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Fingerprint Image Enhancement Using Haar Based Wavelet Transform Over Other Techniques

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Abstract: Image enhancement is the one of the key factor to get better visual. The main purpose of image enhancement is to increase the brightness, noise removal. These conditions lead to image may suffer from loss of information. The main purpose of image enhancement is to bring out detail that is hidden in an image or to increase contrast form in a low contrast image. It provides multitude of choices for improving the visual quality of images. That's why, it is used in huge number of applications with important challenges such as noise reduction, blurring etc. In this study some of image enhancement techniques for biometrics on spatial and frequency domain like thinning, thickening, skeleton and Gabor filters, etc. are applied and it is observed that Haar based wavelet transform gives better performance over other techniques.

Key words: Fingerprints, thinning, thickening, Gabor filter, wavelets, spatial domain and frequency domain, image enhancement

INTRODUCTION

Image enhancement is to improve the perception information in images to provide automated image processing devices. The fingerprint images may acquire using different types of sensors. Sometimes sensors may not be given better outputs, so to get better quality from the image captured by sensors image enhancement technique is implemented. Here, some of the basic, enhancement techniques and its limitation are described by comparison. Image enhancement can be divided into two categories' namely:

- Spatial domain
- Frequency domain

In spatial domain, enhancement is done based on pixel by pixel operation. In this domain, the technique enhancement by dealing directly with the intensity values in the pixel. Large number of techniques has been focused on the gray scale fingerprint images under spatial domain.

These methods include high pass filter, low pass filter and homomorphic filtering by using mask W(i, j). Spatial domain function is:

$$G(x,y) = \sum_{i,j=0}^{L-1} W(i,j)\big[F(x+i, y+j) \qquad (1)$$

In frequency domain transform the image intensity data in to a specific domain by using methods such as Fourier, Discrete Fourier, Fast Fourier, Discrete Cosine, and Discrete Sine Transform, etc. and image is enhanced by multiplying with the filters like low pass filters, high pass filters The frequency domain approach is: convert the image into frequency domain:

$$F(u,v) = F \times T\big(f(x,y)\big) \qquad (2)$$

Multiply frequency domain image with filter:

$$G(u,v) = H(u,v) \times F(u,v) \qquad (3)$$

Applying inverse to this product:

$$g(x,y) = IFT(G(u,v) \qquad (4)$$

Here, f(x,y) is a two dimensional grayscale image and it transformed by applying Fourier transform. F(u,v) is Fourier image. Once, we get the Fourier image simply multiplying with the filter and inverse of this product is the output image g(x,y). The product of the filter is termed as G(u,v).

The aim is to enhance the quality of the fingerprint images to by preprocessing it. Here, the PSNR (Signal to Noise Ratio) and MSE (Mean Square Error) are the

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measuring parameters used to have comparison on the different basic techniques of both the spatial domain and frequency domain (Bronte *et al*., 2009; Ghimire and Lee, 2011).

MATERIALS AND METHODS

Flow of work

Spatial domain techniques: Finger print images is enhanced by applying thinning, thickening, skeleton and its performance is analyzed (Fig. 1).

Thinning: Since, interested only in pattern matching with the help of structuring elements. So, no background operation is required in the hit or misses transform. A more useful expression for thinning X symmetrically is based on a sequence of structuring elements. The thinning of a set X by a structuring element B, denoted (Hasikin and Isa, 2012; Jha *et al*., 2012):

$$A \otimes B = A - (A \times B)$$
$$= A \cap (A \times B)$$

$$\{B\} = \{B^1, B^2, B^3, \ldots, B^n\}$$

Algorithm; input and thinning operation:

- Step 1: read an input image
- Step 2: convert it into a binary image and apply complement
- Step 3: apply thinning operation on complement image

Figure 2 Show the original template and the image enhanced by thinning.

