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Data Fusion-Based Multimodal Biometric System for Face Recognition Using Manhattan Distance Penalty Weight

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Abstract - In this paper, we propose a multimodal biometric face recognition technique which is mainly based on the 2D Discrete Wavelet Transform (DWT) and Data Fusion (DF) and utilizes data fusion techniques at the score level of the system algorithm. The technique employs three discrete unimodal feature extraction and classification methods. The first two feature vectors are generated from raw images by using Principal Component Analysis (PCA) and Local Binary Pattern (LBP) methods. During the generation of the third feature vector, images are initially transformed into the DWT domain. In result, approximation, vertical, horizontal and diagonal detail matrices are combined to form a Joint Feature Vector (JFV). K-Nearest Neighbor (KNN) classifier algorithm is separately applied to the three generated feature vectors to compute different score values for the same individual. These raw score values are fused together using a newly proposed data fusion technique based on Manhattan Distance Penalty Weighting (MDPW). The proposed MDPW penalizes an individual for scoring low points and further pushes it away from the potentially winning class before data fusion is conducted. The proposed approach was implemented on ORL and YALE public face databases. The results of the proposed approach are evaluated using the recognition rates and receiver operating characteristics of the biometric classification systems. Experimental results show that the proposed multimodal system performs better than the unimodal system and other multimodal systems that use different data fusion rules (e.g. Sum Rule or Product Rule). In ORL database, the recognition rate of up to 97% can be achieved using the proposed technique.

Keywords - *Face recognition, discrete wavelet transform, principal component analysis, discrete wavelet transform, local binary pattern, data fusion, Manhattan distance, k-nearest neighbor (KNN)*

1. Introduction

The need for a reliable system which is capable of establishing genuine peoples' and impostors' identities has snowballed over the years, especially with the increase in the global trend of crimes. These needs spurred active research in the field of biometrics. Over the years, imposters have been looking for loopholes that exist in the unimodal biometric system to fake identity leading to breach of privacy and security. The multimodal biometric system seeks to alleviate some of the drawbacks encountered by the unimodal biometric system. This improvement is achieved by consolidating the evidences presented by multiple biometric traits or sources. This system significantly improves the recognition performance, increases the degree of freedom and reduces spoof attacks and failure-to-enroll rate [1-3].

Advanced research on challenges related to the automatic identity establishment in individuals has been of keen interest to both governments and corporate organizations all around the world. With an increasing global integration of nations' economies and bilateral relationships, the need for tracking economic activities, social movements of individuals and forestalling crimes become equally important. One of the key platforms which frequently addresses some of these global challenges is the area of biometric systems [4].

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One of the key perspectives explored by recent researches in this regard is the use of more than one biometric trait or data from an individual for representation in the system. This method, usually referred to as a multimodal biometric system, may combine data of the same person from different biometric traits (e.g. Fingerprint and face), or use different algorithms on the same trait to arrive at a more robust representation of the individual in the biometric system [5-6]. In a situation where the multimodal system exploits different algorithms, more flexibility is added whereby the data fusion techniques implemented at different levels of the algorithm stages (e.g. Feature extraction level, score level, decision level). The evidence in literature indicates that the multimodal system significantly improves the performance of the unimodal biometric systems [6-7].

A comprehensive literature review on multimodal biometric systems was compiled by Ross et al. [8]. They extensively investigated different fusion schemes at score level. Also in ISO/IEC Technical Report, many explanations and analyses on the recent developments regarding various multimodal biometric fusions have been compiled. There are various researches on different levels of fusion in multimodal biometric systems. An approach based on mosaicking scheme was proposed by Ratha et al. [9]. They have constructed a combination of fingerprint samples from many other samples as the user rolls over his finger over the sensor surface area. Singh et al. [10] developed a multimodal face recognition system by fusing images from visible and thermal Infrared (IR) cameras at different levels. Kong et al. described the performance of a multimodal recognition system based on a fusion of thermal infrared camera and visible light camera samples [11]. Authors in [12] performed a fusion of iris and face at the feature level. In [13] fusion at feature level was conducted on hand and faces data. The process is done in three different phases. Authors in [14] proposed a platform for fusing classifiers and discussed the various methods involved in the combination schemes. In [15], authors study the performance comparison of score level fusion using three different classifiers that are the k-nearest-neighbor (k-NN) classifiers, decision trees, and logistic regression.

