The Various Levels of Fusion for Face and Palmprint

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Abstract- Recent years have witnessed researchers paying enormous attention to design efficient multi-modal biometric systems because of their ability to withstand spoof attacks. Single biometric sometimes fails to extract adequate information for verifying the identity of a person. On the other hand, by combining multiple modalities, enhanced performance reliability could be achieved. In this paper, we have fused face and palmprint modalities at all levels of fusion viz sensor level, feature level, decision level and score level. For this purpose, we have selected modality specific feature extraction algorithms for face and palmprint such as LDA and LPQ respectively. Popular databases AR (for face) and PolyU (for Palmprint) were considered for evaluation purposes. Rigorous experiments were conducted both under clean and noisy conditions to ascertain robust level of fusion and impact of fusion strategies at various levels of fusion for these two modalities. Results are substantiated with appropriate analysis.
Keywords – Face Recognition, Palmprint, Multibiometrics.

I. INTRODUCTION

Biometric techniques are unique and efficient methods for person identification/authentication; many organizations rely on unimodal biometric systems to identify individuals. Multimodal biometric system is a relatively new application in biometric field, while single (unimodal) biometrics has been used for a long time. For example, fingerprint has been widely used by law enforcement agency for person verification and identification. These biometric systems based on single modality suffers with various challenges such as noise in sensed data, intra-class variations, inter-class similarities, nonuniversal and spoof attacks etc. To overcome drawback of unimodal and to increase the reliability of system, biometric fusion especially multi-modal biometric fusion has drawn a lot of attention recently. Multimodal biometric system is subset of Multibiometric system which depends on multiple source of evidence to identify an individual [1].

The advantages of multimodal systems over the unimodal are increase in the population coverage, high performance, more robust and increase the resistance for spoof attacks [2]. Biometrics is a rapidly growing technology that aims to identify or verify people identities based on their physical or behavioral properties. Multibiometrics use more than one biometric recognition approach in a unified frame in an effort to solve problems faced by the conventional uni-modal biometrics. The multi-biometric approach aims at improving biometrics by increasing accuracy, and robustness to intra-person variations and to noisy data. It also aims to solve uni-modal biometrics problems with non-universality and vulnerability to spoof attacks. Information fusion in multi-biometrics is used to build an identification/verification decision based on the information collected from different biometric sources. The fusion can be done on different levels such as data-level, feature-level, score-level, ranklevel or decision-level. In this work, score-level fusion will be inspected as it is widely used to integrate different modalities (based on different biometrics, algorithms and manufacturers) through fusion. Score here refers to the comparison score (similarity) between each captured biometric property and a stored- reference. Biometrics recognition technologies are usually developed under one of two scenarios, verification or identification. Biometric verification is the use of biometrics information to verify a persons claimed identity. Identification, on the other hand, can be defined as the process of assigning a previously registered identity to a person based on the captured biometrics information of the person. The different nature between verification and identification scenarios effects the implementation of multi-modal biometrics solutions, especially the fusion process. This is due to the different available information in both scenarios, as well as, the different nature of the expected fusion decision. Figure 1 presents an overview of multi-biometric score-level fusion. Scores from different sources (algorithms and modalities) are normalized then passed into a fusion algorithm [3].

The fusion then results in a fused score. Multimodal biometric systems use various levels of fusion to combine two or more modalities[6]: (i) Fusion at the sensor level, where the two images from different sensors are combined; (ii) Fusion at the feature extraction level, where the features extracted using two or more modalities are concatenated;(iii) Fusion at the matching score level, where the matching scores obtained from multiple matchers are combined; (vi) Fusion at the decision level, where the accept/reject decisions of multiple systems are consolidated.In this paper, we have combined face and palmprint modalities and evaluated the performance. The prominent contributions of this paper are: a) Fusion of face and palmprint modalities at four levels of fusion. Fusion is performed, at each level, by various fusion strategies. This is to determine robust level of fusion. b) Performance evaluation of different fusion strategies for each level of fusion under both clean and noise conditions. Face and palmpprint modalities have several advantages that makes it preferable in many multimodal biometric applications such as non-intrusiveness in nature (for face), availability of strong feature extraction algorithms (for instance subspace for face, texture for palmprint), low cost image acquisition etc. On the other hand, even though there exists several studies in the literature that showed fusion of these two modalities employing particular fusion strategy, there exist not a solitary work that reports fusion at all levels. In order to evaluate the deployment of these two modalities in real time scenarios, performance analysis needs to be carried out under noise conditions. In this work, we have evaluated the performance under modality specific noise conditions. These are the reasons that instigated us to carry out this work [4].

