ISSN: 2581-3064
sjrmcseditor@scischolars.com Online Publication Date: May 29, 2018 Volume 3, No. 1

SCHOLARS SCITECH RESEARCHORGANIZATION

Scholars Journal of Research in Mathematics and Computer Science

www.scischolars.com

Manhattan Penalty Based Multi-Modal System for Face Recognition

Abubakar M. ashir[1], Bayram akdemir[2], Bilal I. Ahmed[2]

[1]Dept. of Electric & Electronic Engineering, Selçuk University Turkey.

[1]muhammad.ashir@admotomasyon.com.

[2] Dept. of Electric & Electronic Engineering, Selçuk University Turkey.

[2]bayakdemir@selcuk.edu.tr.

[3]Dept. of Information technology, Ishik University Erbil, Iraq.

[3]bilal.ahmed@ishik.edu.iq

Abstract

In this paper, a new approach for multimodal biometric techniques has been proposed. The new proposed approach utilizes data fusion techniques at score level of the system algorithm. Three different feature extraction algorithms have been chosen to extract features from the face image database of the individuals. These feature extraction algorithms (Principal Component Analysis, Local Binary Pattern, and Discrete wavelets transform) are used alongside K-nearest neighbor classifier to compute different score values for the same individual. These raw score values are fused together using a newly proposed data fusion techniques based on Manhattan distance penalty weighting. The proposed Manhattan penalty weighting 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 two public face recognition databases; ORL face database and YALE face database. The results of the proposed approach were evaluated using the recognition rates and receiver operating characteristics of the biometric classification systems. Experimental results have shown that the proposed multimodal system performs better than the unimodal system and other multimodal systems that used different data fusion rules (e.g. Sum Rule or Product Rule). In ORL database, the recognition rate of up to 97% can be obtained using the proposed technique.

Keywords: Principal Component Analysis, Discrete Wavelet Transforms Local Binary Pattern, Data Fusion, Manhattan Distance, K-nearest Neighbors.

1. Introduction

To The need for a reliable system which is capable of establishing genuine peoples' identities and fake 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 a 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, reduce spoof attacks, increase the degree of freedom and reduce failure-to-enroll rate [1, 2, 3].

Advanced research on challenges related to 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 frequently uses to address some of these global challenges is a biometric system [4].

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 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 the different level of the algorithm stages (e.g. Feature extraction level, score level, decision level). Evidence in the literature has indicated that multimodal system significantly improves the performance of the unimodal biometric system [6, 7].

For instance, a comprehensive literature 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 analysis of the recent developments on 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 Retha et al. [9]. They construct a combination of fingerprint samples from many samples as the user roll 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 performance of the multimodal recognition system based on the fusion of performing fusion thermal infrared camera samples and visible light camera [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. Hence, using three different classifiers based on the k-nearest-neighbor (k-NN) classifier, decision trees, and logistic regression.

In this paper a different approach is proposed for multimodal biometric system. The technique considered 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 same normalization algorithm. Three feature extractions were used to present different biometric evidences from the same trait. Using Discrete Wavelength Transform (DWT), a new feature extraction was introduced where by the four representations 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 unimodal biometric system was proposed based on Manhattan distance penalty weighting. Scores of individual are penalized based on their weighed distance from the supposed winning class before fusion.

The rest of the paper has been classified 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. In section **IV** results from the experiments are presented. In the end, section **V** contains the conclusion on our findings and observations

2. Literature Background

In any face recognition system or generally a pattern recognition system, feature extraction and classifier algorithms become the backbone of the overall success of the system. Hence choice of these feature extractors and classifiers become pertinent. In this section a background on these algorithms used in the build-up to the proposed approach is presented as preliminaries.

2.1 Principal Component Analysis (PCA)

The PCA algorithm tries to extract salient features from a vector that best represents a class to with 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 to project all the vectors into a vector space that best represent their class. For Eigenface approach, the projected vector space is used as a feature to represent a subject [21]. Fig. 1 describes the PCA algorithm steps.