In this paper, a different approach is proposed for the multimodal biometric system. The technique considers data fusion at score level of the classifier but instead of using different classifiers for each unique feature evidence (as is the case in literature), the same classifier is used with the same normalization algorithm. Three feature extractions were used to present different biometric pieces of evidence from the same trait. Using DWT, a new feature extraction was introduced whereby the four representation from the DWT were concatenated, and the Principal Component Analysis (PCA) was used to extract final reduced features from the concatenated DWT features. Similarly, a method for fusion scores from a unimodal biometric system was proposed based on the Manhattan distance penalty weighting. Scores of the individual are penalized based on their weighted distance from the supposed winning class before fusion.

The rest of the paper is organized as follows: Section II provides literature background on the PCA, DWT, LBP and K-NN. Section III presents and discusses the proposed multimodal system using the proposed data fusion. Section IV clarifies the results of the simulations. Finally, Section V contains the conclusion on our findings and observations.

2. Preliminaries

The feature extraction and classifier algorithms are the most important factors in the overall success of the system. Hence, the choice of these feature extractors and classifiers become pertinent. In this section, a background that is used from the build-up to the proposed approach on these algorithms is presented as the preliminaries.

2.1 Principal Component Analysis (PCA)

The PCA algorithm tries to extract salient features from a vector that best represents a class to which that vector belongs [16-20]. The algorithm forms a Difference Matrix (DM) by subtracting the average of all the training set from each sample (vector) and concatenating the results. It then statistically computes the covariance of the DM and finds its eigenvectors and eigenvalues. This information (eigenvectors, DM) is used for projecting all the vectors into a vector space which best represents their class. For eigen-face approach, the projected vector space is used as a feature to represent a subject [21]. Figure 1 describes the PCA algorithm steps.

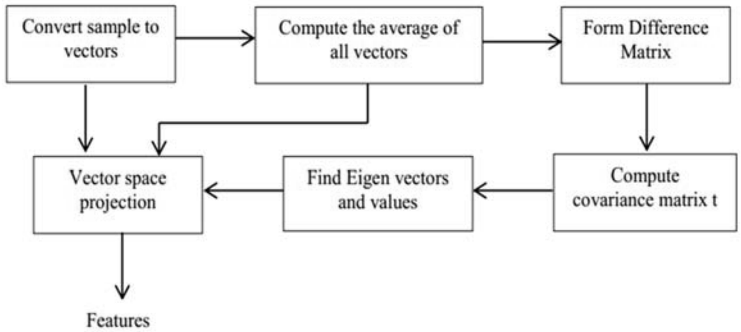


Figure 1. Block diagram of PCA feature extraction

2.2 Local Binary Pattern (LBP)

Due to its simplicity, LBP has been successfully applied in many applications. It uses *3x3* windows of the neighborhood pixels in the image to determine the new value of the center pixel that is under consideration [22]. Taking Figure 2 into account, initially the algorithms probe all the 8-neighborhood pixels around pixel I (z); any pixel greater than I (z) is assigned binary value *1* while those whose values are less than or equal to I (z) are assigned the bit value of *0*. *8-bit* code which is generated and converted to decimal for finding the new value of I(z). The procedure is applied to all the pixels in the image as the window slides from the top-left corner to the bottom-right corner of the image. In the end, each pixel's gray intensity is replaced by the *8-bit* code generated by the algorithm using local surrounding pixel information. The code is arranged clock or anti-clockwise consistently throughout the operation and then each code is converted back to a decimal integer. Figure 2 demonstrates how the algorithm operates.