The outline of the paper is as follows: Section II gives review of literature related to different face and palmprint multimodal systems. Section III presents the proposed work. Section IV discusses analysis of experimental results. Conclusion and future work are drawn in Section V.

II. RELATED WORK

A personal identification system that uses finger vein patterns has been proposed [5]. The technique was based on special line tracking that starts at different positions. Here the personal identification using finger vein patterns was proved to be much healthier than the conventional method based on a matched filter. Based on hand vein pattern, [6] have proposed biometric recognition system. By means of a simple modified webcam, they proposed a very low-cost hand vein pattern recognition system. A blob removal algorithm is introduced by them that makes the results of the segmentation attractive and uses a modified version of Hausdorff distance for feature matching and for the recognition purposes. Hand vein recognition has been presented [7] based on the statistical processing of the hand vein patterns. The BOSPHORUS Hand vein database has been collected together [8] under practical conditions and subjected to go through the procedures. The normal procedure is of holding a bag, pressing an elastic ball and cooling with ice and all these exercises will force changes in the vein patterns. Recognition techniques have been applied that were a combination of geometric and appearance-based techniques. This technique gave superior identification performances on the database. A broad line detector for feature extraction, which has been obtained to extract width information of the vein and the extracted feature provides increased information from low quality image, has been presented by [9]. Based on the theory that the finger's cross-sections were roughly ellipses and the vein that could be closed to the finger's surface, a pattern normalisation model has been created by them. The alteration caused by the pose is being efficiently reduced. In recent years, a Finger-vein-based biometrics to personal identification has been presented [10-11]. They have addressed the problems of finger vein ROI localisation, vein ridge enhancement and vein restoration for recognition. Wu and Liu have addressed vein pattern identification using support vector machine (SVM) and neural network. Palm-dorsal vein recognition method based on histogram of local Gabor phase XOR Pattern was proposed by [12-13]. They have used chi-square distance measure for recognition. [14] proposed a personal verification approach using palm vein patterns based on modified two directional two-dimensional linear discriminant analysis [(2D)2LDA].

III. PROPOSED METHODOLGY

Figure: 1 shows the block diagram of the proposed multimodal biometric system based on the fusion of face and palmprint at various levels of fusion [15]. Fusion of information in biometric can be performed in different form a) Fusion prior to matching b) Fusion after the matching. In the case of prior to matching, the multiple information of biometric sources can take place either at sensor level or at the feature level. On the other hand, combining the information after the matching/classification can be performed at score level and decision level. In our multimodal biometric system, the fusion is performed at all four levels [16]. There are different kinds of approaches for consolidating information from two different modalities. At sensor level we have used wavelets based image fusion scheme [17] to fuse palmprint and face images, at feature level we employed different normalization techniques namely Min-Max, Z-Score and Hyperbolic tangent (Tanh) [18]. At score level, we considered fusion rules, such as sum, max and min rule, to combine the two matching scores. Finally, at decision level we adopted logical AND and OR to combine the output decisions by different matchers [19].