ISSN: 2581-3064
sjrmcseditor@scischolars.com Online Publication Date: May 29, 2018 Volume 3, No. 1

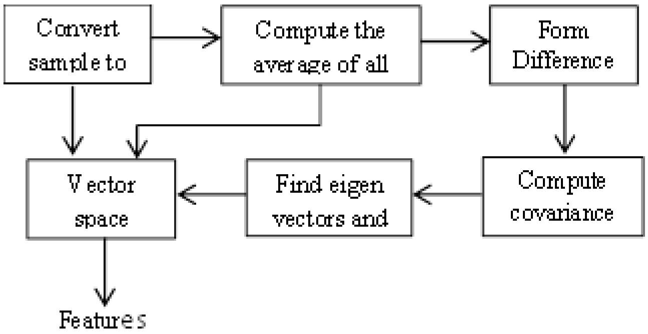


Fig. 1. Block diagram of PCA feature extraction.

2.2 Local Binary Pattern (LBP)

LBP, with its simplicity, has been applied successfully in many applications. LBP uses 3x3 windows of neighborhood pixels in the image to determine the new value of the center pixel under consideration [22]. Consider Fig. 2 initially the algorithms probe all the 8-neighborhood pixels around pixel I (z), any pixel greater than I (z) is assigned binary bit value 1 while those whose values are less than or equals to I (z) are assigned the bit value 0. 8-bit code is generated and is converted to decimal to find the new value for 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 from 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. Fig. 2. shows how the algorithm operates.

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

Fig. 2. LBP feature extraction.

2.3 Discrete Wavelet Transform (DWT)

It belongs to 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 to achieve 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 called wavelets of varying frequency and limited duration [22].

It uses 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 called wavelet function encodes the difference between adjacent approximations. Fig. 3 shows how DTW features can be extracted. The last four wavelets are vectorized and fused using the sum rule to get the feature vector for that sample [22-27].

The Discrete Wavelet Transform (2D-DWT) is an extension of one-dimensional discrete wavelet transforms [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 being applied to the rows of the input image. The convolution operation produces two sets of images, where one of the images contains in its coarse row coefficients, and the other contains 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 being analyzed with a high pass filter are designated with a symbol H. Likewise, those columns and rows being 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. At the end, for wavelets are produce thus: approximate

wavelet (A), horizontal wavelet (H), vertical wavelet (V) and the diagonal wavelet (D) as shown in Fig. 3.

ISSN: 2581-3064
sjrmcseditor@scischolars.com Online Publication Date: May 29, 2018 Volume 3, No. 1

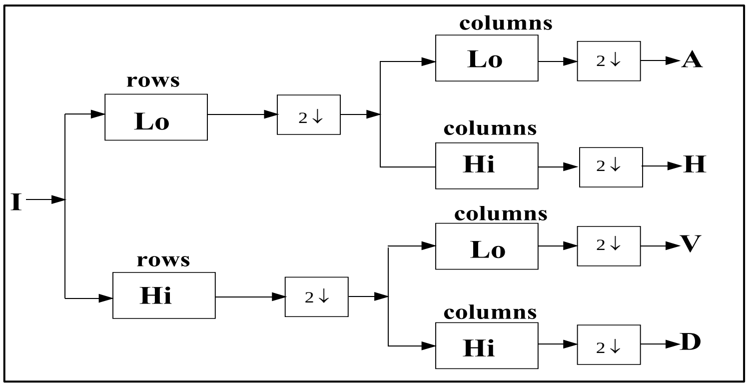


Fig. 3. DWT Decomposition Process.

2.4 K-Nearest Neighbour (KNN)

k-NN can be described as a sort of instance-based learning, or passive learning, 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. Equation 1 and 2 shows 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 as represented in Eqn. 1 and 2 respectively.

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

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

3 Proposed Multimodal Biometric System

In this proposed approach, the multimodal system is implemented at the score level. Single trait from an individual was used with PCA, LBP and DWT to create three different unimodal version of the biometric system. To avoid some of the problems resulting from a different classifier score distribution, we used the same classifier with the same score normalization algorithm 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 for fair participation and contribution in the fusion process is created for all the unimodal systems.

3.1 Creating Multimodal system

In our proposed method we 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 evidence presented is unique and differs from one another and hence gives a different unimodal system. As can be seen in Fig. 4, the input biometric trait (face data) is used to create the first unimodal representation by using PCA to extract features. The second unimodal system is obtained from LBP. In the third unimodal system, initially DWT is applied to the input face image to obtain four oriented wavelets from the decomposition process. The four oriented wavelets are concatenated together to form a single Joined Feature Vector (JFV). PCA is applied to the JFV to extract Reduced JFV (RJFV) which are shorter in size and contained more robust features than JFV alone. Fig.4 depicts how these unimodal systems are created for a given input face image I.

