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Research Article
Evaluation of Multimodal Biometrics at Different Levels of Face and Palm Print Fusion Schemes

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Abstract

Background: Presently much attention is being paid to biometrics in the user authentication system, because multimodal is considered an accurate method to achieve higher degree of accuracy. Multimodal systems always give enhanced performance compared to unimodal. **Methodology:** The present study evaluated the performance of multimodal system by applying fusing face and palm print biometrics. Different levels of fusion schemes with optimal strategies were employed and the performance was evaluated over the all levels. **Results:** Overall, the best results of multimodal were obtained at the score level fusion by applying AND rule as 91 at 0.01% FAR, 94.5 at 0.1% FAR and 97.5 at 1.0% FAR. Whereas the best results of unimodal system were 42 at 0.01% FAR, 68 at 0.1% FAR and 84.75 at 1.0% FAR obtained with palmprint. The study showed that by fusing multimodal biometrics, a higher level of verification can be achieved. **Conclusion:** From the experimental results, it can be found that score level fusion with sum rules is reliable and feasible method for fusion of face and palmprint.

Key words: Fusion, biometrics, fusing face, palm print, unimodel, multimodels, accuracy

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Competing Interest: The author has declared that no competing interest exists.

Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

There is a worldwide issue to implement a particular person's verification in various aspects of social and professional life such as banking, travel and security services by applying biometrics such as face, fingerprint, iris, etc. The high level of security has influenced two main things as how to find new and more universal biometric traits and the multibiometric options. Most of the biometric systems employed in the real-world are unimodal due to its reliance on the evidence of a single source of information for authentication which is easier to install and computationally less hectic. The multimodal system is a subset of multi-biometric system which establishes the identity based on the evidence of multiple-biometric traits[1].

According to Klare and Jain[2], it gives a certain degree of freedom to user during enrollment, since he/she can use different traits, e.g., face, fingerprint, iris, voice, hand, etc. Based on the application and user's convenience, some of these traits may be utilized during authentication. Hence, it solves the problem of non-universality (i.e., limited population coverage). Furthermore, it is very difficult to spoof more than one modality of multibiometric system for an imposter and also a multibiometric system ensures that the system is interacting with an alive user. Multibiometric system also effectively addresses the problem of noisy data. When the biometric signal, acquired from a single trait, is corrupted with noise; for example, in the presence of ambient noise or when voice characteristics of an individual cannot be accurately measured[3]. Then the authentication may switch over to another biometric trait like fingerprint.

The physiological modalities namely face and palmprint are well known for their advantages that make these preferable in this multimodal biometric system which are known as non-intrusiveness and low image cost acquisition devices. The deployment of fusion of these two modalities in the real world has more degree of acceptance in authentication world[4]. In this study, the performance was evaluated under the fusion of face and palmprint modalities at all levels[5].

Most of the biometric systems perform well on a clean biometric trait. However, the effectiveness of any biometric system in a real situation can be best judged when its performance on a biometric trait is corrupted by noise. While, Huang *et al.*[6] developed robust multimodal system by combining face and ear biometric using spare representation. A novel index called Sparse Coding Error Ratio (SCER) is employed to develop an adaptive feature weighing approach for reducing the negative effect of less reliable biometric. Gomez-Barrero *et al.*[7] discussed the prevention of fraudulent use of the biometric system and also considered a trait combination of face and iris. Furthermore, the multimodal biometric system did not present an enhancement in the security level against this kind of attack compared to the face and iris individual modalities. This fact states that on spoofing attacks were listed even though multimodal biometric systems identification performance was higher, they do not necessarily upgrade the nature of robustness at unimodal approaches to external attacks. Singh *et al.*[8] and Huang *et al.*[6] presented a new biometric classifier which updates algorithm incrementally and re-trains the classifier using online learning and progressively establishes a decision on Support Vector Machine (SVM) hyper-plane for improved classification. Online classifier is employed for feature classification and feasible decision making in a face biometric verification system on a heterogeneous Near Infra-Red (NIR) face database in a study using the Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA)[9] and modified C2 feature algorithm. Bugdol and Mitas[10] proposed a novel approach on the combined behavior of biometric ECG and sound signals. Furthermore, discriminating feature is extracted from both the modalities, such as for voice, Mel-Frequency Cepstral Coefficients (MFCC) and RR values of distance between successive R peaks which were extracted from ECG. Dimensionality techniques are used to reduce the feature space and performance results are obtained.

