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Wencheng Yang
Edith Cowan University, w.yang@ecu.edu.au

Song Wang

Guanglou Zheng
Edith Cowan University, g.zheng@ecu.edu.au

Craig Valli
Edith Cowan University, c.valli@ecu.edu.au

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Impact of feature proportion on matching performance of multi-biometric systems

Wencheng Yang[a,*], Song Wang[b], Guanglou Zheng[a], Craig Valli[a]

[a] *Security Research Institute, School of Science, Edith Cowan University, WA 6027, Australia*
[b] *School of Engineering and Mathematical Sciences, La Trobe University, VIC 3086, Australia*

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Abstract

Biometrics as a tool for information security has been used in various applications. Feature-level fusion is widely used in the design of multi-biometric systems due to its advantages in increasing recognition accuracy and security. However, most existing multi-biometric systems that use feature-level fusion assign each biometric trait an equal proportion when combining features from multiple sources. For example, multi-biometric systems with two biometric traits commonly adopt a 50–50 feature proportion setting, which means that fused feature data contains half elements from each biometric modality. In this paper, we investigate the impact of feature proportion on the matching performance of multi-biometric systems. By using a fingerprint and face based multi-biometric system that applies feature-level fusion, we employ a random projection based transformation and a proportion weight factor. By adjusting this weight factor, we show that allocating unequal proportions to features from different biometric traits yields different matching performance. Our experimental results indicate that optimal performance, achieved with unequal feature proportions, could be better than the performance obtained with the commonly used 50–50 feature proportion. Therefore, the impact of feature proportion, which has been ignored by most existing work, should be taken into account and more study is required as to how to make feature proportion allocation benefit the performance of multi-biometric systems.

Keywords: Fingerprint; Face; Feature proportion; Matching; Multi-biometric system

1. Introduction

Multi-biometric systems collect biometric measurements from two or more biometrics, such as fingerprint, face, iris and signature, and therefore demonstrate higher recognition accuracy than uni-biometric systems [1–3]. Moreover, multi-biometric systems can provide strong anti-spoofing capabilities because it is hard to spoof multiple biometrics at the same time [4]. In the design of multi-biometric systems, feature-level fusion is a preferable technique [5], since fused features tend to have more discriminative power, making multi-biometric systems perform better than their uni-biometric counterpart. However, fusion of multiple biometric sources on the feature level is non-trivial. Most existing feature-level fusion based multi-biometric systems do not consider the impact of feature proportion on system performance. For example, either the original lengths of feature data extracted from different biometric traits are directly used [5] or a universal equal feature proportion (e.g., 50%–50%) is applied, namely half of the fused features coming from the first trait and the other half from the second trait [6–8]. These feature-level fusion methods may not be able to provide the best matching performance, because feature proportion plays a critical role in the matching process of multi-biometric systems that use feature-level fusion. In this paper, we investigate the impact of unequal feature portion allocations on matching performance based on the case study of a multi-biometric system. Specifically, we use a fingerprint

* Corresponding author.
E-mail addresses: W.Yang@ecu.edu.au (W. Yang), Song.Wang@latrobe.edu.au (S. Wang), G.Zheng@ecu.edu.au (G. Zheng), C.Valli@ecu.edu.au (C. Valli).
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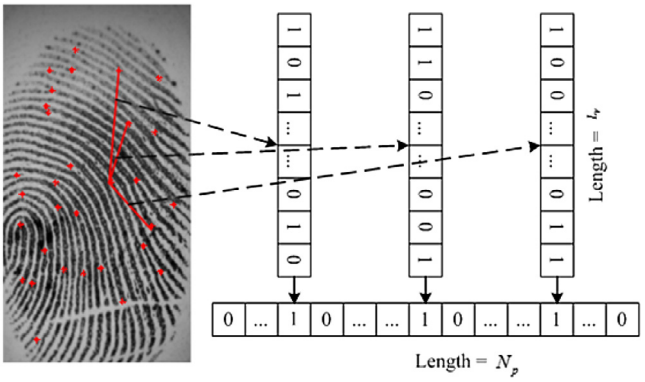

Fig. 1. Process of fingerprint feature extraction and transformation, with three minutia-pairs illustrated as examples in the fingerprint image.

and face based multi-biometric system, which combines feature data fused from both traits on the feature level. By utilizing a random projection based transformation and a proportion weight factor, we vary the proportion of each biometric trait's feature vector in the fused feature data so that we can ascertain how feature proportion affects system performance.

