Anchor University Journal of Science and Technology (AUJST)
A publication of the Faculty of Natural, Applied and Health Science, Anchor University Lagos

URL: fnas.aul.edu.ng

In AJOL: https://www.ajol.info/index.php/aujst

Vol. 4 No 1, September 2023, Pp. 8 - 14

ISSN: 2736-0059 (Print); 2736-0067 (Online)

MULTIMODAL BIOMETRIC IMAGE FUSION USING DISCRETE WAVELET TRANSFORM METHOD

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Submitted 03 March, 2023
Accepted 21 April, 2023

Competing Interests: The authors declare no competing interests.

ABSTRACT

Background: Security is a key component to every application in the modern world. One of the most effective methods for ensuring security in many sectors is the use of personal characteristics. **Objectives**: The objective of this study is to enhance the accuracy and robustness of biometric recognition through the utilization of a Discrete Wavelet Transform-based multimodal image fusion approach.

Methods: Multimodal biometric techniques were designed to resolve unimodal biometrics' deficiencies. In this research, discrete wavelet transform (DWT)-based multimodal fusion algorithms are proposed, in which database images are fused. Face, iris images and fingerprint are fused and the performance metric of different decomposition level were determined.

Result: This work provides a comparison of various decomposition filters for face, iris and fingerprint fused images. The result of metric performance on the fused images showed that the fused of face-iris have the highest value of entropy and principal component analysis which imply quality information to the source image.

Conclusion: The performance of DWT fusion techniques show that it provides better spatial and spectral localization of image information

Keywords: Security, biometric, fusion, entropy, multimodal-image

1. INTRODUCTION

Technologies for biometric recognition have demonstrated exceptional performance to meet the growing need for precise and effective identification (Hu *et al.*, 2018). These technologies rely on an individual's physical traits, such as their face, fingerprint, iris, and palmprint (Alrahawe *et al.*, 2021). Large intra-class variations, non-universality, potential ,risk and poof attacks are associated problems of unimodal biometric recognition systems(Xu *et al.*, 2019). Numerous studies have discovered that the combination of two or more biometric modalities can significantly increase the classification accuracy and generalization capacity of biometric recognition applications, thus resolving the issues with unimodal biometric recognition that currently exist(Alay & Al-Baity, 2020 ; Bhardwaj *et al.*, 2017 ; Galbally *et al.*, 2014 ; Kumari, 2020 ; Nappi *et al.*, 2018 ; M. Singh *et al.*, 2019 ; Song *et al.*, 2020). Simple average fusion techniques were used in digital images by Malviya & Bhirud,2009. Though simple in implementation, however, the resultant fused image is not clear. Naidu & Raol, 2008 used principal component analysis techniques in fusing images, which resulted in strong fused images with spectral degradation. Though spatial fusion techniques, such as simple average, simple maximum, simple minimum, and PCA gives high spatial resolution

https://dx.doi.org/10.4314/aujst.v4i1.2

with the blurred result. Tabassum *et al.*, 2022 presented human face recognition with a combination of DWT and machine learning to address the major issue of intruders and impostors, Discrete Wavelet Transform (DWT) is combined with different algorithms; vector of principal component analysis (PCA), eigen vector of PCA, eigen vector of Linear Discriminant Analysis (LDA) and Convolutional Neural Network (CNN), four results were produced recognition rate of 89.56% for the worst case and 93.34% best case for face recognition nevertheless the recognition is found dependent on image and diversity of database. In this paper new model is proposed where without extracting the features, biometric images are fused using the discrete wavelet transform method. Discrete wavelets generate new coefficients by decomposing transform images into several levels. This co-efficient is combined to create a new co-efficient that contains the data from both images. The fused image is obtained by using the inverse discrete wavelet transform.

2. METHODOLOGY

2.1 Discrete wavelet transforms (DWT) for proposed work

Discrete wavelet transform is used to find regional characteristics in a signal processing and also utilized for the multiresolution analysis of two-dimensional (2D) signals, such as 2D grayscale image signals. In wavelet transforms, a signal is split into low- and high-frequency bands. DWT process is shown in Figure 1. Using the wavelet transform, a signal is decomposed into a set of integrals (wavelets). It expresses in term of time and frequency. Two-channel filter bank is utilized in discrete wavelet transform (DWT). The detail and approximation components can be separated during decomposition. 2-D The discrete wavelet transform (DWT) changes the image's frequency domain from spatial to frequency. The first-order of the DWT is represented by the image, which is divided into four portions by vertical and horizontal lines labeled LL1, LH1, HL1, and HH1.