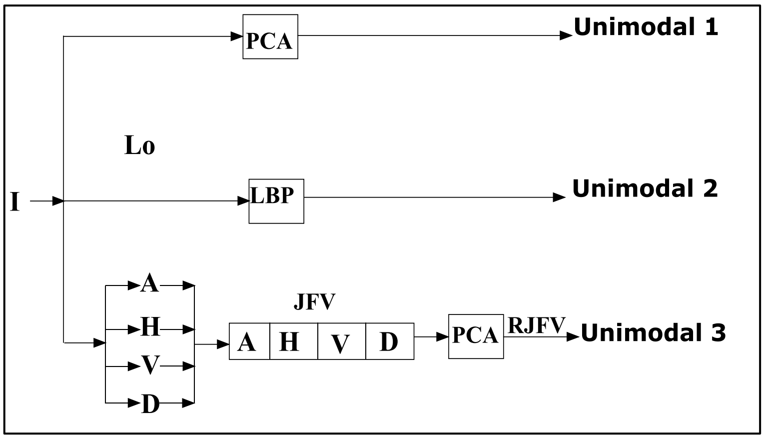


Fig. 4. Unimodal Feature Extractions.

3.2 Score Normalisation

The scores obtained from different unimodal systems have different statistical distributions and ranges, being from different sources. In order to make the distributions and 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 (Eqn. 3) normalization is often suitable where the maximun and minimum bounds of the score produced by mathcher 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 Score Normalisation

The Manhattan distance penalty weighting is a new approach we proposed to punish or penalize vector score in the training data (during test run) that have its scores away from the supposed 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 move severe is the penalty, whereas 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. Equation 4 described how this penalty weights are computed using Manhattan distance metric. For a given winning vector score x_w and and score from some non-winning neighbors x_{nw}, the Mantattan penalty (x_{mp-nw}) ,of x_{nw} can be computed using 4.

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

Where by α is an integer constant and | | 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. Fig.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 are the initial score distribution, whereas the blue ones are the new scores after Manhattan penalty weighting.

sjrmcseditor@scischolars.com Online Publication Date: May 29, 2018 ISSN: 2581-3064 Volume 3, No. 1

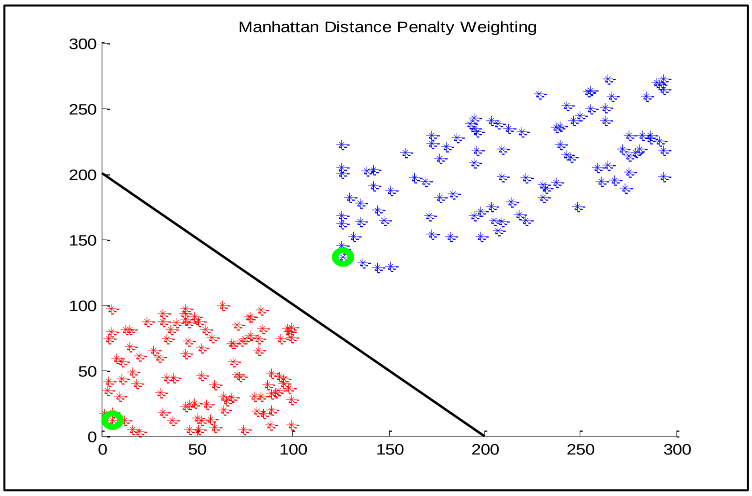


Fig.5. Manhattan Penalty Weighting scattered Plot.

4 Proposed Multimodal Biometric System

In this paper, two (ORL and YALE) databases are used to evaluate the performance of the proposed approach. The performance metrics 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 experiment, both training sets, and testing sets were picked randomly from the database and each experiment is 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 were taken with a dark background, and the subjects were 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 was set up using the proposed fusion technique with the ORL database. The database was randomly divided into two equal parts; five samples from each subject in both training sets (200 images) and testing set (200 images) were used. The simulations were run in phases; (a) with three unimodal biometric setups with PCA, LBP and DWT alone and (b) with multimodal biometric set formed from the four possible combinations of the PCA, LBP and DWT feature extractors. Each experiment was repeated 10 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 would generate 5×200 (1,000) genuine claims and 195×200 (39,000) imposter claims. All the 1000 genuine claims and 2000 imposter claims were used to compute the FAR, FRR and ROC of the algorithm for performance evaluation. Fig. 7 shows the comparison in ROC performance curve of all the system. Fig. 8(a)-3(b) show the plot of genuine and imposter score distributions of the three unimodal systems. Whereas, in Figure 9(a)-4(d), genuine and imposter scores of the four possible combination of the multimodal system which are derived from the three unimodal system.