100	240	30		0	1	0
20	I(z)=120	185	→	0		1
70	100	200		0	0	1

Figure 2. LBP feature extraction

2.3 Discrete Wavelet Transform (DWT)

DWT is one of the multi-resolution signal and image processing algorithms. It tries to view signal or image at different resolutions so that features that cannot be seen at one resolution can be detected in another resolution. Two orthogonal or bi-orthogonal filters are used for achieving the transformation. One of the filters is high pass (Hi) while the other is Low pass (Lo). DWT can be seen as a departure from the famous Fourier Transform (FT) whose basis function is sinusoids. DWT is based on small waves that are called wavelets of varying frequency and limited duration [22].

DWT employs a scaling function to create a series of approximation of functions (images) each differing by a factor of 2 in resolution from its neighboring approximation. Additional functions which called wavelets encode the difference between adjacent approximations. Figure 3 shows how DTW features can be extracted. The last four wavelets are vectorized and fused using the sum rule to obtain the feature vector for that sample [22-27].

The 2D-DWT, on the other hand, is an extension of the one-dimensional discrete wavelet transform [28]. At a time, it simply functions in one dimension by evaluating the columns and rows of an image in a distinct way. In the initial stage, an analysis filter is applied to the rows of the input image. The convolution operation produces two sets of images where one set of the images are contained in its coarse row coefficients section whereas the other set of images are stored in its row detail coefficients. The other set of analysis filters is applied to the columns of each of the input image. This operation produces four different images called sub-bands, wavelets or sub-images. Usually, the columns and rows that are analyzed with a high pass filter are designated with a symbol H. Likewise, those columns and rows that are analyzed with a low pass filter are designated with a symbol L. For instance, if a sub-image was obtained from convolution with a high pass filter on its rows and a low-pass filter on its columns, it is referred as (HL) sub-band. As a result, four wavelets are produced; approximate wavelet (A), horizontal wavelet (H), vertical wavelet (V) and the diagonal wavelet (D) as shown in Figure 3.

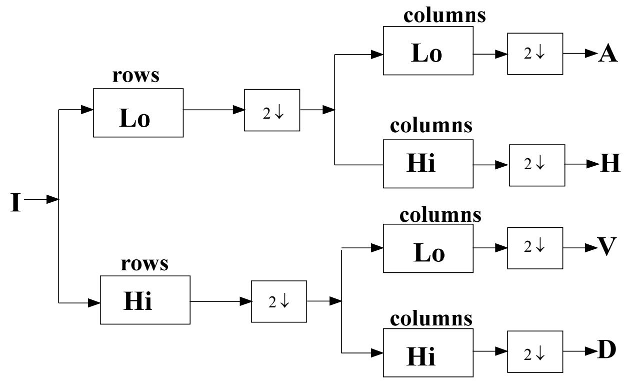


Figure 3. DWT decomposition process

2.4 K-Nearest Neighbor (K-NN)

K-NN can be described as a sort of instance-based learning or passive learning algorithm whereby the function is only approximated locally, and all computation is deferred until classification. The k-NN algorithm is among the simplest of all machine learning algorithms. Both for classification and regression, it can be useful to assign weights to the contributions of the neighbors so that the nearer neighbors contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbor a weight proportional to its closeness or otherwise to the test data. To compute the distance between a test vector and the training set vector distance metric algorithms such as Euclidean distance (l_2-norm), Manhattan Distance (l_1-norm), etc. are frequently used. Eq. (1-2) show how the distance between two n-dimensional vectors x and y can be computed using Euclidean distance $\delta_{\ell_2}(x, y)$, and Manhattan Distance $\delta_{\ell_1}(x, y)$ metrics.

$$\delta_{\ell_1}(x,y) = |x-y| \tag{1}$$

$$\delta_{\ell_2}(x,y) = \|x-y\|^2 \tag{2}$$

3. Proposed Multimodal Biometric System

In the proposed approach, the multimodal system is implemented at the score level. A single trait from an individual is used with PCA, LBP and DWT algorithms to create three different unimodal versions of the biometric system. We have used the same classifier with the same score normalization algorithm to avoid some of the problems resulting from a different classifier score distribution and to bring the scores distributions from different feature extractors into a uniform distribution pattern before applying the proposed fusion techniques. In this way, an avenue is created for fair participation and contribution in the fusion process for all the unimodal systems.

