Image fusion by discrete wavelet transform for multimodal biometric recognition

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## Article Info

ABSTRACT

In today's world, security plays a crucial role in almost all applications. Providing security to a huge population is a more challenging task. Biometric security is the key player in such type of situation. Using a biometric-based security system more secure application can be built because it is tough to steal or forge. The unimodal biometric system uses only one biometric modality where some of the limitations will arise. For example, if we use fingerprints due to oiliness or scratches, the finger recognition rate may reduce. In order to overcome the drawbacks of unimodal biometrics, Multimodal biometric systems were introduced. In this paper, new multimodal fusion methods are proposed, where instead of merging features, database images are fused using discrete wavelet transform (DWT) technique. Face and signature images are fused, features are extracted from the fused image, an ensemble classifier is used for classification, and also experiments are conducted for finger vein and signature images.
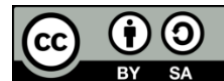
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1. INTRODUCTION

The multimodal biometric systems give better results when compared to unimodal biometric systems. In multimodal biometric, more information is available compared to unimodal biometric. More than one biometric information is available in multimodal biometrics [1]–[3]. But designing the multimodal biometric system is a challenging task since to fuse the information of more than one biometric modalities, there will be a lot of compatibility issues. If two biometric modalities features are fused, then there may be chances of unwanted features stored as a template, or most important data may lose due to feature compatibility like data types. To overcome such limitations in multimodal biometrics raw image fusion is used, in the literature [4]–[6] we observed that discrete wavelet transform (DWT) image fusion techniques is not used on multimodal biometric recognition. The biometric fusion at the feature and sensor level is noticeable from the many research work [7]–[10]. In this paper new model is proposed where without extracting the features, raw images are fused using the discrete wavelet transform method, and experiments are conducted on Histogram oriented gradient and uniform local binary pattern features [11]. In discrete wavelets, transform images are decomposed into different levels, and new coefficients are generated. This

co-efficient is combined or merged to form a new co-efficient that holds the information of both images [12]. And in the next stage, inverse -discrete wavelet transform is applied to get back the fused image.

2.   RESEARCH METHODOLOGY

In discrete wavelets transform, images are fused by converting them into wavelets, as shown in Figure 1. In order to fuse the images, more than one image is required. These images can be either with the same resolution or a different resolution. Two different methods are used to fuse, as shown in Figures 1(a) and (b).

Figure 1(a) is used to fuse the images of the same resolution, and Figure 1(b) is used to fuse the image with a different resolution [12]. In the initial stage of sampling and registration, the technique is applied to make sure; images are of the same size and registered to the same sensor. After completion of sampling and registration process DWT is applied to images in order to generate coefficient values for very individual pixel of input image. These coefficients are merged to form new coefficient values. In the next step, inverse DWT is applied to a new co-efficient to obtain the fused image. The information of both input images and present in final fused image. Figure 1(a) shows the transformation of image fusion using wavelets for the same resolution image, and Figure 1(b) shows the transformation of image fusion using wavelets for different resolution images. The top left corner shows the levels of decomposition of an image [6], [12].
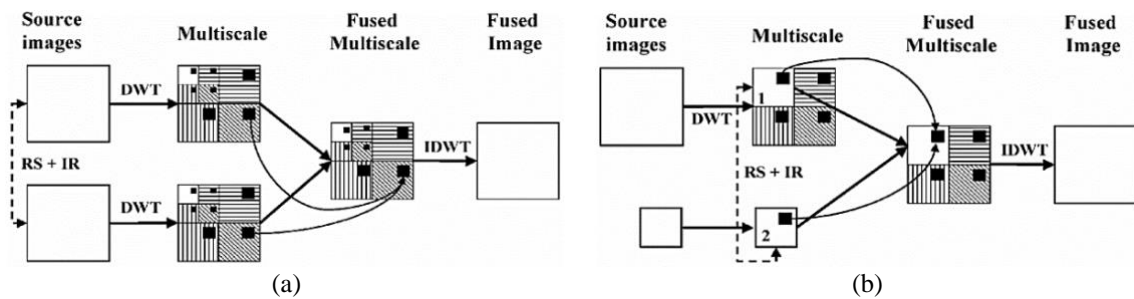

(a)   (b)