Thickening: The structuring element used for thickening have the same form as thinning, but withal 1 and 0s interchanged. However, a separate algorithm for thickening is seldom used in practice. Instead, the usual procedure is to thin the background of the set and then complement the result. Thickening is the morphological dual of thinning and is defined by expression. The thickening is defined by the expression:

$$AB = A \cup (A \times B)$$

The thickening of A by a sequence of structuring element (B):

$$A\{B\} = \left(\left(\ldots\left(\left(AB^1\right)B^2\right)\ldots\right)B^n\right)$$

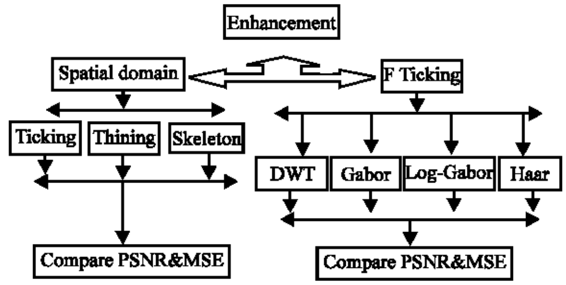

Fig. 1: Discrete wavelet transforms

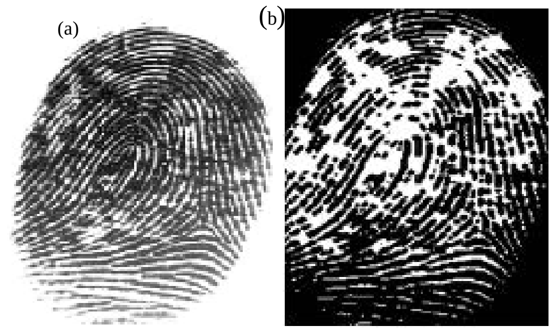

Fig. 2: Original template of a) Input image and b) Thinning

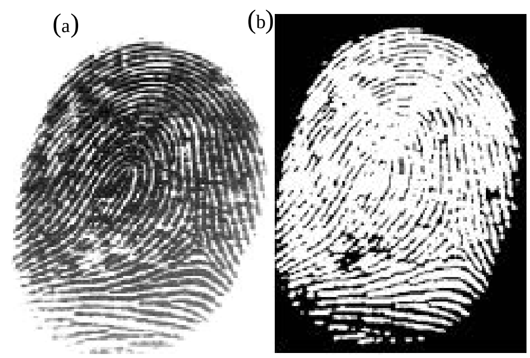

Fig. 3: a) Input image and b) Thinning

Algorithm; Input and thickening operation:

- Step 1: read an input image
- Step 2: convert it into a binary image and apply complement
- Step 3: apply thickening operation on complement image

Figure 3 shows the input image and thickening process of enhanced image.

Skeletons: The notation of skeleton S(X) of a set X is intuitively simple. The skeleton of X can be expressed in terms of opening and closing.