3.1 Creating multimodal system

In our proposed method, we have created the multimodal biometric representation of an individual from a single trait (face data) but using different feature extraction algorithms (PCA, LBP and DWT). Since each feature extractor is different in its way of extracting feature, subsequently, each presented evidence is unique and differs from one another and hence gives a different unimodal system. As can be seen in Figure 4, the input biometric trait (face data) is used for creating the first unimodal representation by employing PCA algorithm to extract features. The second unimodal system is obtained with LBP. In the third unimodal system, initially DWT algorithm is applied to the face image input to obtain four oriented wavelets from the decomposition process. The four oriented wavelets are concatenated together to form a single Joined Feature Vector (JFV). Subsequently, PCA is applied to the JFV to extract Reduced JFV (RJFV) which is shorter in size and contains more robust features than JFV alone. Figure 4 depicts how these unimodal systems are created for a given face image input named I.

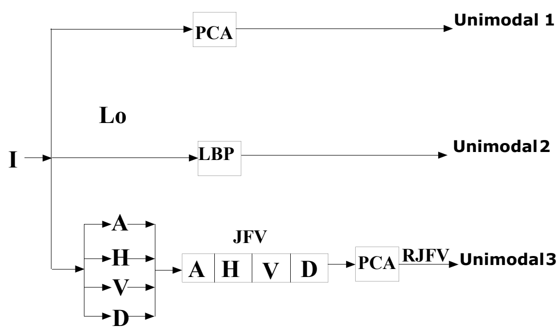


Figure 4. Unimodal feature extractions

3.2 Score normalization

The scores obtained from different unimodal systems have different statistical distributions and ranges since they belong to different sources. For making the distributions and the range similar so that each unimodal can contribute fairly in the fusion process, normalization becomes pertinent. Out of the many normalization schemes that exist, Min-Max (Eq. (3)) normalization is often suitable where the maximum and minimum bounds of the score produced by the matcher are known and hence it is adopted here [29-32].

$$S'_k = \frac{S_k - min}{max - min} \tag{3}$$

where S'_k is the normalised score, S_k is the original score and *min* and *max* are the minimum and maximum values of the scores distribution respectively.

3.3 Manhattan weighting penalty fusion

The MDPW is a new approach we propose to punish or penalize vector score in the training data (during test run) that have its scores away from the supposedly winning class which is a class with minimum Euclidean distance to the test data. Here the penalty is weighted, meaning that it is not the same for all vectors, and it linearly depends on how far is the vector from the winning class; the further the distance the more severe is the penalty while the closer the distance the more lenient the penalty. This penalty distance is added to each vector to put it further away from the supposed winning class based on its weighted penalty. Eq. (4) describes how this penalty weights are computed using Manhattan distance metric. For a given winning vector score x_w and score from some non-winning neighbors x_{nw}, the Manhattan penalty
(x_{mp-nw}) of x_{nw} can be computed using Eq. (4).

$$x_{mp-nw} = x_{nw} + \alpha |x_w - x_{nw}| \tag{4}$$

Where α is an integer constant and $|\quad|$ is the Manhattan operator or l_1-norm. Hence the new score is given as in the equation above. For *n* unimodal system the proposed fusion rule is given as the sum of the corresponding scores in each unimodal system.

Figure 5 depicts how scores are penalized based on their proximity or otherwise from the winning score. The score encircled in green indicates the winning class, and the rest are the non-winning classes. The red plots at the bottom of the figure denote the initial score distribution while the blue ones show the new scores after Manhattan penalty weighting.

