operation so as to reduce the number of computations and increase the speed.

There are many fingerprint enhancement algorithms in literature. One is using contourlet transform and it is a new geometrical image based transform, which is recently introduced by Do and Vetterli [2]. S. Chikkerur [3] proposes an algorithm for fingerprint enhancement based on short time Fourier transforms (STFT) analysis. Hong et al.[4] used the Gabor filter. The output of a contextual fingerprint enhancement can be a gray-scale or binary image, depending on the filter parameters chosen.

You et al.[5] constructs a new non-separable wavelet filter bank using centrally symmetric matrices. This filter bank consist of polyphase filters therefore by performing polyphase decomposition the computation can be reduced and thereby improve the speed. The non-separable wavelet can capture the singularities in all directions. The high-frequency sub-images of non-separable wavelet transform can reveal more desirable features in comparison with the separable wavelet transform. Proposed method is expected to work well in fingerprint enhancement without under-enhancement and over enhancement, and it will be more effective and robust than other existing methods.

The rest of this paper is organized as follows. Section 2 presents the construction of non-separable filter banks. Section 3 will give a precise description of polyphase decomposition in two dimension. Section 4 will give a description about how the enhancement is performed. Experiment results are provided in Section 5.

2 Non-separable wavelet

Multidimensional sampling is represented by a lattice which can be separable or non-separable. In most of the previous works on two and three dimensional MultiMate processing the sampling rate changes are separable and can be performed along one dimension at a time. But for multidimensional signals true multidimensional processing will hold good. Multidimensional processing includes non-separable filters (the filters can be separable as well as non-separable) and as for the filtering part, there are design constraints such as orthogonality, linear phase (symmetry) and regularity [8].

According to MRA (multidimensional analysis), refinable functions (scaling functions) and wavelets are completely determined by a low-pass filter and high-pass filters, respectively. In subband code schemes, a low-pass filter and high-pass filters are respectively used as analysis filter and synthesis filters which form perfect reconstruction filter banks. A commonly used method builds multivariate filter banks by the tensor products of univariate filters.Here we describe a general construction of bivariate non-tensor product wavelet filter banks with linear phase by using centrally symmetric matrices in [6, 7].

A general construction of non-separable wavelet filter banks with linear phase by using centrally symmetric matrices is described in this section. A matrix B [6] of order n is called centrally symmetric orthogonal matrix (condition for PR) if it is both of centrally symmetric matrix and orthogonal matrix. To describe the centrally symmetric matrix and centrally symmetric orthogonal matrix, we need to use [9] the $n \times n$ S_n as defined in [9].

$$B = S_n \begin{bmatrix} Z_1 & 0 \\ 0 & Z_2 \end{bmatrix} S_n^T$$

If Z_1 and Z_2 are orthogonal then B will also be orthogonal [5].

$$B_{(\alpha,\beta)} = \frac{1}{2} S_4 \begin{bmatrix} \cos\alpha & -\sin\alpha & 0 & 0 \\ \sin\alpha & \cos\alpha & 0 & 0 \\ 0 & 0 & \cos\beta & -\sin\beta \\ 0 & 0 & \sin\beta & \cos\beta \end{bmatrix} S_4^T$$

The low pass filter $h_0(u,v)$ is defined as follows:

$$h_0(u,v) = \frac{1}{4}(1,u,v,uv) \left[\prod_{k=1}^{N} B_{(\alpha_k,\beta_k)} T(u^2,v^2) B^T_{(\alpha_k,\beta_k)} \right] E_0$$

where

$$T(u,v) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & u & 0 & 0 \\ 0 & 0 & v & 0 \\ 0 & 0 & 0 & uv \end{bmatrix}$$

$$E_0 = (1,1,1,1)^T$$

N represent the decomposition level, and filter size increase with N. Filter size is $(2N+2) \times (2N+2)$ and in this experiment $N = 1$ therefore 4×4 matrix. It is easy to see that $h(0,0) = 1$ which means that h_0 is a low pass filter. For any fixed positive integer N, we arbitrarily choose real number pairs (α_k, β_k) , $k = 1, 2, 3, \ldots, N$ (for $k \neq j$, (α_k, β_k) may be equal to (α_j, β_j).

The three high pass filters (h_1, h_2, h_3) are defined as

$$h_j(u,v) = \frac{1}{4}(1,u,v,uv) \left[\prod_{k=1}^{N} B_{(\alpha_k,\beta_k)} T(u^2,v^2) B^T_{(\alpha_k,\beta_k)} \right] E_j$$

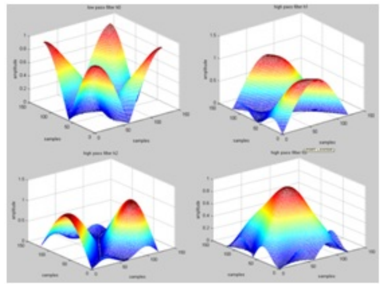

Figure 1: Frequency response of filters

Figure 2: Input image that is given to filters

where $j = 1, 2, 3$ and

$$E_1 = (1, -1, 1, -1)^T$$
$$E_2 = (1, 1, -1, -1)^T$$
$$E_3 = (1, -1, -1, 1)^T$$

It is easy to find that $h(0, 0) = 0$ which means that h_j is high pass filter.