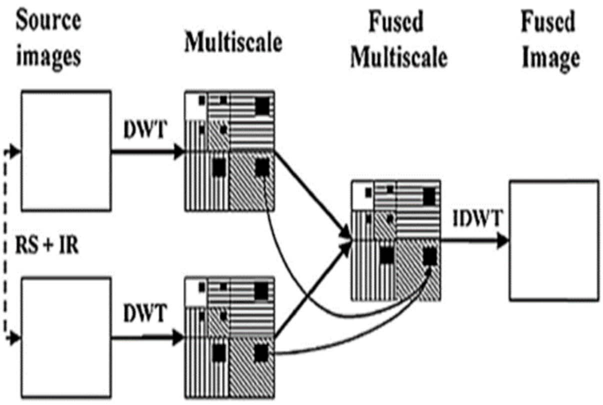

Figure 1: Discrete Wavelet Transform

Step 1. Discrete Wavelet Transform is applied on both input images to produce the wavelet lower decomposition. The images signal is decomposed simultaneously using high pass filter. So, the two filters are related to each other and they are known as a quadrature mirror filter.

$$x(n) = \sum_{j=0}^{n-1} z(j).g(n-j) \tag{1}$$

$$x_{low}(n) = \sum_{j=-\infty}^{\infty} z(j)g(2n-j) \tag{2}$$

$$x_{high}(n) = \sum_{j=-\infty}^{\infty} z(j)h(2n-j) \tag{3}$$

Step 2. The decomposition level is fused using mean fusion rule.

Step 3. Inverse Discrete Wavelet Transform (IDWT) is carried out on the fused decomposition to reconstruct the final fused image.

Once the fusion volume coefficients are finalized then the image is put through the inverse transform of the transform used to create the coefficients. The inverse transform will get back the image into spatial domain.

In this study, face, iris, and fingerprint images were combined using multi-resolution wavelet technology. For experiments, we combined a face and iris as well as a face and fingerprint.

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2.2 Performance Metric for Fusion Analysis

Peak Signal to Noise Ratio (PNSR) is the peak signal-to-noise ratio, between fused and reference image, and it is expressed in terms of decibels (Chowdhary *et al.*, 2020).

$$PSNR(dB) = 20log\frac{255}{\sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(I_{r_{ij}}-I_{f_{ij}}\right)^2}} \quad (4)$$

where Ir represents the reference image and If is the fused image, i and j are the row index and column index

The Entropy of an image is the measure of information present in an image and is defined as follows:

$$E = -\sum_{i=0}^{n-1} p_i log_b p_i \quad (5)$$

where n is the number of gray, p_i is the probability of a pixel having gray level intensity, and b is the base of the logarithm function. It gives the information content of the image. A Higher value of entropy indicates a higher amount of information present in the image.

Fusion symmetry (FS): Suppose A and B are input images, while F is a fused image, the contribution of the image A (or B) to the fused image F can be found using FS to evaluate the fusion performance (R. Singh & Khare, 2014).

$$FS = abs\left(\frac{M_{AF}}{M_{AF}-M_{BF}}\right) - 0.5 \quad (6)$$

where MAF denotes mutual information of images A and F. MBF denotes mutual information of images B and F. Measure of mutual information gives the amount of correlation between two distributions (Haghighat *et al.*, 2011). Given two images A and F, the mutual information is defined as

$$M_{AF} = \sum_{x,y} P_{AF}(x,y) log\frac{P_{AF}(x,y)}{P_A(x)P_F(y)} \quad (7)$$

where PA(x) and PF (y) are the probability density functions in individual images and PAF (x, y) is the joint probability density function. Estimations for the joint and marginal density functions can be obtained by simple normalization of the joint and marginal histograms of both the images.