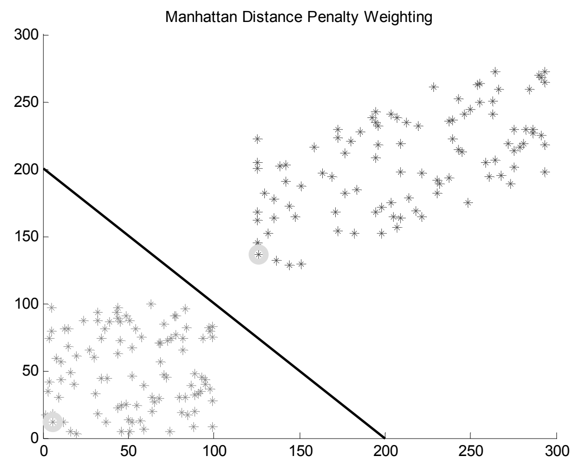


Figure 5. Manhattan penalty weighting scattered plot

4. Experimental Results

In this paper, two (ORL and YALE) databases are used to evaluate the performance of the proposed approach. The performance metrics that were used include; the percentage of Recognition Rate, False Accept Rate (FAR), False Reject Rate (FRR), and Receiver Operating Characteristics curve (ROC). To ensure adequate training and fidelity on the results obtained from the experiments; both training sets and testing sets were picked randomly from the database and each experiment was repeated ten times. In the end, an average of the performance of the ten runs is given as the system performance.

4.1 Simulation results using ORL database

The ORL database consists of 400 images acquired from 40 persons taken over a period of two years with variations in facial expression and facial details. All images are taken with a dark background, and the subjects are in an upright frontal position with tilting and rotation tolerance up to 20 degrees and tolerance of up to about 10% scale. All images are gray-scale with a 92×112 pixels resolution. The experiment is set up using the proposed fusion technique with the ORL database. The database is randomly divided into two equal parts; five samples from each subject in both training sets (200 images) and testing set (200 images) are used. The simulations are conducted in phases: (a) with three unimodal biometric setups with PCA, LBP and DWT alone and (b) with a multimodal biometric set formed from the four possible combinations of the PCA, LBP and DWT feature extractors. Each experiment is repeated ten times; each time randomly drawing training and testing sets from the database. The recognition rate for each set was recorded and presented in Table 1.

During the testing stage of the algorithm, each test image from the 200 images of the testing set makes a total of 5 genuine claims and 195 imposter claims from the training set. In total, 200 test images generate 5×200 (1,000) genuine claims and 195×200 (39,000) imposter claims. All the 1000 genuine claims and 2000 imposter claims are used for computing the FAR, FRR and ROC of the algorithm for performance evaluation. Figure 6 shows the comparison in ROC performance curve of all the system. Figure 7(a-c) show the plot of genuine and imposter score distributions of the three unimodal systems. On the other hand, Figure 8(a-d) show genuine and imposter scores of the four possible combinations of the multimodal system that are derived from the three unimodal systems.

Table 1. Comparison of the Recognition rates on ORL Database between the proposed fusion and others

Fusion	PCA	LBP	DWT	1+2	1+3	2+3	1+2+3
Proposed	94.50	94.1	93.55	96.55	96.15	96.6	97.05
Sum rule	94.70	93.35	93.10	95.85	95.95	95.60	96.65
Product rule	94.9	94.5	94.05	94.20	94.00	93.85	91.65

