

Analysis of Image Fusion Techniques for fingerprint Palmprint Multimodal Biometric System

S. Anu H Nair^a, Dr. P. Aruna^b

^a Asst. Professor, Department of CSE, Annamalai University, Tamil Nadu, 608002, India

^b Professor, Department of CSE, Annamalai University, Tamil Nadu, 608002, India

Abstract

The multimodal Biometric System using multiple sources of information has been widely recognized. However computational models for multimodal biometrics recognition have only recently received attention. In this paper the fingerprint and palmprint images are chosen and fused together using image fusion methods. The biometric features are subjected to modality extraction. Different fusion methods like average fusion, minimum fusion, maximum fusion, discrete wavelet transform fusion and stationary wavelet transform fusion are implemented for the fusion of extracting modalities. The best fused template is analyzed by applying various fusion metrics. Here the DWT fused image provided better results.

Keywords: Multimodal biometrics, feature fusion, average fusion, discrete wavelet, stationary wavelet, minimum fusion, maximum fusion

I. Introduction

Biometrics acts as a source for identifying a human being. This is used for authentication and identification purposes. In order to overcome the limitations of unimodal biometric system multimodal biometrics came into existence. A multimodal biometric system combines two or more biometric data recognition results such as a combination of a subject's fingerprint, face, iris and voice. This helps to increase the reliability of personal identification system that discriminates between an authorized person and a fraudulent person.

Multimodal biometric system has addressed some issues related to unimodal such as, (a) Non-universality or insufficient population coverage (reduce failure to enroll rate which increases population coverage). (b) It becomes absolutely unmanageable for an impostor to imitate multiple biometric traits of a legitimately enrolled individual. (c) Multimodal-biometric systems offer climbing evidence in solving the problem of noisy data (illness affecting voice, scar affecting fingerprint).

In this paper, a novel approach for creating a multimodal biometric system has been proposed. The multimodal biometric system is implemented using the different fusion schemes such as Average Fusion, Minimum Fusion, Maximum Fusion, DWT Fusion and SWT Fusion. In modality extraction level, the information extracted from different modalities is stored in vectors on the basis of their modality. These modalities are then blended to produce a joint template. Fusion at feature extraction level generates a homogeneous template for fingerprint, iris and palmprint features.

II. Literature review

[1] proposed a fingerprint classification method where types of singular points and the number of each type of point are chosen as features. [2] designed an orientation diffusion model for fingerprint extraction where corepoints and ridgeline flow are used. [3] created a novel minutiae based fingerprint matching system which creates a feature vector template from the extracted core points and ridges. [4] modeled a palmprint based recognition system which uses texture and dominant orientation pixels as features. [5] identified a palmprint recognition method which uses blanket dimension for extracting image texture information. [6] presented a typical palmprint identification system which constructed a pattern from the orientation and response features. [7] designed a new palmprint matching system based on the extraction of feature points identified by the intersection of creases and lines. [8] proposed an efficient representation method which can be used for classification. [9] created a model that fused voice and iris biometric features. This model acted as a novel representation of existing biometric data. [10] proposed user specific and selective fusion strategy for an enrolled user. [11] identified a new geometrical feature Width Centroid Contour Distance for finger geometry biometric. [12] developed a face and ear biometric system which uses a feature weighing scheme called Sparse Coding error ratio. [13] proposed the fusion method based on a compressive sensing theory which contains over complete dictionary, an algorithm for sparse vector approximation and fusion rule. [14] identified the feature extraction techniques for three modalities viz.

fingerprint, iris and face. The extracted data is stored as a template which can be fused using density based score level fusion.

III. Proposed work

The proposed work describes the fusion of multimodal biometric images such as fingerprint and

palmpoint. The fingerprint and palmpoint images are subjected to modality extraction. The extracted modalities are fused together using several fusion methods. The best fused template is identified by applying different metrics. The proposed work is shown in Figure 1.