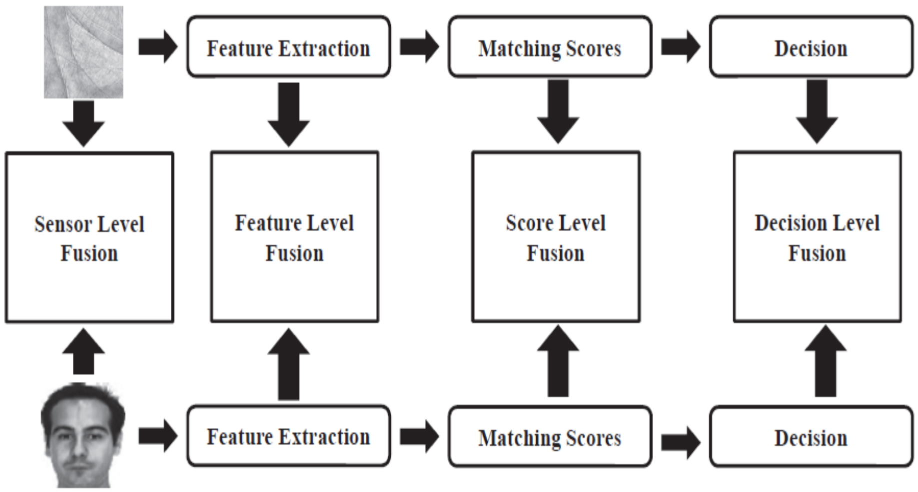

Figure 1. Block diagram on different levels of fusion of face and palmprint.

IV. EXPERIMEENTATION AND RESULTS

In this section, we describe the experimental setup made in our study. For face samples, we used AR database [18] which contains samples of 119 individuals. Each individual has 26 images spread over two different sessions. For palmprint the Hong Kong Polytechnic University. The palmprint database used in the experiment contains 189 individuals. Each individual has 20 images. Some sample images of these databases are in Fig 2. In all the experiments, training was performed by considering six views of each user and four views were used for subsequent testing. The performance was studied under both clean and noise conditions.

4.1. Results obtained using clean data

First an empirical study was conducted to choose the best performing modality specific algorithms for face and palmprint traits. We considered popular appearance based algorithms for face: PCA, LDA, LPP and ICA1. Refer paper [8] for complete description regarding these algorithms. On the other hand, for palmprint we have used well know texture based feature extraction algorithms [16]. The recognition performance of the face and palmprint systems when operated as unimodal systems. We observe that there is a significant improvement in result when LDA for face and LPQ [14] for palmprint modality were used. Hence, for all our further investigation on multimodal approach and validating the effectiveness of fusion, we have considered LDA and LPQ algorithms respectively for feature extraction from face and palmprint modalities. The LDA requires only a feature vector of size 9 whereas LPQ takes only 256 features to produce optimal performance. Subsequent experiments had these setup for these two algorithms.

In the next stage, we conducted set of experiments by fusing face and palmprint modalities at all level of fusion using their corresponding fusion strategies. The results are also substantiated with appropriate analysis. This is shown in Table: 1. the results tabulated are for representative FARs for 0.01, 0.1 and 1.0. From the table, important observations are as below:

1. Sensor level fusion is not performing satisfactorily and in fact its performance is worse than unimodal counterparts. This may be due to the fact that the sensor level fusion produces a kind of image that lacks adequate discriminatory information.
2. Score level fusion using Sum rule attained highest accuracy. This is because the scores of palmprint and face give best discriminatory information after their fusion.
3. Z-score and tanh normalization schemes in feature level fusion exhibited similar performance. This is due to the fact that feature set of face and palmprint are heterogeneous. Hence, after normalizing using these measures (Z-score and tanh), feature sets were transformed into a unique range.
4. In the decision level fusion, the OR rule performed better than AND rule. It is primarily due to the reason that if any one of the matchers classifies the test sample as genuine, the final decision will be regarded as genuine. This is unlike the AND rule where both matchers have to deem the test sample as genuine to in turn classify the sample as genuine.

To fully observe behavior of various levels of fusion, extensive set of experiments were conducted by varying False Acceptance Rate (FAR) from 0.01 to 1.0 insteps of 0.01. In this experiment, we have chosen only best performing fusion rule at each level of fusion. The ROC curve of the same is plotted in Fig.5. It is clearly evident from the figure that the performances of Unimodal systems are much lower than multimodal system barring sensor level fusion. It is to be noted that, sensor level fusion produces image samples by taking mean of approximate and detailed coefficients (by using wavelet decomposition) of face and palmprint images. These images are used for training and subsequent decision making. This in turn causes the images obtained by sensor level fusion to lack discriminatory information. This is unlike the other levels of fusion techniques where training and decision making are made by considering contribution of face and palmprint samples separately.
It is also ascertained from the figure that the score level fusion adopting the sum rule obtained best results since contribution made by both palmprint and face matchers will be considered for decision making. This is in contrast to min and max rules where respectively, min score and max score alone would be considered.