The non-separable wavelet can reveal more singularities compared with separable wavelet. Below, a comparison is made between separable and non-separable wavelets. For separable wavelet db4 is taken and after performing DWT we get four subimages (approximation, horizontal, vertical and diagonal). Similarly for non-separable wavelet, after performing DNWT we get four sub images.

3 Polyphase decomposition in two dimension

While performing decomposition using non-separable wavelet, direct implementation was used. First image is passed through four filters (1 LPF and 3 HPFs) and then downsampled [7]. In the above case if the FIR filter length is N and, for each computed sample, N multiplications and $N - 1$ additions are required. This is an inefficient use of computing resources. Instead of that polyphase form [7] can be utilized.

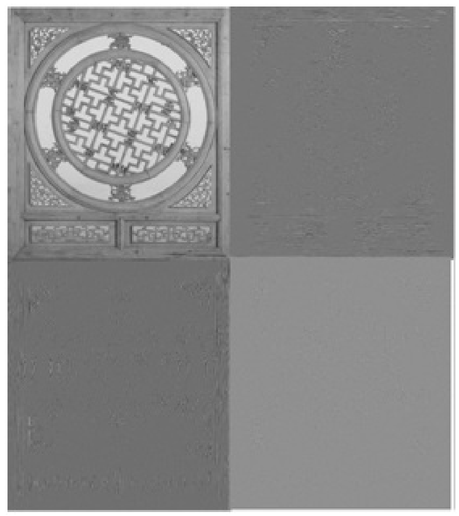

Figure 3: Image decomposed using db4 wavelet: corresponding four subimages

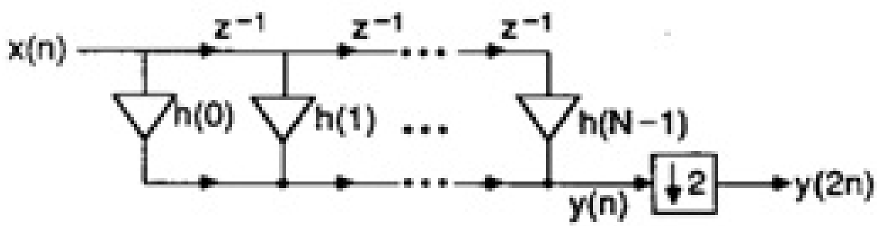

Figure 4: Direct implementation of FIR decimation filter

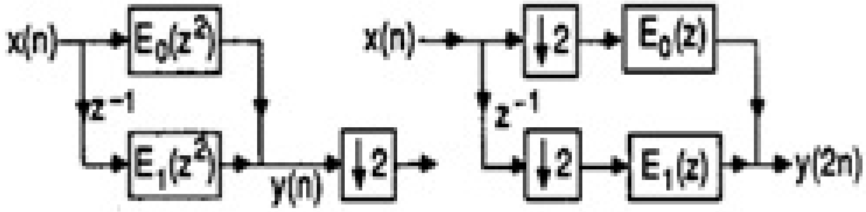

Figure 5: Polyphase implementation of FIR decimation filter

Figure 6: Image decomposed using non-separable wavelet: corresponding four sub images

The input signal is a one dimensional signal and the digital filter which is also one dimensional is divided into two even numbered samples $e_0(n)$ (corresponding Z transform is $E_0(z)$) and odd numbered samples $e_1(n)$.

Now the polyphase factors are receiving samples at half the rate (that is, one sample in two units of time). Therefore the number of multiplications got reduced by $N/2$ and addition reduced by $(N-1)/2$. The polyphase representation enables us to rearrange the operations thereby reducing the number of computation and hence the complexity.

Polyphase decomposition for one dimension is discussed; same can be extended to two dimension. A two dimensional filter can be represented using a bivarite trigonometric polynomial

$$h_0 = \sum_{j \in \mathbb{Z}^*} \sum_{k \in \mathbb{Z}} C_{j,k} u^j v^k.$$

Its polyphase factors $h_{0,1}$ defined in [5] for $i = 0, 1, 2, 3$. Reversing the process, we can construct the bivariate trigonometric polynomials h_0 from its polyphase factors. Given four filters h_0, h_1, h_2 and h_3, polyphase decomposition can be performed on the image. Figure 7 shows polyphase decomposition using filter h_0. $h_{0,0}$, $h_{0,1}$, $h_{0,2}$ and $h_{0,3}$ are the polyphase factors of the filter. The filter h_0 is a 4×4 and it is given below:

$$h_0 = \begin{bmatrix} 0.0060 & 0.0410 & -0.0396 & 0.0058 \\ -0.0365 & 0.2483 & 0.2397 & 0.0352 \\ 0.0352 & 0.2397 & 0.2483 & -0.0365 \\ 0.0058 & -0.0396 & 0.0410 & 0.0060 \end{bmatrix}$$