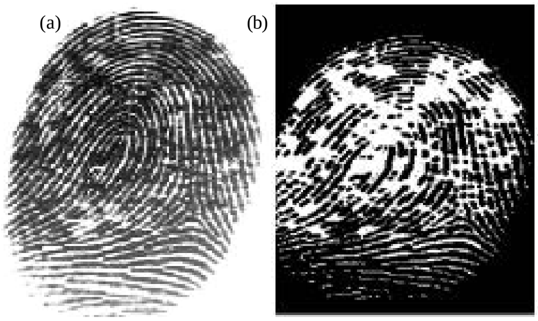

Fig. 4: a) Input image and b) Skeleton

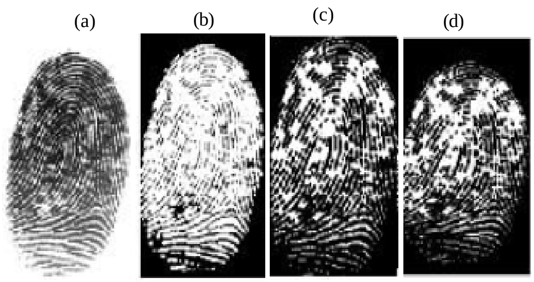

Fig. 5: a) Input image; b) Thickening; c) Thinning and d) Skeleton

Table 1: Comparison of PSNR & MSE of template using thinning and skeleton

Template	thinning		skeleton	
	PSNR	MSE	PSNR	MSE
TEMPLATE1	48.2874	0.96458	48.2655	0.96946
TEMPLATE2	48.4518	0.92875	48.3713	0.94612
TEMPLATE3	48.5325	0.91165	48.4365	0.93202
TEMPLATE4	48.4566	0.92773	48.3787	0.94452
TEMPLATE5	48.6029	0.897	48.4839	0.92192
TEMPLATE6	48.3686	0.94672	48.328	0.95561
TEMPLATE7	48.4072	0.93834	48.3519	0.95036
TEMPLATE8	48.3693	0.94658	48.3174	0.95795
TEMPLATE9	48.3902	0.94202	48.3509	0.95059
TEMPLATE10	48.2362	0.97602	48.227	0.97808
TEMPLATE11	48.5067	0.91708	48.4118	0.93734
TEMPLATE12	48.4663	0.92565	48.388	0.9425
TEMPLATE13	48.4509	0.92894	48.3831	0.94356
TEMPLATE14	48.2981	0.9622	48.2751	0.96731
TEMPLATE15	48.4026	0.93934	48.3455	0.95177
TEMPLATE16	48.4495	0.92924	48.3622	0.94812
TEMPLATE17	48.3994	0.94003	48.3492	0.95096
TEMPLATE18	48.2515	0.97259	48.2328	0.97678
TEMPLATE19	48.4832	0.92206	48.3855	0.94304
TEMPLATE20	48.5059	0.91725	48.4146	0.93674

Algorithm; input image and skeleton operation:

- Step 1: read an input image
- Step-2: convert it into a binary image and apply complement
- Step-3: apply skeleton operation on complement image

Figure 4 shows the input image and skeleton process of enhanced image. Figure 5 it is shown as an observation that the input image enhanced by using all the three techniques to have analysis on quality of the image by comparison to view. Table 1 shows the value of PSNR and MSE value to have a comparison on thinning and Skeleton imposed on finger print image template of reasonable quantity (Jung *et al.*, 2012; Parthasarathy and Sankaran, 2012).

RESULTS AND DISCUSSION

Frequncy domain techniques

Discrete wavelet transforms: The wavelet transform is a tool that cuts up data, functions into different frequency components and then studies each component with a resolution matched it 's scale (Fig. 6). Two dimensional dwt is (Fig. 7 and 8):

$$g(x,y) = \sum_{mm,n} w_{\varphi}(j_0,m,n)\varphi_{j0,m,n}(x,y) + \sum_{\substack{i=H,V,D,\\ j=j0,m,n}} w_{\psi}^{1}(j,m,n)\psi_{j,m,n}^{i}(x,y)$$

The inverse discrete wavelet transform is:

$$f(x,y) = \frac{1}{MN\sum m,nW\varphi(j_0,m,n)\varphi_{j0,m,n}(x,y)} + \frac{1}{MN\sum_{i=H,V,D,j=j0,m,n} W_{\psi}^{1}(j,m,n)\psi_{j,m,n}^{i}(x,y)}$$

Algorithm; input image:

- Step-1: read the input image
- Step-2: apply dwt transform either daubechies wavelet or haar wavelet
- Step-3: apply inverse to the result

Figure 9 shows the input applied with DWT on Daubechies.

Gabor filters: Its impulse response is defined by a sinusoidal wave (a plane wave for 2D Gabor filters) multiplied by a Gaussian function. Because of the multiplication-convolution property (Convolution theorem), the Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function. The filter has a real and an imaginary component representing orthogonal directions. The two components may be formed into a complex number or used individually (Poljicak *et al.*, 2012; Rivera *et al.*, 2012; Zhang *et al.*, 2012).