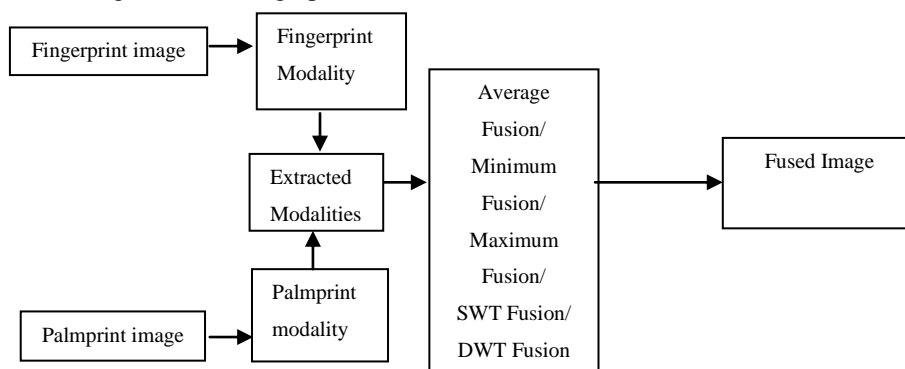


Fig. 1: Structure of proposed work

IV. Biometric modality extraction

4.1 Modality extraction from a Fingerprint image:

The fingerprint image is fed as the input. The first step is to apply the Adaptive histogram equalization technique to increase the contrast of the grayscale image. The next step is to apply Orientation process that is used to find the direction of the ridges in the fingerprint image. This can be achieved by using the SOBEL filter to detect the edges of the image. ROI selection is used to give maximum

magnitude of convolution in the region of core point which is the next step. This fingerprint masking is used to select the region where the fingerprint images are present. Thinning operations reduce connected patterns to a width of a single pixel while maintaining their topology. Once this is done, the feature of the fingerprint is successfully extracted. The process of feature extraction of the fingerprint image is represented in Figure 2.

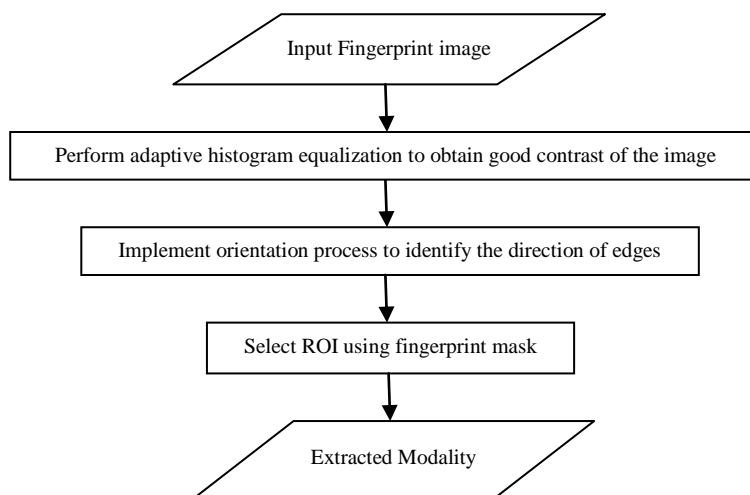


Fig. 2: Modality extraction from fingerprint image

4.2 Modality extraction from a Palmpoint image:

The palmpoint image is fed as the input. The contrast of the grayscale image is enhanced by using the Adaptive histogram equalization technique. The noise from the image is removed by applying a

diffusion filter. Edge detection is performed using a Sobel filter to identify the ridges. Thinning algorithms reduce connected patterns to a width of a single pixel while maintaining their topology. Once this is done, the modality of the Palmpoint is

successfully extracted. The above steps are depicted in Figure 3.