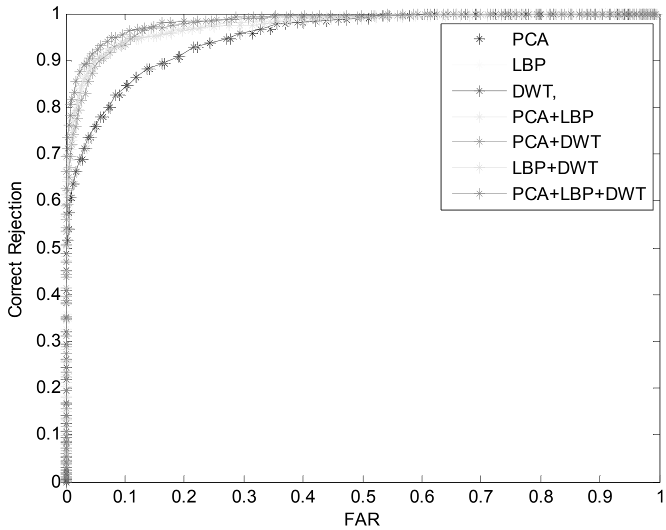
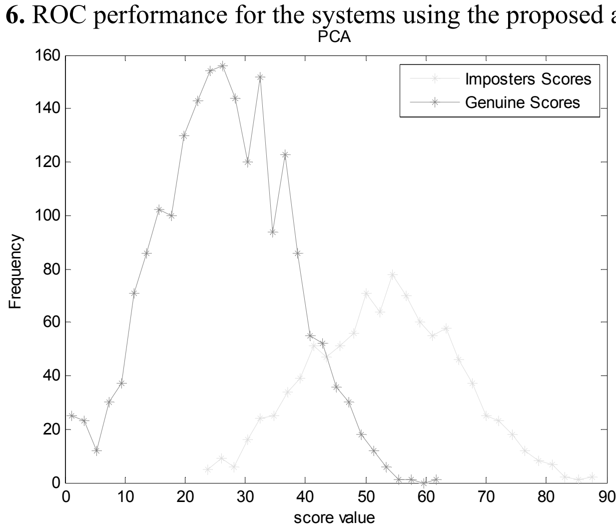
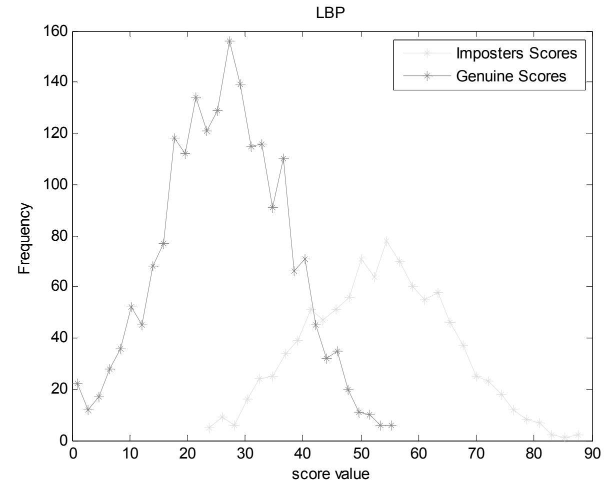


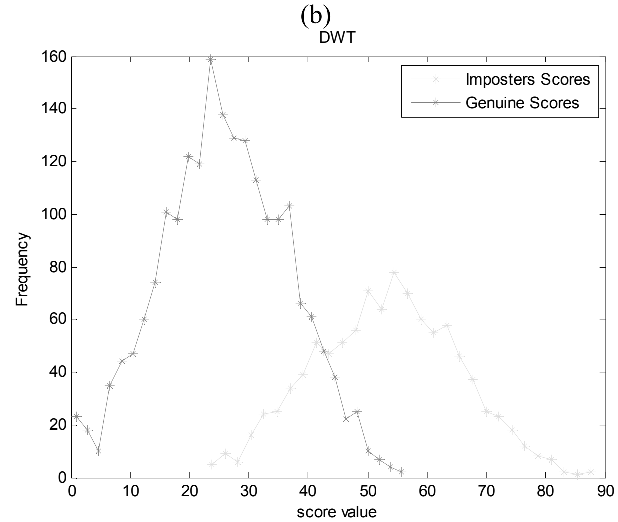
Figure 6. ROC performance for the systems using the proposed approach



(a)

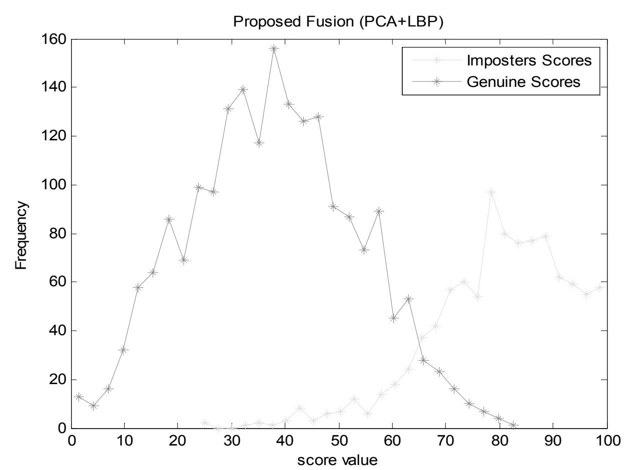


(b)