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

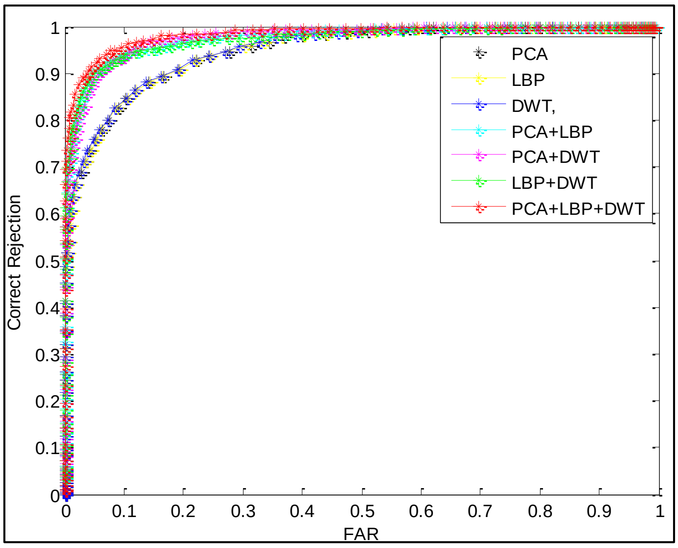
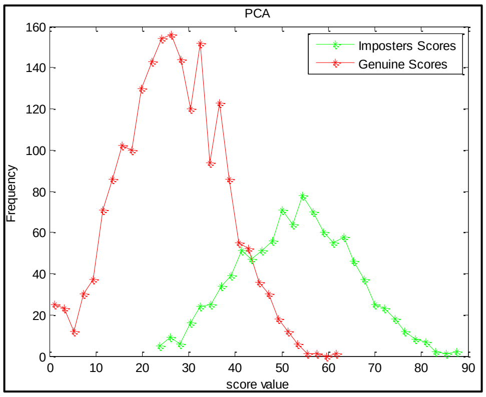
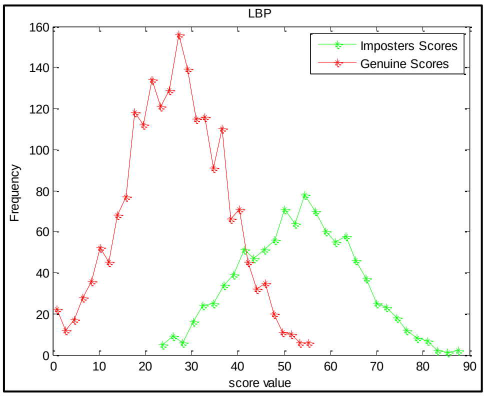


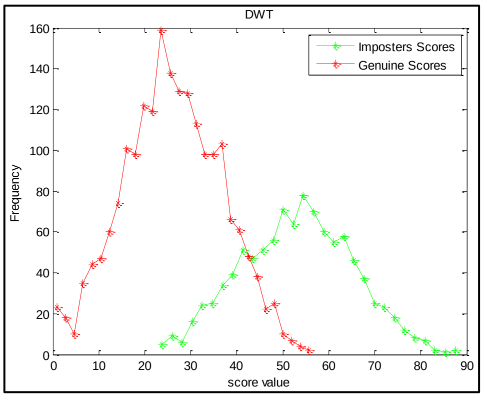
Fig. 7. ROC performance for the systems using proposed approach



(a)

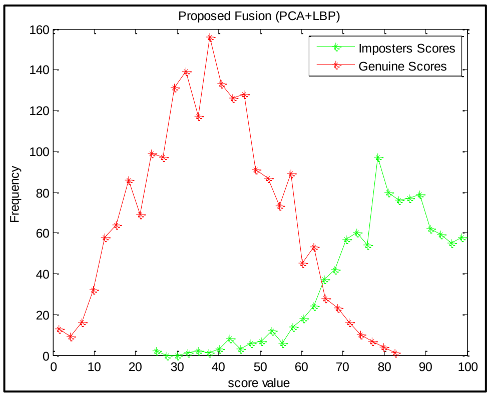


(b)