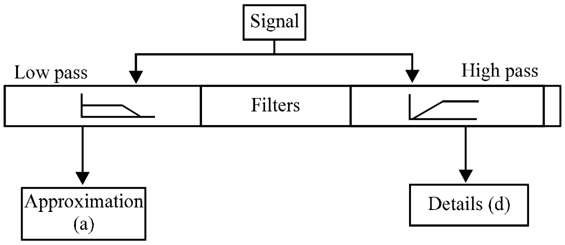

Fig. 6: Discrete wavelet transforms

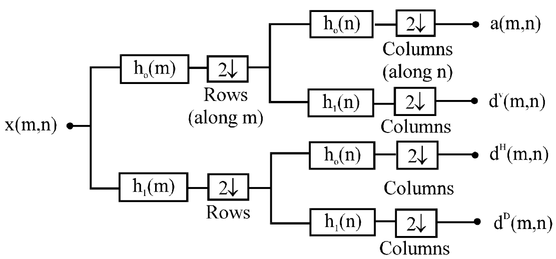

Fig. 7: The D4 band filter bank

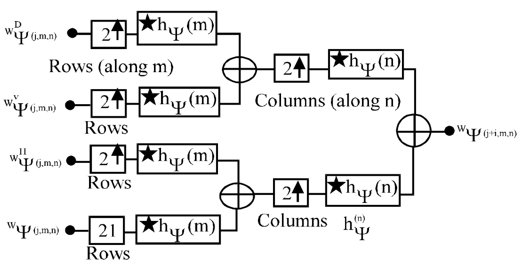

Fig. 8: The D4 band filter bank to get output image

Complex:

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma)=\exp\left(-\left(x^2+\gamma^2y^2\right)/2\sigma^2\right)\exp\left(i\left(2\pi x^1/\lambda+\psi\right)\right)$$

Real:

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma)=\exp\left(-\left(x^2+\gamma^2y^2\right)/2\sigma^2\right)\cos\left(\left(2\pi x^1/\lambda+\psi\right)\right)$$

Imaginary:

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma)=\exp\left(-\left(x^2+\gamma^2y^2\right)/2\sigma^2\right)\sin\left(\left(2\pi x^1/\lambda+\psi\right)\right)$$

Where:

$$X^1 = x\cos\theta + y\sin\theta$$

And:

$$y^1 = -x\sin\theta + y\cos\theta$$

Where:

λ = Represents the wavelength of the sinusoidal factor
θ = Represents the orientation of the normal to the parallel stripes of a Gabor function

(a) (b)

Fig. 9: a) Input image and b) DWT

(a) (b)

Fig. 10: a) Input and b) Gabor filter

ψ = The phase offset
σ = The sigma/standard deviation of the Gaussian envelope
γ = The spatial aspect ratio and specifies the ellipticity of the support of the Gabor function

Algorithm; Gabor function:

- Step 1: read the input image
- Step 2: convert into a double and crop the image
- Step-3: create Gabor filter
- Step 4: the filter of the input image with Gabor filter

Figure 10 shows the input image applied with Dwt on gabor filter.

Log-Gabor filters: Like the Gabor filter, the log-Gabor the 2-dimensional extension of the log-Gabor filter. With t filter has seen great popularity in image processing. Because of this it is useful to consider his added dimension the filter is not only designed for a particular

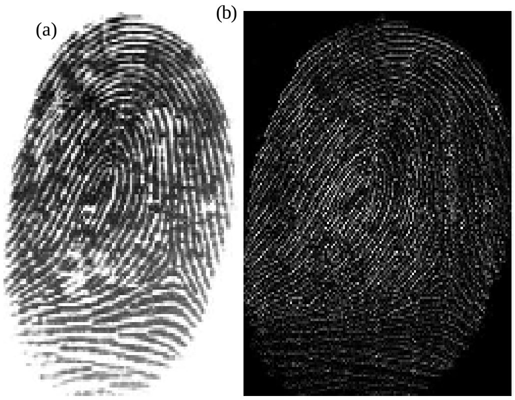

Fig. 11:a) Input and b) Log gabor filter

Fig. 12: a) Input image and b) Haar wavelet

frequency but also is designed for a particular orientation. The orientation component is a Gaussian distance function according to the angle in polar coordinates:

$$G(f,\theta) = \exp\left(-(\log f / f_0)\right)^2 / \left(2\left(\log(\sigma_f / f_0)\right)^2\right)$$
$$\exp\left(-(\theta - \theta_0)^2\right) / \left(2\sigma_\theta^2\right)$$

Where:

f_θ = The center frequency
σ_f = The width parameter for the frequency
θ_0 = The center orientation
σ_0 = The width parameter of the orientation

An example of this filter is shown below. The bandwidth in the frequency is given by:

$$B = 2|\left(2/\left(\log(2)\right)\right)\left(\left\|\log(\sigma_f / f_0)\right\|\right)$$