2. Fingerprint and face based multi-biometric system

A fingerprint and face based cancellable multi-biometric system is proposed and used as the platform to determine the impact of feature proportion on the system's matching performance. First, two feature vectors are extracted from the fingerprint image and face image, respectively. They are subsequently transformed into the same data format, binary-valued feature vectors. In particular, to extract the fingerprint feature vector, a minutia-pair based local structure [9] is used in our application. Given a set of minutiae $M = \{m_i\}_{i\in 1}^{N_M}$ extracted from a fingerprint image f_p, for any two minutiae, e.g., m_i and m_j, in minutiae set M, three rotation- and transformation-invariant features can be defined, which are (1) l_{ij}, the length of edge between m_i and m_j; (2) α_i, the angles between the orientation of minutia m_i and the edge; and (3) α_j, the angles between the orientation of minutia m_j and the edge. To mitigate intra-user variation caused by elastic distortion, these three features are further quantized into three short binary strings and concatenated into a new binary string V_{ij} of length L_v. Since every two minutiae in minutiae set M can generate a minutia-pair, there is a total of $C_{N_m}^2$ minutia-pairs. To integrate all these $C_{N_m}^2$ binary strings, e.g.,V_{ij}, into one binary string, we generate a zero vector $\mathbf{b}_p$ of length $N_p = 2^{L_V}$ based on the fact that the integer value of each binary string V_{ij} is in the range of $[0, N_p - 1]$. If the integer value of a binary string, e.g., V_{ij}, equals the index of an element of $\mathbf{b}_p$, then the value zero of that element is replaced by 1. By calculating the integer value of each binary string V_{ij}, we can produce one long binary string of length N_p. The whole process of fingerprint feature extraction and transformation is shown in Fig. 1.

The face feature vector is extracted using the image based technique, which is similar to [10]. Gabor filter and linear discriminate analysis (LDA), which are powerful tools in image processing and data compression, help to generate a real-valued feature vector $\mathbf{r}_c$ of length N_r from each pre-processed face image. The image pre-processing process contains two steps, reliable region of interest (ROI) chopping and image enhancement [10]. To convert the extracted real-valued feature vector $\mathbf{r}_c$ into the binary feature vector $\mathbf{b}_c$, we apply the well-known random projection based transformation, Bio-hashing [11]. Specifically, we compute the inner product of a randomly generated matrix $\mathbf{M}_c$ in the size of $N_c \times N_r$ and $\mathbf{r}_c$, i.e., $Y = \mathbf{M}_c\mathbf{r}_c$, where $Y = [y_1, y_2, \ldots, y_i, \ldots, y_{N_c}]^T$ and $1 \le i \le N_c$. For each y_i, it is calculated by the following rules: $y_i = 0$, if $y_i \le 0$ and $y_i = 1$, if $y_i > 0$. In this way, a binary feature vector $\mathbf{b}_c$ of length N_c is formed. The whole process of face feature extraction and transformation is shown in Fig. 2.

To protect the original features in $\mathbf{b}_p$ and $\mathbf{b}_c$, we resort to random projection based feature transformation, which is a commonly used template protection approach in cancellable biometrics [9]. Specifically, two random matrixes $\mathbf{M}_1$ and $\mathbf{M}_2$ are generated in the size of $N_1 \times N_p$ and $N_2 \times N_c$, respectively, where $N_1 \le N_p$ and $N_2 \le N_c$. Then the random projection based transformation is applied to the fingerprint feature vector $\mathbf{b}_p$ through $C_p = \mathbf{M}_1\mathbf{b}_p$ and to the face feature vector $\mathbf{b}_c$ through $C_c = \mathbf{M}_2\mathbf{b}_c$. As the lengths of transformed feature vectors C_p and C_c are N_1 and N_2, respectively, it is not hard to see that N_1 and N_2 determine the amount of individual feature components assigned to the resultant combined feature vector. Let $C = C_p \parallel C_c$ be the fused feature vector of length N, in which there are $N_1 = PN$ elements from the fingerprint image and $N_2 = (1 - P)N$ elements from the face image, where $0 \le P \le 1$ is a proportion weight factor. We can simply adjust the proportion of fingerprint and face features in the fused feature vector C by changing the value of P.