Figure 1. Discrete wavelets transform for (a) method 1 and (b) method 2

3.   MULTI-RESOLUTION DISCRETE WAVELET TRANSFORM (DWT) FOR PROPOSED WORK

This paper used multi-resolution wavelet fusion, face, signature, and finger vein images with different resolution images to combine. We used a combination of face and signature also finger vein and signature for experiments. Consider a face sample in multi-resolution wavelet transform shown in Figure 2, shows the stage 1 wavelet transform and Figure 3 shows the 1st, 2nd and 3rd degree decomposition levels of face image where low pass and high pass filters are applied for each row and column, and four sub-images are created. These four images represent the different decomposed degrees [6], [12].
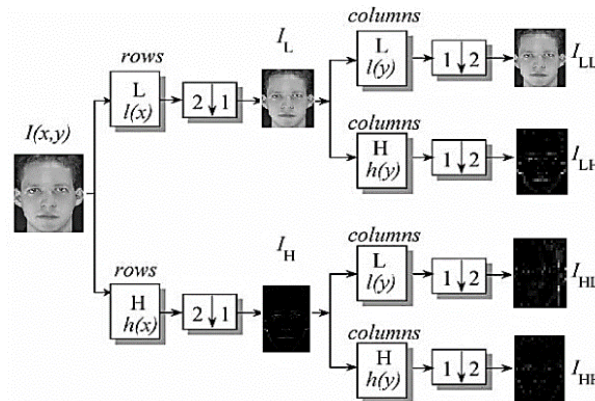

Figure 2. Stage 1 wavelet transform
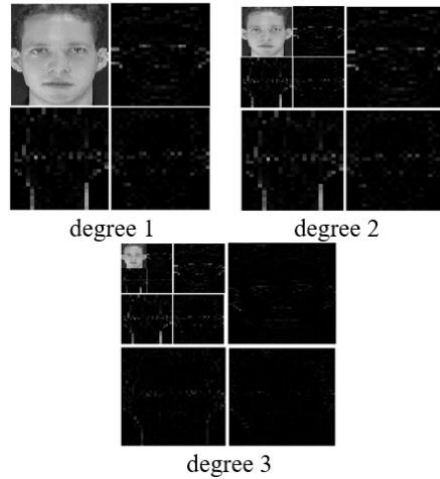
degree 1   degree 2

degree 3

Figure 3. First, second, and third degree decomposition levels

After stage 1, with the 3-degree decomposition of the face image, Figure 3 shows the details of 3-degree wavelet decomposition, where the top left corner shows the decomposition degrees. After applying stage 1 transform, the inverse transformation of wavelet is applied to co-efficient, which are obtained as the output of stage 1. In stage 2, inverse DWT is applied, and the final merged image is obtained. The detailed steps are showed in Figure 4. Figure 5 gives the detailed steps of stage 1 and stage 2 transformations with notations.
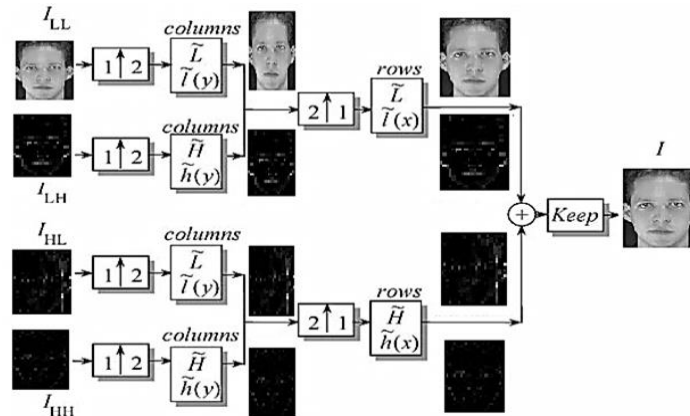