We also have:

$$h_{0,0} = \begin{bmatrix} 0.0060 & -0.0396 \\ 0.0352 & 0.2483 \end{bmatrix}$$

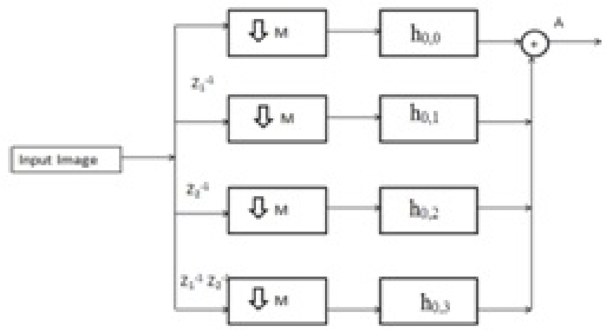

Figure 7: Polyphase decomposition of image

$$h_{0,1} = \begin{bmatrix} 0.0410 & 0.0058 \\ 0.2397 & -0.0365 \end{bmatrix}$$

$$h_{0,2} = \begin{bmatrix} -0.0365 & 0.2397 \\ 0.0058 & 0.0410 \end{bmatrix}$$

$$h_{0,3} = \begin{bmatrix} 0.2483 & 0.0352 \\ -0.0396 & 0.0060 \end{bmatrix}$$

In this technique the image is first down sampled. This will reduce the size by four times and number of computations reduce by $N/4$ and this will improve the speed. The output of this decomposition is approximation subimage. Similarly the other three polyphase filters can be used to perform decomposition to produce horizontal, vertical and diagonal subimages.

4 Adjusting the coefficients

After decomposing the image in to four parts A, H, V, and D, as usual, approximation coefficients (A) are unchanged and only change H, V and D coefficients are changed.

One way to prevent our filter coefficients from overflowing and to maintain well behaved filters is to normalize the coefficients.

$$x_{\text{nor},j} = \frac{x_{\text{old},j}}{M} \quad \text{where} \quad M = \max\{|x_{\text{old},j}|\}.$$

We then adjust the normalised coefficients to get

$$x_{\text{adj},j} = |x_{\text{nor},j}|^p \times T^{1-p} \quad \text{where} \quad 0 < |x_{\text{nor,j}}| \leq T$$

Then we have

$$|x_{\text{nor},j}|^{1-p} \times (1-T)^{1-p} T < |x_{\text{nor},j}| \leq 1.$$

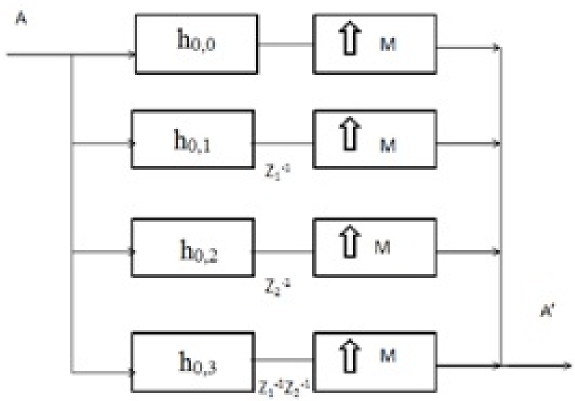

Figure 8: Reconstruction of approximation subimage

Here $P \in [0, 1]$ and $T \in [0, 1]$ are the parameters of the proposed algorithm. Parameter P decides the enhancement strength. The value of P should be less than 1. The threshold is selected using the equation given below:

$$T = \frac{\sum_{x \in D} |x|}{(m \times n) \times \max |x|_{x \in D}}$$

where $m \times n$ is the size of D.

Finally we compute the enhanced coefficients using :

$$x_{\text{enh},j} = x_{\text{adj},j} \times M.$$

5 Non-separable reconstruction

After adjusting the coefficients using the above technique, image is reconstructed. The same polyphase filters are used for enhancement. For reconstruction, polyphase technique is used [7].

In Figure 8, approximation subimage is passed through same polyphase filter then we will get A. Similarly all the other subimages are passed through filters and finally all the images are combined together. This is done by adding the pixels present in each subimage. Finally it will produce an enhanced fingerprint image without over enhancement and under enhancement. Experimental results are shown below.

6 Results

An input fingerprint image taken from database FVC2002 is shown in Figure 9. This image is passed through a non-separable wavelet and later enhanced using the above method.

Figure 9: Input fingerprint image

Figure 10: Enhanced fingerprint image

Finally reconstructed to get the enhanced fingerprint image shown in Figure 10.

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