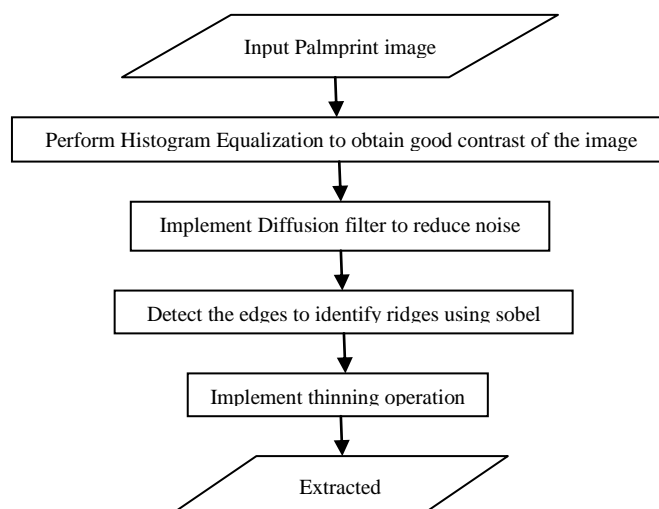


Fig.3: Modality extraction from palmprint image

V. Implementation of Image Fusion Algorithms

Image fusion is proposed for creating a fused template which further serves as an input to the watermarking system.

5.1 Simple Average

It is a well-documented fact that regions of images that are in focus tend to be of higher pixel intensity. Thus this algorithm is a simple way of

obtaining an output image with all regions in focus. The value of the pixel $P(i, j)$ of each image is taken and added. This sum is then divided by 2 to obtain the average. The average value is assigned to the corresponding pixel of the output image which is given in equation below. This is repeated for all pixel values [15].

$$K(i, j) = \{ X(i, j) + Y(i, j) \} / 2 \quad (1)$$

Where $X(i, j)$ and $Y(i, j)$ are two input images.

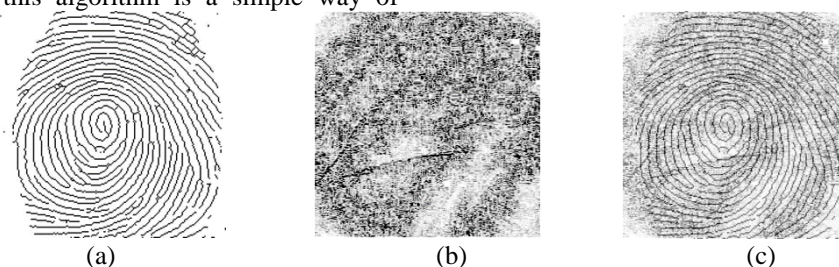


Fig. 4 (a) – Extracted Fingerprint Modality,(b)-Extracted Palmprint Modality,(c)-Fused Image

5.2 Select Maximum

The greater the pixel values are the more in-focus regions in the image. Thus this algorithm chooses the in-focus regions from each input image by choosing the greatest value for each pixel,

resulting in highly focused output. The value of the pixel $P(i, j)$ of each image is taken and compared to each other. The greatest pixel value is assigned to the corresponding pixel [15].

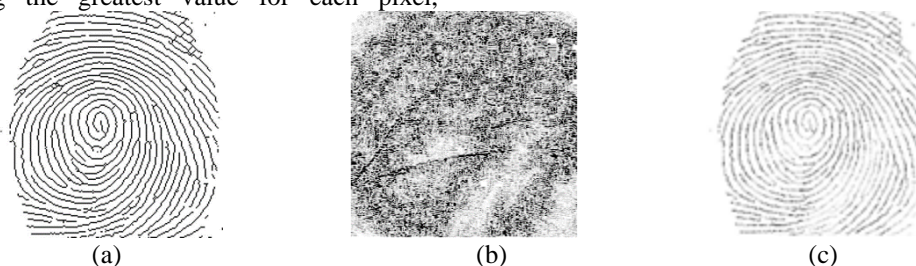


Fig.4 (a) – Extracted Fingerprint Modality,(b)-Extracted Palmprint Modality,(c)-Fused Image

5.3 Select Minimum

The Lower the pixel values the more in focus the image. Thus this algorithm chooses the in-focus regions from each input image by choosing the greatest value for each pixel, resulting in Lower

focused output. The value of the pixel P (i, j) of each image is taken and compared to each other. The Lower pixel value is assigned to the corresponding pixel [15].