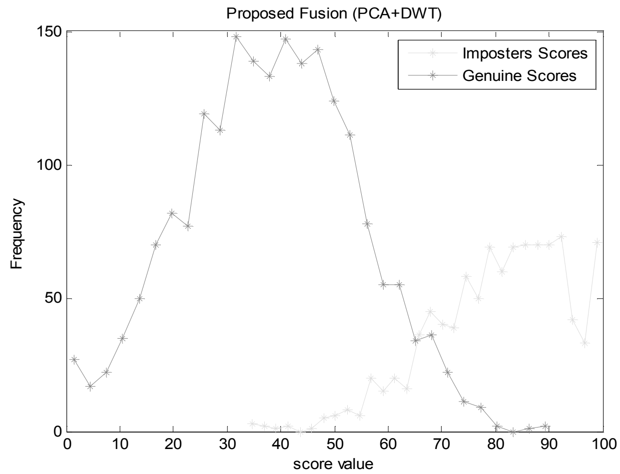


(c)

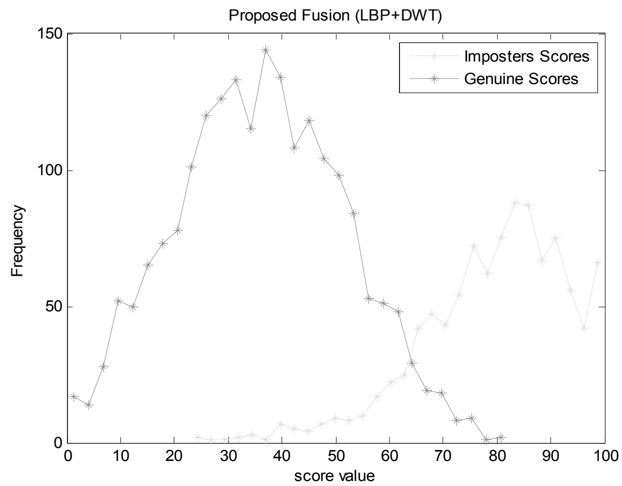
Figure 7 (a-c). Genuine and Imposter score distributions of the three unimodal systems based on the proposed approach



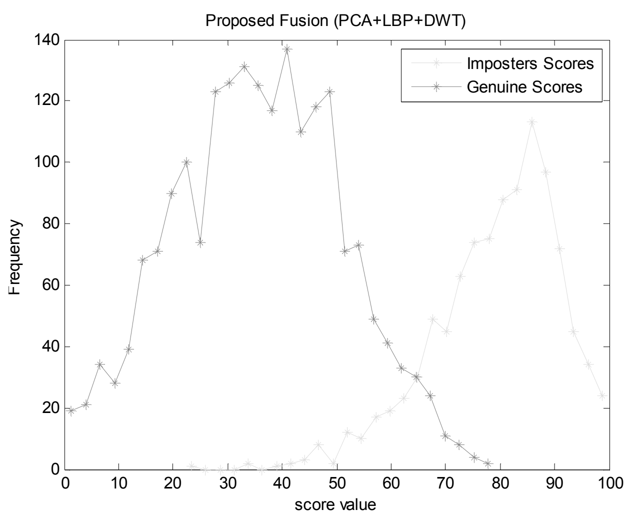
(a)



(b)



(c)



(d)

Figure 8 (a-d). Genuine and imposter score distribution of the multimodal system using the proposed approach

4.2 Simulation results using YALE database

Yale database contains 165 gray-scale images in GIF format belonging to 15 individuals. There are 11 images per subject, one per different facial expression or configuration: center-light, wearing glasses, happy, left-light, not wearing glasses, normal, right-light, sad as well as sleepy, surprised, and winking. The database is more complicated than the ORL and usually is used for facial expression recognition [33]. The same training procedures are adopted as in ORL and recognition rates of the proposed approach are compared with the other fusion rules available in the literature for performance comparison. Table 2 presents a comparison of the results obtained using the proposed method and other state-of-the-art fusion methods. Figure 10 depicts the similar results in a bar chart.