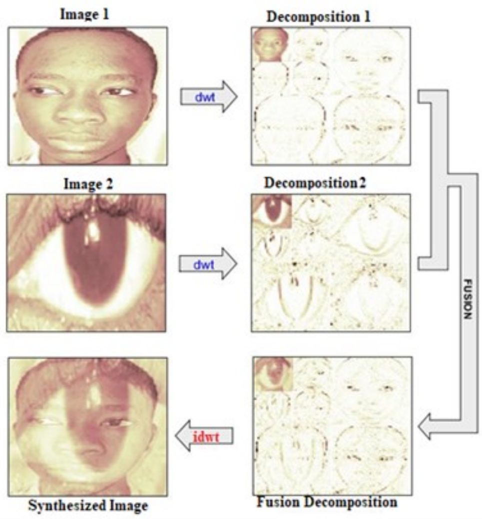

Figure 2a: Fusion of Face images and Iris

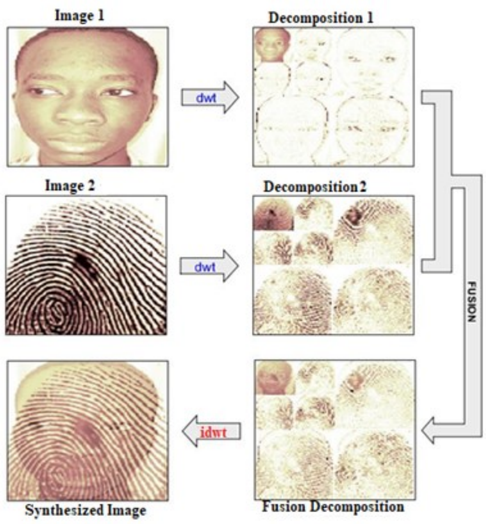

Figure 2b: Fusion of Face images and Finger-

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Input images in Figure 2a and 2b are subjected to DWT in order to produce coefficient values for each input image pixel. The obtained coefficients are combined, in order to generate new coefficient values. The fused image is created by applying inverse DWT to a new co-efficient. The resulting fused image contains the information from both the input and output images. Information from face, iris, and fingerprint biometric samples is contained in this new database with fused images. Using both the DWT stage 1 and the IDWT stage 3 of Figures 1 and 3, Figure 3 depicts the fusion of a face, an iris, and a fingerprint.

3. Proposed Fusion Model

In this research, image fusion is applied using the discrete wavelet transform technique. The images were decomposed using four DWT filters, namely: Daubechies (db), Haar (haar), Coiflets (coif) and Fejér-Korovkin (fk) wavelets type 1 level 2. We investigated the trials by fusing the face with the finger print and the face with the iris, and then by fusing all three biometrics. Figure 4 represent the suggested model for face, iris, and fingerprint biometric samples; both the face and fingerprint model and the face and iris model are implemented using the same way.