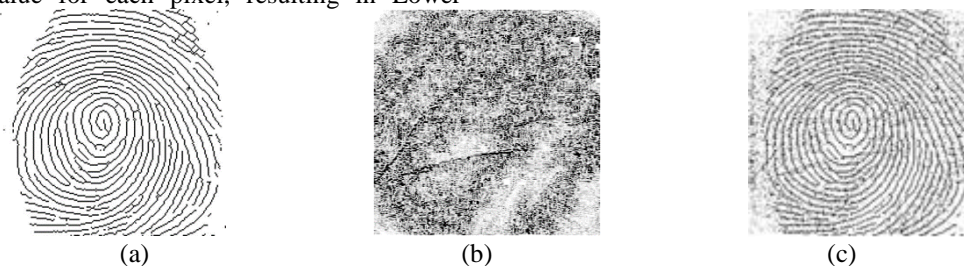


Fig.5 (a) – Extracted Fingerprint Modality,(b)-Extracted Palmprint Modality,(c)-Fused Image

5.4 Discrete Wavelet Transform (DWT)

The wavelets-based approach is appropriate for performing fusion tasks for the following reasons: - (1) It is a multiscale (multi resolution) approach well suited to manage the different image resolutions, useful in a number of image processing applications including the image fusion. (2) The discrete wavelets transform (DWT) allows the image decomposition in different kinds of coefficients preserving the image information. (3) Once the coefficients are merged the final fused image is achieved through the inverse discrete wavelets transform (IDWT), where the

information in the merged coefficients is also preserved [16].

$$y[n] = (x * g)[n] = \sum_{k=-\alpha}^{\alpha} x[k]g[n - k] \quad (2)$$

$$y_{low}[n] = \sum_{k=-\alpha}^{\alpha} x[k]g[2n - k] \quad (3)$$

$$y_{high}[n] = \sum_{k=-\alpha}^{\alpha} x[k]h[2n - k] \quad (4)$$

where x is the DWT signal, g is the low pass filter and h is the high pass filter. The 2x2 Haar matrix that is associated with the Haar wavelet is $\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$.

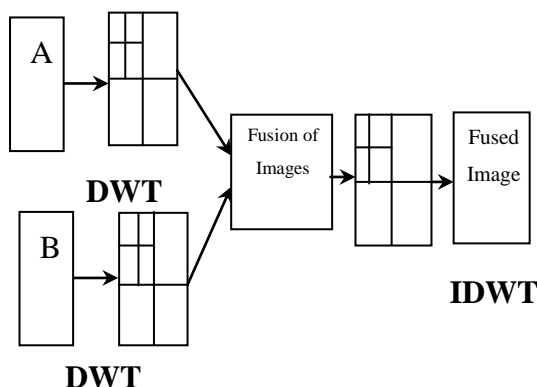


Fig 6: DWT Flow Chart

The wavelet transform decomposes the image into low-high, high-low, high-high spatial frequency bands at different scales and the low-low band at the coarsest scale which is shown. The L-L band contains the average image information whereas the other bands contain directional information due to spatial orientation. Higher absolute values of wavelet coefficients in the high bands correspond to salient features such as edges or lines. The basic steps performed in image fusion given.

The method is as follows:

- Perform independent wavelet decomposition of the two images until level L

- DWT coefficients from two input images' are fused pixel-by-pixel
- It is obtained by choosing the average of the approximation coefficients.
- Inverse DWT is performed to obtain the fused image

The wavelets-based approach is appropriate for performing fusion tasks for the following reasons:-

Once the coefficients are merged the final fused image is achieved through the inverse discrete wavelets transform (IDWT), where the information in the merged coefficients is also preserved.