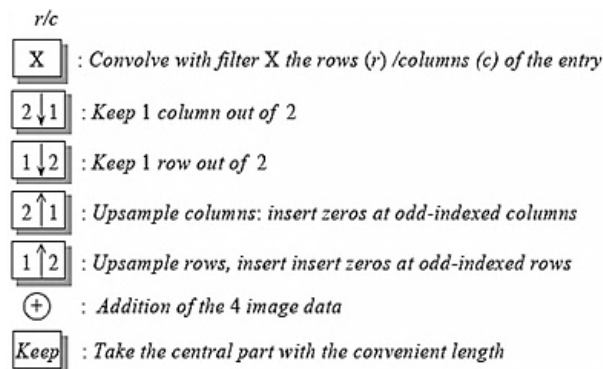Figure 4. Stage 2 wavelet transform

Figure 5. Steps of stage 1 and stage 2 wavelet transformation

4.   DATABASE USED FOR EXPERIMENTATION

− Face database: american telephone and telegraph company (AT and T) laboratories Cambridge face database [13] is used, 40 persons, six samples of each individual is used for experimentations.
− Finger vein database: machine learning and data-mining lab, Shandong University (SDUMLA) finger vein database [14] is used. Six samples of the left index finger of the first 40 subjects are used for experimentations.
− Signature database: biometric research lab (ATVS) Madrid Spain's MCYT signature database [13] is used. In this paper, we considered the first 40 subjects/individuals with the first six genuine samples of each individual. Finally 720 samples of face, signature and finger vein are used for experimentation. The samples are mapped one to one for forty individuals. Mapping of data base is commonly used by all the researchers due to non availability of standard data bases, and also it has been showed that the performance of the fusion models will be same when compared with mapped data base and original data base of same person. Figure 6 shows the image samples of MCYT face, SDUMLA finger vein, and MCYT signature is shown in Figure 6(a), Figure 6(b), and Figure 6(c) respectively.
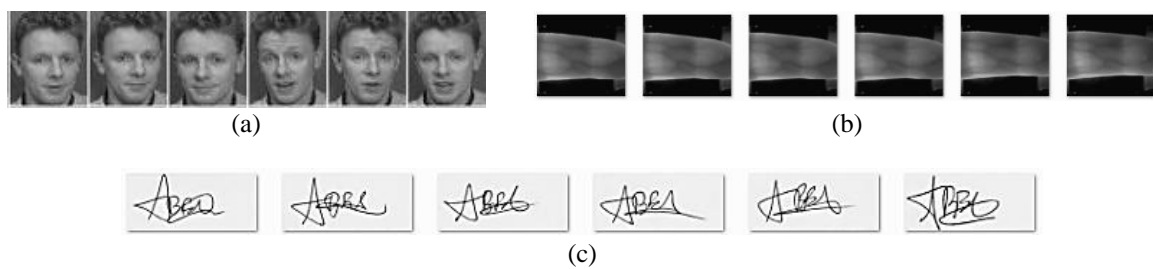

(a)   (b)

(c)

Figure 6. Image samples for (a) MCYT face, (b) SDUMLA finger vein, and (c) MCYT signature

5.   PROPOSED IMAGE FUSION TECHNIQUE

In this paper, research work is carried out to increase the recognition rate of multimodal systems over unimodal systems by applying the wavelet fusion technique to multimodal biometrics. In the proposed method, we fused face and signature images directly by fetching the images from the standard database. Experiments are also explored on finger vein and signature database. The fusion of images using DWT for biometric recognition for the face with signature and finger vein with signature for the standard database is a novel approach.

5.1. Fusion of face images and signature images

In the proposed work, standard data samples or images of face and signature are fused using DWT, 240 samples of signatures are fused with 240 samples of face one to one, and new data samples are created. This new database with fused images has information from both signature and face biometric samples. The Figure 7 shows fusion of face and signature and Figure 8 shows the fusion of Finger vein and signature by using both DWT stage 1 and IDWT stage 2 of Figure 2 and Figure 4. The final output image contains a rich information source than the original images.

Figure 7. Wavelet fusion face signature   Figure 8. Wavelet fusion finger vein signature

5.2. Fusion of finger vein images and signature images

In the proposed work, standard data samples of finger vein and signature are fused using DWT, 240 samples of signatures are fused with 240 samples of finger vein one to one, and new data samples are created. This new database with fused images has information from both signature and finger vein biometric samples. Figure 8 shows the fusion of finger vein and signature by using both DWT stage 1 and IDWT stage 2 of Figure 2 and Figure 4. The final output image contains a rich information source than the original images.
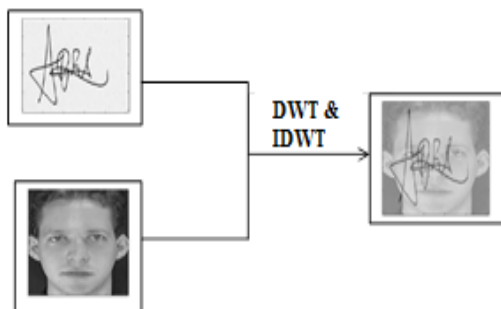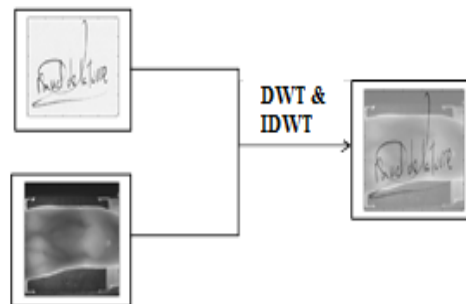
5.3. Fusion of finger vein, signature and face