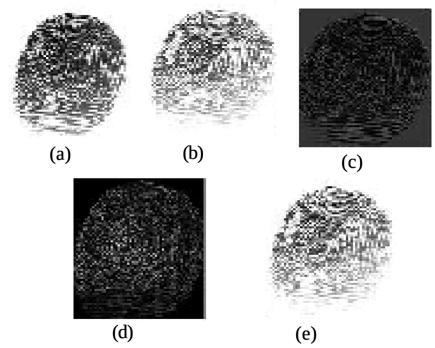

Fig 13: a) Input image; b) DWT; c) Gabor; d) Log-Gabor and e) Haar

The angular bandwidth is given by:

$$B_\theta = 2\sigma_\theta\sqrt{2\log 2}$$

In many practical applications, a set of filters are designed to form a filter bank. Because the filters do not form a set of orthogonal basis, the design of the filter bank is somewhat of an art and may depend upon the particular task at hand. The necessary parameters that must be chosen are: the minimum and maximum frequencies, the filter bandwidth, the number of orientations, the angular bandwidth, the filter scaling and the number of scales.

Algorithm; log-gabor filter:

- Step 1: read the input image
- Step 2: convert into a double and crop the image
- Step 3: create Log-Gabor filter
- Step 4: filter the input image with Log-Gabor filter

Figure 11 shows the input image with Log Gabor filter.

Haar wavelet: The implementation of the same DWT with HARR instead of Daubchies gives better performance is shown in Fig. 12.

For the comparison of performance on different techniques in frequency domain is analyzed and the same is given in Fig. 13 where it is observed the Haar wavelet gives the better performance.

Table 2, it is observed that the Haar transform gives the better PSNR value on comparing with other techniques in the frequency domain and the values are tabulated for the reasonable quantity of finger image templates.

Table 2: Comparison of PSNR and MSE 's using DWT, SVD, Gabor, Log-gabor and Haar wavelet

	DWT (Daubuchies)		Log gabor		Gabor		DWT (Haar)	
Templates	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE
TEMP-1	40.738	5.4858	50.933	0.580	47.850	1.066	305.231	1.949
TEMP-2	42.109	4.0005	52.763	0.344	49.647	0.705	305.84	1.692
TEMP-3	41.750	4.3458	51.994	0.410	49.137	0.793	305.414	1.868
TEMP-4	41.999	4.1031	51.227	0.490	48.140	0.997	305.373	1.888
TEMP-5	42.019	4.0840	50.917	0.551	47.747	1.092	305.269	1.932
TEMP-6	41.305	4.8144	50.792	0.541	50.792	0.966	305.413	1.869
TEMP-7	41.393	4.7175	50.795	0.541	47.734	1.095	305.366	1.89
TEMP-8	41.214	4.9157	54.510	0.230	50.339	0.601	305.939	1.656
TEMP-9	40.657	5.5894	52.875	0.335	49.075	0.804	305.276	1.927
TEMP-10	42.326	3.8057	54.638	0.223	50.745	0.54	306.090	1.599
TEMP-11	41.612	4.4857	53.284	0.305	48.500	0.729	305.836	1.696
TEMP-12	41.757	4.3388	52.374	0.376	48.676	0.881	305.419	1.867
TEMP-13	41.188	4.9454	51.775	0.432	48.247	0.973	305.939	1.656
TEMP-14	41.504	4.5983	50.519	0.577	47.599	1.130	305.916	1.667
TEMP-15	41.757	4.3386	50.086	0.637	46.955	1.310	306.278	1.532
TEMP-16	41.757	4.3386	51.136	0.500	47.903	1.053	305.328	1.906
TEMP-17	41.242	4.8850	50.136	0.591	46.674	1.398	306.576	1.434
TEMP-18	40.824	5.3785	54.969	0.201	50.616	0.565	305.382	1.882
TEMP-19	42.51	3.6482	51.642	0.445	47.815	1.075	305.27	1.926
TEMP-20	41.990	4.1116	52.918	0.332	49.419	0.734	305.734	1.736

CONCLUSION

This study presents description about of various image enhancement techniques in order to familiar with the noise removal and contrast enhancement. Here, it 's observed from the above result, Haar wavelet transforms gives better performance on image de-noising on comparing with other techniques used in frequency domain. On compare basic method of finger print enhancement under spatial domain as well as frequency domain techniques with respect to PSNR&MSE on finger print image templates. It is concluded that Haar transform is better on other frequency domain techniques. In feature image enhancement can be carried by resolving image on different levels or bands on directional perspective.

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