In the biometric matching process, to compare a query against a template, we calculate the similarity score of feature vector C^T from the template image pair (fingerprint image plus face image) and C^Q from the query image pair, expressed by:

$$S(C^T, C^Q) = 1 - \frac{\|C^T - C^Q\|_2}{\|C^T\|_2 + \|C^Q\|_2} \tag{1}$$

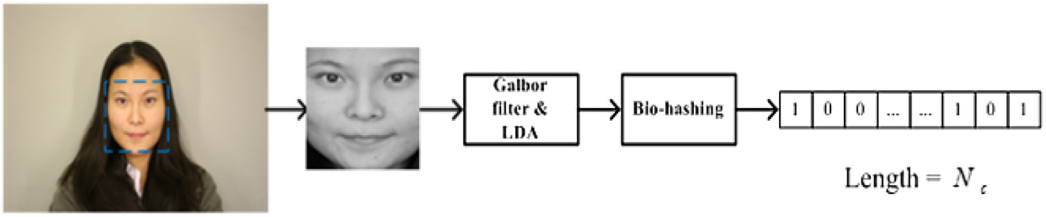

Fig. 2. Process of face feature extraction and transformation.

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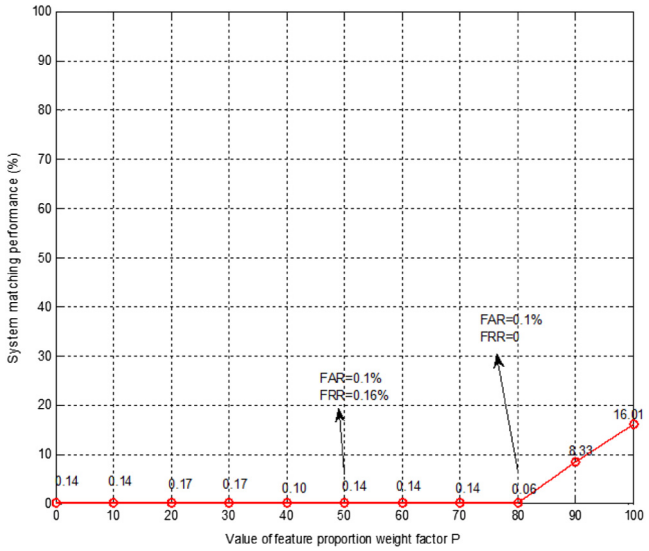

Fig. 3. The system matching performance under different feature proportion weight factor P on dataset *CD_one*.

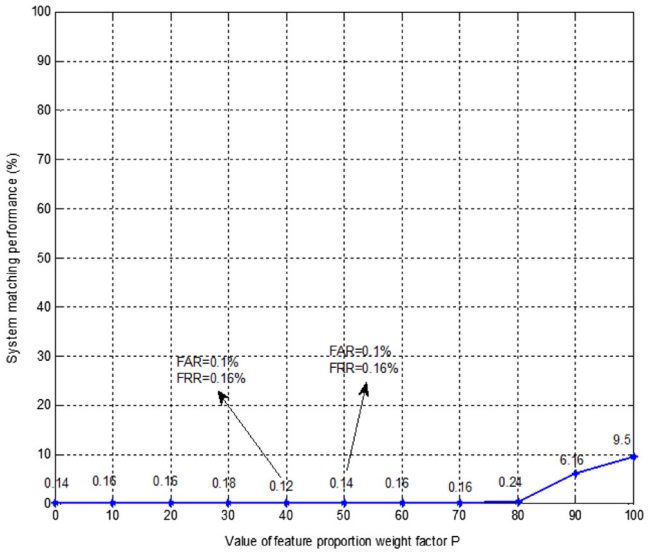

Fig. 4. The system matching performance under different feature proportion weight factor P on dataset *CD_two*.

where $\|\cdot\|_2$ represents the 2-norm. If the similarity score $S(\cdot)$ is larger than a pre-defined threshold S_t, the template and query are considered to be matched.