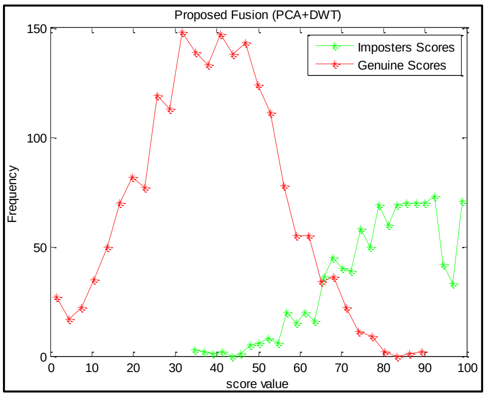


(c)

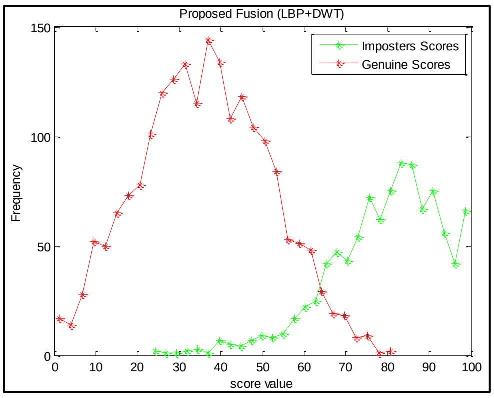
Fig.8. (a)-(c). Genuine and Imposter score distribution of three unimodal system based on the proposed Approach.



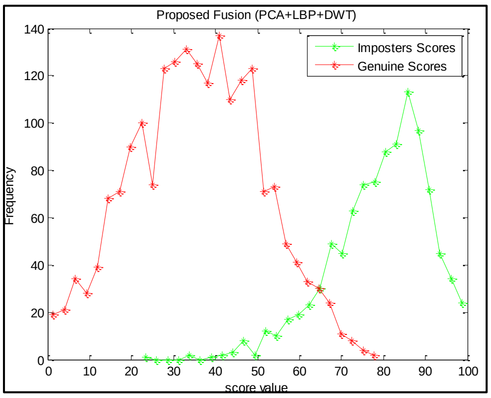
(a)



(b)



(c)



(d)

Fig. 9(a)-(d). Genuine and imposter score distribution of the multimodal system using the proposed approach.

4.2 Title and Authors

Yale database contains 165 gray-scale images in GIF format of 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, and sleepy, surprised, and wink. The database more complicated than the ORL and usually is used for facial expression recognition [33]. The same training procedures were adopted as in ORL and recognition rates of the proposed approach were compared with the other fusion rules available in the literature for performance comparison. Table. 2. Presents comparison of the results obtained using the proposed method and other state-of-the-art fusion methods. Fig. 10. Similar results in 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