Table 2. Comparison of the recognition rates on YALE Database between the proposed fusion and others

Fusion	PCA	LBP	DWT	1+2	1+3	2+3	1+2+3
Proposed	69.06	73.73	70.80	75.33	73.80	77.73	83.60
Sum rule	68.40	74.27	71.20	75.33	72.80	76.13	79.20
Product rule	71.20	71.20	63.80	70.00	66.67	68.80	61.47

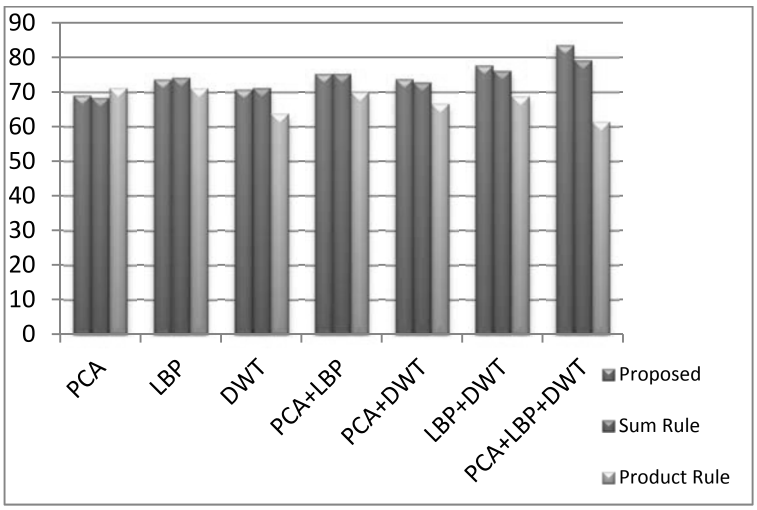


Figure 10. Bar chart of the recognition rate comparison on YALE database

5. Discussions

It is obvious from the experimental results that the proposed fusion rule based on Manhattan penalty weighting outperformed its counterparts (i.e. product and sum fusion rule). It is noteworthy that almost all the multimodal systems have better performance than the unimodal system in terms of recognition rates, FAR, FRR and ROC characteristics. The FAR and FRR curve performance of the proposed system has the list overlap (Figure 9(a)-(d)), which makes it a much more desirable system for both public convenience and high security applications. This property is more important than the overall recognition rate of the system in many access control applications. Moreover, it can be seen that fusion of more than two unimodal systems do not necessarily perform better than two unimodal systems as indicated by the experimental results. This trend may be traced to the fact that some models may have a very robust representation and other less robust, which overall may affect the fusion process.

6. Conclusion

A new approach for data fusion in the multimodal biometric system is proposed and implemented. Two face databases and data fusion techniques are used for implementing and comparing the obtained results with the proposed approach. Using ORL as a database, the experimental results show that the multimodal system has better performance than the unimodal system using PCA, LBP or DWT alone. Furthermore, results indicate that the proposed data fusion approach using Manhattan penalty weighting outperforms both of the two fusion techniques that use sum and product. This better performance concerns the recognition rate, FAR, FRR and EER of the algorithm. Similarly, in YALE database, the proposed approach has a lead in all the performance indices that are used for evaluating the algorithm performance. It is, however, noteworthy that the recognition rate in YALE database is not as good as that in ORL database. This is because there are so many variations within samples of the same subject which make it difficult for all algorithms to make a good generalization. Regarding the recognition rate, the proposed method has always had a better receiver operating characteristic which makes it much more suitable for many applications. In general, the new proposed fusion technique is promising and effective based on the experimental results. It performs better than its counterparts that were used in the literature.

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