3. Experimental result and discussion

We evaluate the impact of feature proportion on the matching performance of the multi-biometric system using Database DS2 of the Multimodal Biosecure Database [12] and public available fingerprint database FVC2002 DB2 [13]. Database DS2 contains images from six different biometric traits, obtained from 100 users. Among them, we chose the fingerprint and face traits. Four fingerprint images and eight face images were acquired from each user, so totally 400 fingerprint images and 800 face images were used in our experiments. Database FVC2002 DB2 includes 100 fingers with eight images per finger. The first four images per finger were used in our experiments. By using Database DS2 and FVC2002 DB2, two combined datasets, *CD_one* and *CD_two*, are formed.

Dataset CD_one: Both face and fingerprint images are from Database DS2.

Dataset CD_two: The face images are from Database DS2 and the fingerprint images are from FVC2002 DB2.

In both datasets *CD_one* and *CD_two*, the first four face images were used for training and the remaining four face images were combined with four fingerprint images, respectively, to form four image pairs for each user. The first image pair was considered as the template and other three image pairs served as queries. The commercial fingerprint recognition software Verifinger SDK [14] was employed to extract minutiae from fingerprint images. The performance indicators, Equal Error Rate (EER), False Rejection Rate (FRR) and False Acceptance Rate (FAR), are used in our experiments to evaluate the system's matching performance. Specifically, the FRR is the probability of mistaking biometric images from the same user to be from different users, while the FAR is the probability of mistaking biometric measurements from different users to be from the same user. EER is the error rate when the FRR and FAR are equal.

The feature proportion in the fused feature vector is adjusted by changing the proportion weight factor P from 0% to 100% with a step size of 10% each time. For example, when P is set to be 0, it means only the single face modality is used; when P is set to be 10%, it means that only 10% of the elements in fused feature vector C are from the fingerprint image and the other 90% elements in C are contributed by the face image. Matching performance measured by the EER under different settings of P is shown in Figs. 3 and 4. From Fig. 3, we can see that the performance of the multi-biometric system is non-linear with the increase of P and the system achieves the best performance (EER $=$ 0.06%) when $P = 80\%$, which is more than two times better than the matching performance (EER $=$ 0.14%) under the common parameter setting $P = 50\%$, which is adopted by most existing multi-biometric systems involving two biometric traits. Similarly, from Fig. 4, we can see that the best performance does not happen under the setting $P = 50\%$ either. Our experiments indicate that as far as the performance of multi-biometric systems is concerned, it may not be the best option for each biometric trait to account for an equal amount in the fused feature data.

The feature level fusion strategy is also applied in [7,8]. Specifically, in [7], face, fingerprint and iris features are fused at the feature level and then protected by two well-known biometric cryptosystems, namely, fuzzy vault and fuzzy commitment. It is reported in [7] that FRR $=$ 1% at a security level of 53 bits using either fuzzy vault or fuzzy commitment on a virtual multimodal database. In [8], face and fingerprint features expressed by point sets are concatenated. The best performance reported in [8] is FRR $=$ 1.95% when FAR $=$ 1.02%. We note that the databases used in [7,8] are different from those used in our paper, so it is hard to compare those two methods with the proposed method on the same footing. Moreover, neither [7]

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nor [8] considers the impact of feature proportion on the system matching performance.

4. Conclusion

In this paper, we have investigated the impact of feature proportion on system performance by using the multi-biometric system that applies feature-level fusion. By carrying out experiments under different feature proportion settings, we find that allocating each biometric feature with an equal proportion in the fused feature vector does not necessarily yield optimal matching performance for multi-biometric systems. Although this finding contradicts the common practice of existing multi-biometric systems, it is a sensible result because features extracted from different biometric traits may not have the same level of robustness and discriminative characteristics. Therefore, assigning unequal feature proportions is likely to give rise to better matching performance for multi-biometric systems. Our research shows that it is important to consider the impact of feature proportion when we design a multi-biometric system. As opposed to what is commonly implemented by the existing multi-biometric systems with feature-level fusion, a more judicious feature allocation approach is needed.

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Conflict of interest

The authors declare that there is no conflict of interest in this paper.

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