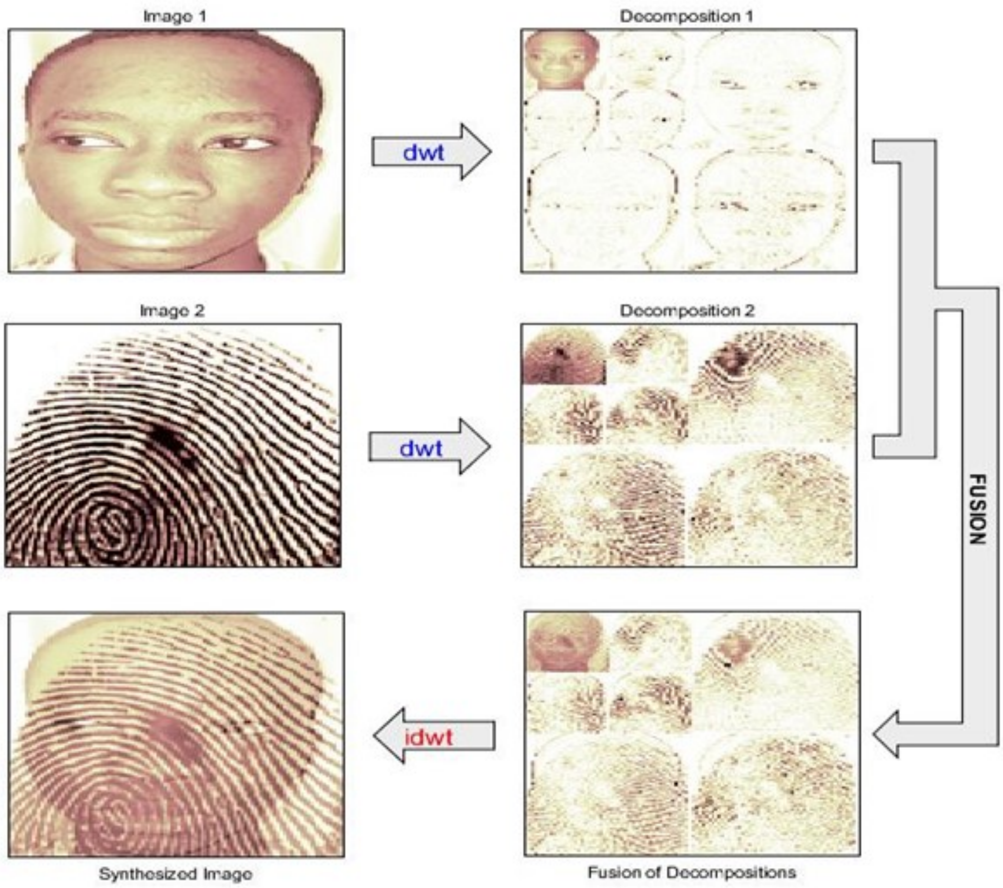

Figure 3: Fusion of face, iris and fingerprint.

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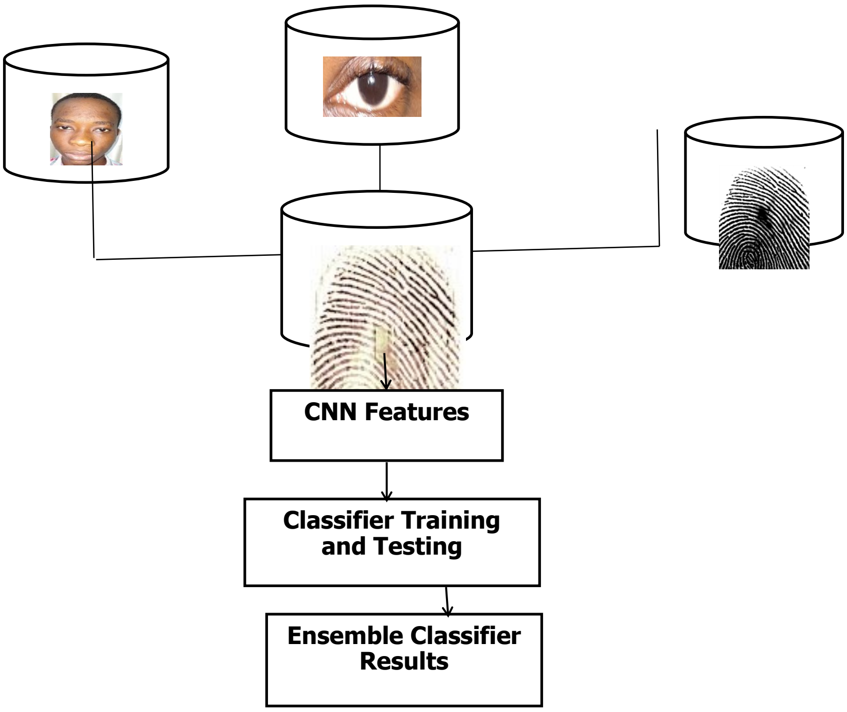