Grother and Tabassi[11] emphasized the performance objective by including a procedure for annotating the samples of a reference corpus with quality values derived from empirical recognition scores. Ross and Govindarajan[12] discussed the fusion of PCA and LDA coefficients of face; fusion of LDA coefficients corresponding to the red, green, blue channels of a face image and fusion of face and hand modalities. Deepamalar and Madheswaran[13] developed a palm vein biometric recognition system using multilevel fusion of features using neural network classifier to classify the vein patterns for decision making. They concluded that the multimodal palm vein recognition system showed better performance than unimodal biometric features.

The information on the performance analysis of multimodel biometrics on fusing face and palmprint at different levels is inadequate locally. Therefore, the main objective of this study was to evaluate the performance of multimodel biometrics on fusion face and palmprint under various traits in Saudi Arabia.

MATERIALS AND METHODS

Figure 1 shows the fundamental diagram of multimodal biometric system which was adopted in this study. In any

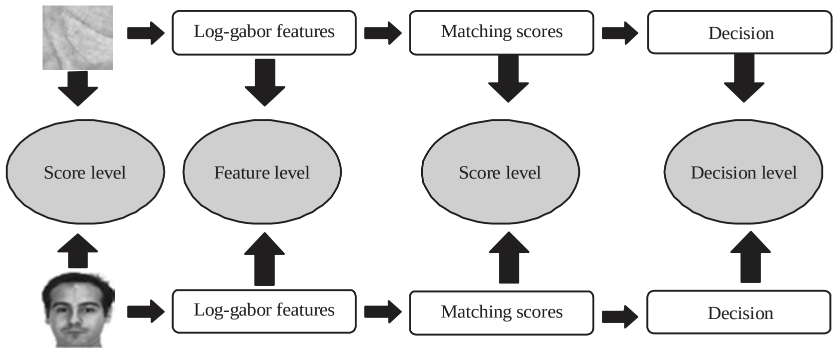

Fig. 1: Block diagram on fusion of face and palm print at different levels

Table 1: Results from unimodal system of face and palm print

	GAR in (%) at		
Modalities	FAR (0.01%)	FAR (0.1%)	FAR (1%)
Face	33	40	72
Palm print	42	68	84.75

Table 2: Results from multimodal system on fusion of face and palm print

		GAR in (%) at		
Fusion	Rules	FAR (0.01%)	FAR (0.1%)	FAR (1%)
Sensor level	Wavelet based	36.5	48	78
	Min-Max	68	85	92
Feature level	Z-score	80	84	94
	Tanh	78	83	92.5
Score level	Minimum	71	84	92.75
	Maximum	89	93	95.0
	Sum	91	94.5	97.5
Decision level	OR	86	90.0	94.5
	AND	68.5	81.5	92.75

multimodal biometrics system, the fusion of biometric modalities can be done by sensor level, feature level, score level and the decision level. In order to evaluate the performance of multimodal system, the face and palm print modality fusion were considered at different levels.

In the proposed authentication system in this study, different fusion schemes were employed. For example: The wavelet based image decomposition scheme at sensor level, to fuse palm print and face images. The features matrix of palm print and face were heterogeneous, This study used Min-Max, Z-score and hyperbolic tangent (Tanh) normalization techniques at feature level. But the sum, minimum and maximum rules were employed at score level. Finally at decision level, the AND and OR rules were followed to fuse the face and palm print decisions.