In the proposed work, standard data samples of finger vein, signature and face are fused using DWT, 240 samples of signatures are fused with 240 samples of finger vein and 240 samples of face one to one, and new data samples are created. This new database with fused images has information from signature, finger vein and face biometric samples. Figure 9 shows the fusion of finger vein, signature and face by using both DWT stage 1 and IDWT stage 2 of Figure 2 and Figure 4. The final output image contains a rich information source than the original images.
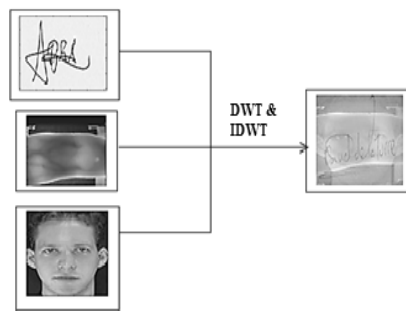

Figure 9. Wavelet fusion finger vein, face, and signature

6.   PROPOSED FUSION MODEL

In this paper, image fusion is applied using the wavelet transformation technique, there are many wavelet filters available, and from the literature [15]–[20], it has been observed that the db2 filter is best suited for multi-resolution images. In this paper, we used the db2 wavelet filter for transformation. And it has been identified in the literature that more decomposition is loose the details and less decomposition will overlap; hence degree 5 decompositions is used for our work. We explored the experiments by combining face with signature and finger vein with the signature and finally combining all the three biometrics. All three multimodal biometric recognition models were explored in this paper. Figure 10 shows the proposed model for face, signature and finger vein biometric samples, and the same method is used to implement the face and finger vein model and face and signature model.
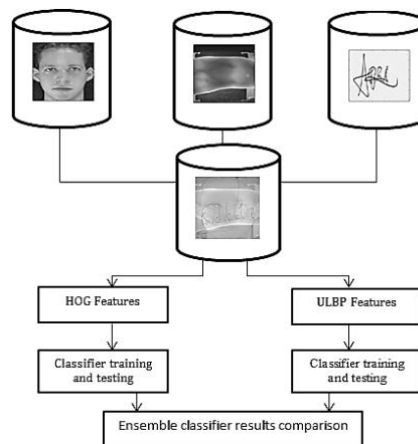

Figure 10. Proposed DWT fusion model

7. EXPERIMENTS AND RESULTS

We identified that image fusion using DWT is used for image enhancement in most of the research work from the literature. In this paper, we used the DWT image fusion technique for multimodal biometric recognition. And in multimodal biometric, not much work is explored on face and signature combination. As per our knowledge, combinations of finger vein and signature with DWT image fusion are novel approaches. All the experiments are conducted on standard databases with larger size data samples. Three experiments are conducted on the proposed model. First experiments on the face and signature biometric modalities were explored. And in the next stage, finger vein and signature biometric modalities have experimented and in last stage face, finger vein and signature are experimented. For the biometric samples of face, signature and finger vein, both unimodal and multimodal biometric investigation is conducted. I to XII represent the experiments in Tables 1 to 5.

7.1. Face and signature fusion experiments

Separate unimodal experiments are conducted on face and signature using uniform local binary pattern (ULBP) features and histogram of oriented gradient (HOG) features [21]–[26]. In the entire case, an ensemble machine learning classifier is used [26]. Unimodal experiment results are shown in Table 1.

Table 1. Unimodal biometric experiments

Unimodal	Biometric	Accuracy of Classifier
I	Face (ULBP)	74%
II	Face (HOG)	82%
III	Signature (ULBP)	85%
IV	Signature (HOG)	91%

In multimodal experiments, fused samples of face and signature are used. From the fused images, ULBP and HOG features are extracted. An ensemble classifier is used for classification [25], [26]. Multimodal experiment results are shown in Table 2.

Table 2. Multimodal experiments

Multimodal	Biometric	Accuracy of Classifier
V	Face Signature (ULBP)	92%
VI	Face Signature (HOG)	94%

7.2. Finger vein and signature fusion experiments

Separate unimodal experiments are conducted on finger vein and signature using ULBP features and HOG features. In the entire case ensemble, a machine learning classifier is used [25], [26]. Unimodal experiments result shown in Table 3.