Figure 4: Proposed DWT fusion model

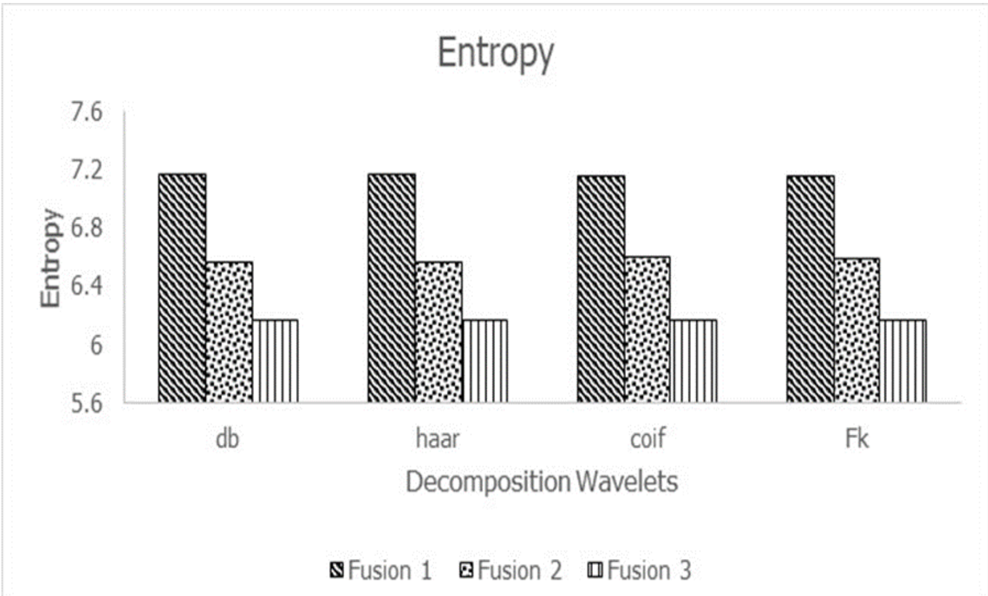

Figure 5: Entropy performance of the fused images for different fil-

Performance of the biometric fusion for different wavelets and images were examined using entropy, PSNR and fusion symmetry (FS) metrics. Fusion 1, Fusion 2 and Fusion 3 in figures (5-7) represent face – iris fusion, face – fingerprint fusion and face – iris – fingerprint fusion respectively. In comparing entropy values of DWT with different wavelet decomposition and different multimodal fusion, Daubechies (db) and haar wavelets decomposition for fusion of face and iris (fusion 1) with highest values gives better results (Figure 5). The obtained entropy result is in agreement with previous work (Haghighat *et al.*, 2011 ; Indira *et al.*, 2016). Fused image of face and iris yield highest value of PSNR for all the wavelets decomposition, which indicate high quality with less error compare to other fusion.

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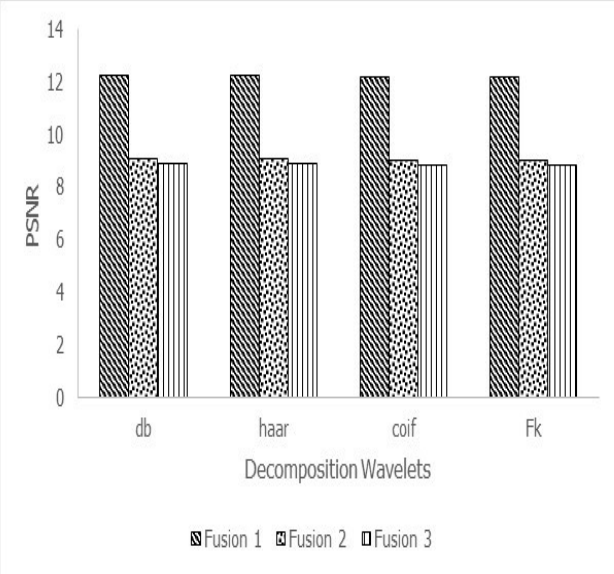

Figure 6: Peak -signal to noise ratio performance of the fused images for different filter

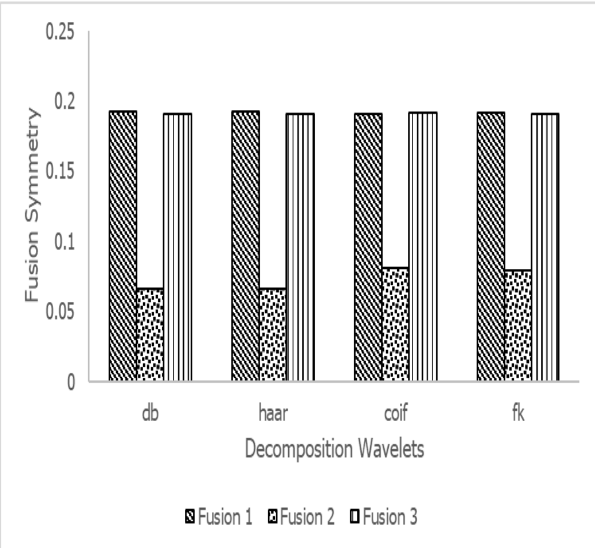

Figure 7: Fusion symmetry performance of the fused images for different filter

Conclusion

In this paper face, iris, and fingerprint images were combined using discrete wavelet transform. Performance of the fusion images were examined using entropy, PSNR and fusion symmetry (FS). Daubechies (db) wavelet decomposition technique was adopted and compared with Haar (haar), Coiflets (coif) and Fejér -Korovkin (fk) wavelets type 1 level 2. Entropy and PSNR performance of face and iris (fusion 1) performed better with higher values than face -fingerprint fusion and face-iris-fingerprint. Likewise, db and haar have equivalent values of entropy, PSNR and FS performed better than other wavelets. Haar and db filter of DWT perform better and provides better spatial and spectral localization of image information. In view of this performance, haar and db DWT filters techniques are recommended for image fusion.

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