4.2. Results obtained using noisy data

In this subsection, another set of experiments were conducted by considering face and palmprint data corrupted by noise. In order to develop the noisy database, modality specific noise were synthetically applied. For palmprint, we have introduced two different types noise: smudging and saltand- pepper. For the face modality, we have applied Gaussian noise of mean 0.1 and variance 0.003. Table II shows the results obtained after fusing face and palm images corrupted by noise at all levels of fusion. From the table it can be observed that sensor level fusion exhibited below par performance even under noisy conditions. This behavior is already explained in previous subsection. On the other hand, in feature level fusion, the tanh normalization scheme obtained robust results compared to zscore and min-max normalization schemes. This endorses the fact that tanh measure are known to perform well under noisy conditions [5]. At decision level fusion, the similar behavior was exhibited as that of clean test conditions. In case of score level fusion, the sum rule continued to exhibit its robust nature even under noise conditions for the reasons stated in above subsection. With this we can conclude that, for face and palmprint modalities, the optimal results (both under clean and noise conditions) can be obtained by fusing at score level using the sum rule.

Table-I Performance of Different Levels of Fusion of Face (LDA) and Palmprint (LPQ) Under Clean Conditions.

Fusion	Rules	GAR in % at		
		0.01% FAR	0.1% FAR	1% FAR
Sensor Level	Wavelet Based	36.5	48	76
Feature Level	Min_Max	62	84.56	95.65
	Z-Score	82	88	96.35
	Tanh	82	88	96.35
Score Level	Min	70	84.65	93.65
	Max	90	96	97.54
	Sum	97.56	98.85	99.4
Decision Level	OR	90	95	98
	AND	68	85.45	93.25

Table-II Performance of Different Levels of Fusion of Face (LDA) and Palmprint (LPQ) Under Noise Conditions.

usion	Rules	GAR in % at		
		0.01% FAR	0.1% FAR	1% FAR
Sensor Level	Wavelet Based	6	14	39.65
Feature Level	Min_Max	55.25	65.45	75.65
	Z-Score	56	61.35	76.35
	Tanh	59.45	72	80
Score Level	Min	37	47.25	58.45
	Max	53.65	67	76.54
	Sum	48	73.55	94.85
Decision Level	OR	47.25	71.85	83.95
	AND	40	48.10	59.34

V. CONCLUSION

In the recent past, there is a tremendous interest shown by researchers towards implementation of multimodal system adopting various fusion strategies. However, to the best of our knowledge, there is minimal reporting in the literature that addresses all levels of fusion in a single paper. This paper addressed fusion of face and palmprint modalities at all levels of fusion to ascertain best level of fusion for these two modalities. In addition, for every level of fusion, we ascertained the optimal fusion strategy for these two modalities. We believe that this study helped us to know the robust level of fusion for face and palmprint modalities. The empirical study evaluated LDA and LPQ as the best modality specific feature extraction algorithms for face and palmprint respectively. Hence for all subsequent experiments, we considered these two algorithms for feature extraction. Two types of experiments were conducted: under clean and noise conditions. Experiments were conducted by using popular databases used in each modality: AR (for face) and PolyU (palmprint). In all our experiments, the performance of multimodal system (at all levels of fusion) performed much better than their uni-modal counterparts barring sensor level fusion. In general, we made following crucial observations based on this study:

a) For fusing face and palmprint modalities, the score level fusion adopting the sum rule obtained best results under both clean and noise conditions. This deserves further study as results may vary based on type of feature extraction algorithms used.

b) Sensor level fusion of face and palmprint modalities leads to undesired result. In fact, the performance is poor than its unimodal counterparts. In our experiments, we used wavelet decomposition to fuse the images. Results may vary by adopting different methods to fuse (DCT could be another choice). Our succeeding work may report results regarding this.

c) In general, the fusion process enhance the system precision significantly which simply endorses well established fact about multimodal system.

VI. REFERENCE

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