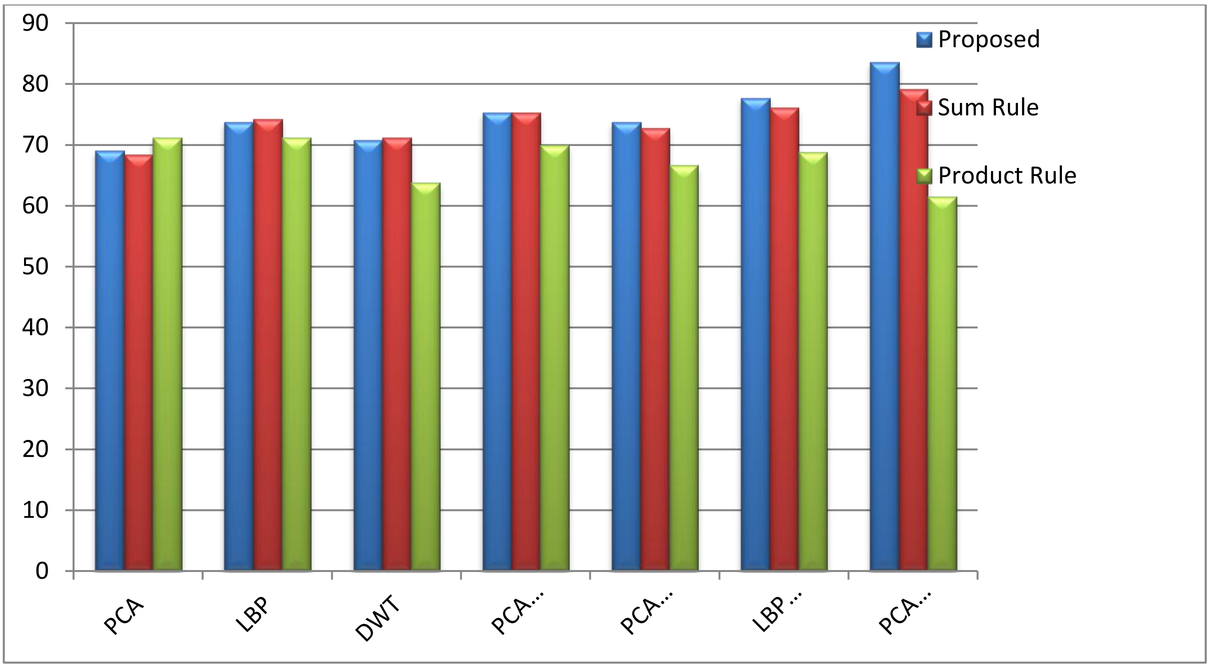


Fig.10. Bar chart of recognition rate comparison on YALE database.

5 Discussion

It is obvious from the experimental results 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 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 (Fig. 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 system does not necessarily performs better than two unimodal system 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

In A new approach for data fusion in the multimodal biometric system has been proposed and implemented. Two face databases and data fusion techniques were used to implement and compare results with the proposed approach. Using ORL as a database, the experimental results show that multimodal system has better performance than the unimodal system using PCA, LBP or DWT alone. Furthermore, it indicates that the proposed data fusion approach using Manhattan penalty weighting outperforms both the two fusion techniques using sum and product. This better performance is in terms of both recognition rate, FAR, FRR and EER of the algorithm. Similarly, in YALE database, the proposed approach has a lead in all the performance indices used to evaluate the algorithm performance. It is, however, noteworthy that the recognition rate in YALE database is not as good as that in ORL database. This because there are so many variations within samples of the same subject which make it difficult for all algorithms to make a good generalization. In terms of 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 has been promising and effective based on the experimental results. It performs better than its counterparts used in the literature.

References

[1] Belhumeur, P., Hespanda, J. and Kriegman, D., “Eigenfaces versus fisherfaces: recognition using class specific linear projection,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp. 711-720, July 1997.

[2] Beyreuther, M., “Speech recognition based automatic earthquake detection and classification”, Ludwig Maximilians University, Muenchen, Fakultaet fuer Geowissenschaften, Ph.D. thesis, 2011.

[3] Bowyer, K. W., Chang, K. I., Flynn, P. J., Chen, X., “Face recognition using 2-D, 3-D, and infrared: is multimodal better than multisample ?”, Proceedings of the IEEE, vol. 94, no. 11, pp. 2000-2012, November 2006.

[4] Bromba, M. U. A., "Bioidentification frequently asked questions", available at http://www.bromba.com/faq/biofaqe.htm#ROC.

[5] Campbell, J., "Speaker recognition: a tutorial", Proceedings of IEEE, 85, 9, pp. 1437-1462, September 1997.

[6] CASIA iris image database, http://www.sinobiometrics.com (March 2006).

[7] Chellappa, R., Wilson, C. L., and Sirohey, S., "Human and machine recognition of faces: a survey" Proceedings of the IEEE, 83, 5, pp. 705-740, May 1995.

[8] Ross, A., Nandakumar, K. and Jain, A.K., "Handbook of Multibiometrics", SpringerScience + Business Media, LLC, 2006.

[9] Ratha, N. K., Connell, J. H., and Bolle, R. M., "Image mosaicing for rolled fingerprint construction", in Proc. Int. Conf. Pattern Recog., vol. 2, pp. 1651–1653, August 1998.

[10] Singh, S., Gyaourova, A., Bebis, G. and Pavlidis, I., "Infrared and visible image fusion for face recognition", SPIE Defense and Security Symposium, pp.585-596, 2004.

[11] Heo, J. Kong, S. G., Abidi, B. R., and Abidi, M. A., "Fusion of visual and thermal signatures with eyeglass removal for robust face recognition", Proc. Joint IEEE Workshop Object Tracking and Classification beyond the Visible Spectrum, June 2004.