Table 3. Unimodal biometric experiments

Unimodal	Biometric	Accuracy of Classifier
VII	Finger vein (ULBP)	88%
VIII	Finger vein (HOG)	82%

In multimodal experiments, fused samples of finger vein and signatures are used, from the fused images ULBP, and HOG features are extracted. An ensemble classifier is used for classification [26]. Multimodal experiments result shown in Table 4. Overall, twelve experiments are conducted in which proposed multimodal experiments outperforms over unimodal experiments.

Table 4. Multimodal experiments

Multimodal	Biometric	Accuracy of Classifier
IX	Finger vein Signature (ULBP)	94%
X	Finger vein Signature (HOG)	97%

7.3. Finger vein, face, and signature fusion experiments

After experimenting the combinations of face-signature and finger vein-signature, All the three biometrics are fused together to conduct new experiment, from the fused images ULBP, and HOG features are extracted. An ensemble classifier is used for classification [26]. Multimodal experiments result shown in Table 5.

Table 5. Multimodal experiments

Multimodal	Biometric	Accuracy of Classifier
XI	Finger vein, Face, and Signature (ULBP)	92.5%
XII	Finger vein, Face, and Signature (HOG)	95.8%

7.4. Comparision of results with previous research works

From the literature survey of the previous work [27]–[36], it has been observed that, very limited work is investigated by the researchers previously on the wavelet fusion for multimodal biometric recognition. The pervious work on finger vein and signature combination is done on cryptography [37], in which the author used only one sample for authentication. The pervious works were not explored on multimodal biometric recognitions. The standard database with larger data samples is not considered in the previous work. In this paper, we explored the work on larger standard databases for face, finger vein and signature combinations. We used 720 data samples of face, signature and finger vein. The Table 6 shows the performance of some latest multimodal biometric research work compared with the proposed system.

Table 6. Comparison with state of art work

Authors	Biometric Traits	Data Base Size	Accuracy/Recognition Rate	Error Rate
Mathkour *et al.* [38]	Fingerprints and Electrocardiogram	70 subjects, 720 samples	95.32%	4.68%
Kong *et al.* [39]	Finger vein, Fingerprint, and Face	50 subjects, 250 samples	93%	7.0%
Tharwat *et al.* [40]	Ear and Finger Kunckle	165 subjects, 6 samples	96.47%	3.53%
Arun *et al.* [7]	Fingerprint and Iris	750 subjects	94.8%	5.2%
Davies [29]	Ear and Face	56 subjects	96.8%	3.2%
Shen [30]	Palm print and Face	119 subjects	91.63%	8.37%
Proposed wavelet based fusion	Signature and Finger vein	40 subjects, 400 samples	97%	3.0%
Proposed wavelet based fusion	Signature and Face	40 subjects, 400 samples	94%	6.0%
Proposed wavelet based fusion	Face, Signature, and Finger vein,	40 subjects, 400 samples	95.8%	4.2%

The proposed method significantly reduced the storage space of the image samples when it is compared with the other state of art work. The combinations of Finger vein and signature using wavelet fusion technique shows significant reduction in error rate when compared with other state of art work shown in Table 6. The wavelet based fusion merges the two images of a different biometric characteristics of a person to single image, which significantly reduce the storage space. The proposed technique also showed the features extraction technique ULBP and HOG can be used to improve the recognition rates. The feature extraction techniques ULBP and HOG give the statistical features of the complete image. In the proposed work complete statistical information of samples is used, which is not done in the previous state of art work. The proposed multimodal biometric authentication schemes showed promising results and improved the classification performance rates, when considered recognition rate. With the comparison of pervious work in Table 6 it has been observed that the proposed model showed promising results in improving the biometric recognition rate.

8. CONCLUSION

In this paper, we proposed the image fusion technique for multimodal biometric using wavelet transform. We introduced a new model where biometric images are fused using DWT, and these fused images can be used for recognition using machine learning algorithms by extracting HOG and ULBP features. We conducted experiments on the face with signature and finger vein with the signature, and face, signature and finger vein combinations. The fusion combinations of the proposed model, performed well over the unimodal biometric system. Both unimodal and multimodal experiments are conducted, and results are plotted. Twelve experiments are conducted on standard mapped databases. After investigation of all the experiments, it has been observed that wavelet-based image fusion with db2 wavelet filter and decomposition degree at 5 shows a better recognition rate in finger vein and signature for the selected database. And also

Histogram oriented gradient features showed better results over uniform local binary patterns in DWT image fusion for multimodal biometrics.

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