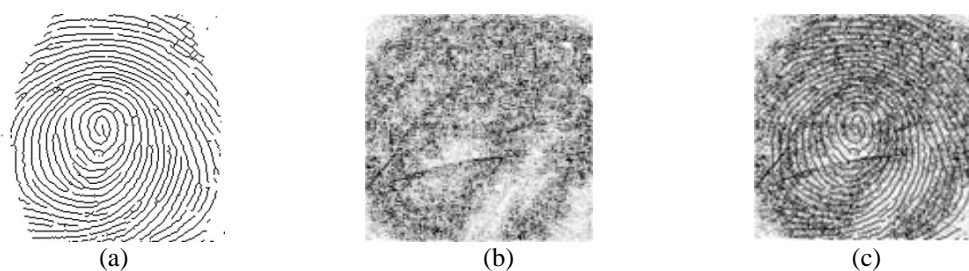


Fig.7 (a) – Extracted Fingerprint Modality, (b)-Extracted Palmprint Modality,(c)-Fused Image

5.5 Stationary Wavelet Transform:-

It fuses two multi-focused images by the means of wavelet but instead of using Discrete Wavelet Transform (DWT) to decompose images into frequency domain we use Discrete Stationary Wavelet Transform (DSWT or SWT). The Stationary Wavelet Transform is a wavelet transform algorithm which is designed to overcome the lack of translation invariance of the Discrete Wavelet Transform. Translation Invariance is achieved by removing the down samplers and the up samplers in the DWT and up-sampling the filter coefficients by a factor of $2^{(j-1)}$ in the j level of the algorithm. The SWT is an inherently redundant scheme as the output of each level of SWT contains the same number of samples as the input – thus for a decomposition of N levels there is a redundancy of N in the wavelet coefficients. The Stationary Wavelet Transform is a wavelet transform algorithm which is designed to overcome the lack of translation invariance of the Discrete Wavelet Transform. Translation Invariance is achieved by removing the down samplers and the up samplers in the DWT and up-sampling the filter coefficients by a factor of $2^{(j-1)}$ in the j th level of the algorithm. The SWT is an inherently redundant scheme as the output of each level of SWT contains the same number of samples as the input – so for a

decomposition of N levels there is a redundancy of N in the wavelet coefficients. In summary, the SWT method can be described as follows[16]

- Decompose the two source images using SWT at one level resulting in three details subbands and one approximation subband (HL, LH, HH and LL bands).
- Then take the average of approximate parts of images.
- Take the absolute values of horizontal details of the image and subtract the second part of image from first.

$$D = (\text{abs}(H1L2) - \text{abs}(H2L2)) >= 0 \quad (5)$$

For fused horizontal part make element wise multiplication of D and horizontal detail of first image and then subtract another horizontal detail of second image multiplied by logical not of D from first.

- Find D for vertical and diagonal parts and obtain the fused vertical and details of image.
- Fused image is obtained by taking inverse stationary wavelet transform.

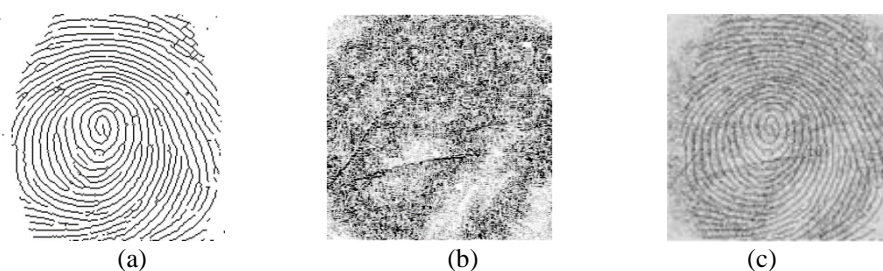


Fig.8 (a) – Extracted Fingerprint Modality,(b)-Extracted Palmprint Modality,(c)-Fused Image

VI. Performance Metrics Used for the analysis of fused images

6.1 Xydeas and Petrovic Metric - Q_{abf}

A normalized weighted performance metric of a given process p that fuses A and B into F , is given as: [12]

$$Q_{AB/F} = \frac{\sum_{m=1}^M \sum_{n=1}^N [Q_{m,n}^{AF} w_{m,n}^A + Q_{m,n}^{BF} w_{m,n}^B]}{\sum_{m=1}^M \sum_{n=1}^N [w_{m,n}^A + w_{m,n}^B]} \quad (6)$$

where A, B and F represent the input and fused images respectively. The definition of Q^{AF} and Q^{BF} are same and given as

$$Q_{(m,n)}^{AF} = Q_g^{AF}(m,n) Q_\alpha^{AF}(m,n) \quad (7)$$

where Q_g^* , Q_α^* are the edge strength and orientation values at location (m,n) for images A and