[12] Son, B., and Lee, Y., "Biometric authentication system using reduced Joint feature vector of iris and face", Lecture Notes in Computer Science, vol. 3546, pp. 261-273, 2005.

[13] Ross A., and Govindarajan, R., "Feature level fusion using hand and face biometrics", in Proc. SPIE Conf. Biometric Technology for Human Identification II, pp. 196–204, March 2005.

[14] Kittler, J., Hatef, M., Duin, R. P. W., and Mates, J. "On combining classifiers", IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 20, no. 3, pp. 226–239, 1998.

[15] Verlinde, P. and Cholet, G., "Comparing decision fusion paradigms using k-NN based classifiers, decision trees and logistic regression in a multi-modal identity verification application," in Proc. Int. Conf. Audio and Video-Based Biometric Person Authentication.

[16] (AVBPA), Washington, DC, pp. 188–193, March 1999.

[17] Chen, X., Flynn, P. J., Bowyer, K. W., "IR and visible light face recognition", Computer Vision and Image Understanding, vol. 99. no. 3, pp. 332–358, September 2005.

[18] Das, R., "Signature Recognition", in Keesing Journal of Documents & Identity, issue 24, 2007.

[19] Dass, S. C., Nandakumar, K., and Jain, A. K., "A principled approach to score level fusion in multimodal biometric systems", In Fifth AVBPA, Rye Brook, pp. 1049–1058, July 2005.

[20] Daugman, J. G., "How iris recognition works", IEEE Trans. Circuits Syst. Video Technol., vol. 14, no. 1, pp. 21–30, January 2004.

[21] Frischholz, R. W., Boebel, F. G., and Spinnler, K. P., "Face recognition with the synergetic computer", Proc. Int'l Conf. Applied Synergetics and Synergetic Eng., Fraunhofer Gesellschaft für Integrierte Schaltungen, Erlangen, Germany, pp. 107-110, 1994.

[22] A. M. Ashir and A. Eleyan, "A multi-resolution Approach for Edge Detection using Ant Colony Optimization", *23nd IEEE International Conference on Signal Processing and Communications Applications (SIU)*, Malatya, Turkey, pp. 1777 – 1780, May 2015.

[23] Hampel, F. R., Ronchetti, E. M., Rousseeuw, P. J. and Stahel, W. A., Robust Statistics: The Approach Based on Influence Functions. New York: Wiley, 1986.

[24] Han, J., and Bhanu, B., "Gait recognition by combining classifiers based on environmental contexts", Lecture Notes in Computer Science, vol. 3546/2005, pp. 113-124, 2005.

[25] Ho, T. K., Hull, J. J., and Srihari, S. N., "Decision combination in multiple classifier systems," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 16, no. 1, pp. 66-75, January 1994.

[26] Huber, P. J., Robust Statistics. New York: Wiley, February 1981.21. "Human identification at a distance" available at http://www.equinoxsensors.com/products/HID.html.

[27] Indovina, M., Uludag, U. Snelick, R., Mink, A., and Jain, A., "Multimodal biometric authentication methods: A COTS approach", Proc. MMUA 2003, Workshop Multimodal User Authentication, pp. 99-106, December 2003.

[28] ISO/IEC 24745:2011, "Information technology - Security techniques – biometric information protection", 2011.

[29] ISO/IEC TR 24722:2007, Information technology– Biometrics: Multimodal and other multibiometric fusion, July 2007.

[30] Jain A., Nandakumar, K., Ross, A., "Score normalization in multimodal biometric systems", Pattern Recognition, vol. 38, no. 12, pp. 2270–228, December 2005.

[31] Jain, A., Hong, L. and Kulkarni, Y., "A multimodal biometric system using fingerprint, face and speech", in: Second Internat. Conf. on AVBPA, Washington, DC, USA. pp. 182-187, 1999.

[32] Jain, A., Hong, L., and Bolle, R., "On-line fingerprint verification", IEEE Trans. Pattern Anal. and Machine Intell., 19, 4, pp. 302-314, 1997.

[33] Jain, A. K., and Ross, A., "Fingerprint mosaicking", in Proc. Int'l Conf Acoustic Speech and Signal Processing, vol. 4, pp. 4064-4067, 200