Collection of samples: The experimental analysis made in this study is discussed in the following pages. Face and palm print biometric samples available publically were used as bench mark databases. The AR and PolyU data sets were employed for the face and palm print, respectively. The total face samples of 119 persons were taken from AR data set with each person having 26 different poses. The palm print samples were taken from the Hong Kong Polytechnic University and consists of 189 persons. In this case, each person has 20 images. In this study in all the experiments, 50% of samples were used for training and 50% of samples were used for subsequent testing. The performance was measured in terms of Genuine Accept Rate (GAR) by varying its False Acceptance Rate (FAR).

Data analysis: Experimental data were analyzed by following appropriate statistical techniques as described in SAS[14].

RESULTS AND DISCUSSION

Different experiments were carried to verify the best recognition method. First one was the unimodal in which the False Acceptance Rate (FAR) varied from 0.01-1.0 with an increment step of 0.01. It is clear from Table 1 that in unimodal, the palm print out performed at each step except only in one case at 0.01% FAR where the face recognition performed 33 which is close to palm print value of 42. The study results agree with the findings of Ross *et al.*[15] and Jain *et al.*[16] who stated that the unimodal systems are prone to a variety of problems which in turn increases the False Acceptance Rate (FAR) and False Reject Rate (FRR). But a good system needs very low value of both the FAR and FRR which can only be achieved by the multimodal system.

Data analysis showed that the results of multimodal fusion of face and palm print were much better (Table 2). The experiment was conducted at different fusion levels varying from 0.01-1.0 with an increment step of 0.01. The results showed the best performing fusion rule at each level of fusion. As can be seen from the results, the lowest results of multimodal were obtained by applying wavelet based rule which are still better than the lowest results of unimodal system. Additionally, the best results of multimodal were obtained at the score level fusion by applying AND rule as 91 at 0.01% FAR, 94.5 at 0.1% FAR and 97.5 at 1.0% FAR. Whereas the best results of unimodal system were 42 at 0.01% FAR, 68 at 0.1% FAR and 84.75 at 1.0% FAR obtained with palm print. The average value of all the results in multimodal at 0.01% FAR was 71 which is higher than the highest result of unimodal with a value of 42 at 0.01% FAR. The best result of multimodal system at 1.0% was 94.5, whereas the best result of unimodal was 84.75 at 1.0% FAR. Similar results were reported by many investigators who emphasized that multi-biometric systems always yield best performance and have more advantages over the traditional unibiometric system[10,15,17]. This study results are in line with those of Kisku *et al.*[18] who reported that multibiometric system also helps the applicants for a continuous tracking of an individual needs due to inefficiency of a single trait. Also, identical findings were reported by Baig *et al.*[19] who proposed a new method for multimodal system for adapting to any type of biometrics modality to afford smaller memory footprint and faster implementation than the conventional multimodal systems.

CONCLUSIONS

In the proposed method of this study, first unimodal face and palm print were evaluated independently. It was found that for log-gabor features, the palm print modality performed better than face due to the existence of more texture in palm print over face. Also, the study evaluated the multimodal system on fusion of face and palm print except the sensor level where the other levels such as multimodal yielded incremental performance accuracy and unimodal. At sensor level, the fusion of palm print and face images by wavelet produced noisy information which caused reduction of accuracy. However, the fusion of face and palm print at the score level using sum rule produced the best result with a value of 97.5%. This result suggested that on fusion of physiological modalities, the score level sum rule is the best choice. The other levels of fusion such as feature level z-score and decision level OR rule were the secondary choice of fusion strategies. In conclusion, all the fusion schemes having multimodal approaches gave significantly better performance than its unimodal.

DISCLOSURE OF THE PROJECT

This study was carried by the author to prove his skill and technical know-how in the field of computer science on self supporting basis.

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