B. The dynamic range for $Q^{AB/F}$ is [0, 1] and it should be close to one for better fusion.

6.2 Visual Information Fidelity(VIF)

VIF first decomposes the natural image into several sub-bands and parses each sub-band into blocks[13]. Then, VIF measures the visual information by computing mutual information in the different models in each block and each sub-band. Finally, the image quality value is measured by integrating visual information for all the blocks and all the sub-bands. This relies on modeling of the statistical image source, the image distortion channel and the human visual distortion channel. Images come from a common class: the class of natural scene. Image quality assessment is done based on information fidelity where the channel imposes fundamental limits on how much information could flow from the source (the reference image), through the channel (the image distortion process) to the receiver (the human observer).

$$VIF = \frac{\text{Distorted Image Information}}{\text{Reference Image Information}} \tag{8}$$

6.3 Fusion Mutual Information

It measures the degree of dependence of two images[6]. If the joint histogram between $I_1(x,y)$ and $I_f(x,y)$ is defined as $h_{I_1 I_f}(i,j)$ and $I_2(x,y)$ and $I_f(x,y)$ is defined as $h_{I_2 I_f}(i,j)$ then Fusion Mutual Information (FMI) is given as

$$FMI = MI_{I_1 I_f} + MI_{I_2 I_f} \tag{9}$$

where

$$MI_{I_1 I_f} = \sum_{i=1}^M \sum_{j=1}^N h_{I_1 I_f}(i,j) \log_2 \left(\frac{h_{I_1 I_f}(i,j)}{h_{I_1}(i,j)h_{I_f}(i,j)} \right) \tag{10}$$

$$MI_{I_2 I_f} = \sum_{i=1}^M \sum_{j=1}^N h_{I_2 I_f}(i,j) \log_2 \left(\frac{h_{I_2 I_f}(i,j)}{h_{I_2}(i,j)h_{I_f}(i,j)} \right) \tag{11}$$

The value is high for a best fused image.

6.4 Average Gradient

The Average Gradient is applied to measure the detailed information in the images.

$$g = \frac{1}{(M-1)(N-1)} \sum_{x=1}^{M-1} \sum_{y=1}^{N-1} \sqrt{\left(\frac{\partial f(x,y)}{\partial x}\right)^2 + \left(\frac{\partial f(x,y)}{\partial y}\right)^2} \tag{12}$$

6.5 Entropy

Entropy is defined as amount of information contained in a signal. The entropy of the image can be evaluated as

$$H = - \sum P(i) \cdot \log_2(P(d_i)) \tag{13}$$

where G is the number of possible gray levels, $P(d_i)$ is probability of occurrence of a particular gray level d_i . If entropy of fused image is higher than parent image then it indicates that the fused image contains more information

Table :1 Quality of Fingerprint and Palmprint Fused Template

Metrics	Qabf	VIF	MI	Average Gradient	Entropy
Fusion Methods					
DWT Fusion	0.61	0.27	3.82	30.70	7.81
AverageFusion	0.34	0.28	2.86	18.67	7.30
Minimum Fusion	0.34	0.28	2.87	18.66	7.31
SWT Fusion	0.24	0.20	1.98	16.57	7.06
MaximumFusion	0.20	0.08	2.52	10.43	4.36

From the above table DWT Fusion method provided better results when compared to other fusion methods.

VII. Conclusion

In this paper a novel feature level fusion algorithm for multimodal biometric images like fingerprint and palmprint is proposed. Each biometric feature is individually extracted and the obtained modalities were fused together. As a result the fusion mechanism has produced successfully the fused template and the best fused template has been identified using several metrics. CASIA database is chosen for the biometric images. All the images are 8 bit gray-level JPEG image with the resolution of 320*280. The experimental results show that the DWT fused template provided better results than other fused templates.

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