Dynamic Weighting for Effective Fusion of Fingerprint and Finger Vein

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Abstract

This paper investigates the feature level fusion of fingerprint and finger vein biometrics. Both features of fingerprint and finger vein are represented by minutiae which are compatible in nature. For effective fusion, redundant point elimination is implemented as the first step prior to fusion. Then the two independent feature point-sets extracted from the two biometric modalities are concatenated. For the purpose of reliable matching, the quality of features at specific interested areas is evaluated. To weaken the influence of low quality images and false features, a dynamic weighting strategy is explored based on the results of feature evaluation. Experimental results based on FVC2000 database and self-constructed finger vein database show that our scheme achieved 98.9% recognition rate, compared with single fingerprint recognition and single finger vein recognition increased by 6.6% and 9.6% respectively, compared with fusion recognition at matching score level increased by 5.4. The extensive tests on public fingerprint databases: FVC2002_DB1_A, FVC2004_DB1-A and self-constructed finger vein database show that the dynamic weighting algorithm can achieve better performance even though poor quality fingerprint images are presented.

Keywords: *Dynamic Weighting, Feature Level, Fingerprint, Finger Vein, Fusion*

1. Introduction

A fundamental component in security systems is identity authentication which provides effective access control to the system resources [1]. Biometrics has the feature of uniqueness and unchanged, or acceptably changed, over the life time of an individual [2, 3] which is deemed as one of the best solutions to control access. By authenticating individual on what you are using behavioral or biological characteristics rather than what you have (tokens) or what you know (passwords/PIN), biometrics recognition has the capability to offer high level of identity authentication than its knowledge and token based counterparts [4, 5]. Among all the biometrics, fingerprint identification has been widely used in commercial and civilian applications [6]. However, due to the imperfect of sensing technology as well as the inter-class variation and intra-class similarity, unimodel fingerprint authentication in some particular applications can not provide ideal performance. Fusion of multiple biometrics is one of the options to improve system performance in such scenarios.

Fusion of multiple biometric sources for identity authentication is an effective method to alleviate the imperfection of sensing and signal processing technology. Fusion before matching considers those raw data acquired directly from sensing devices and those from the processed date after feature extraction. Sensor-level fusion and feature-level fusion are the main two categories of fusion before matching [7]. Sensor-level fusion makes use of the first hand source information captured [8, 9]. Feature set is usually the first group of data resulted from source information. It contains much richer information than the matching score or the output decision of a matcher. Therefore, the idea of fusion at the feature-level is primarily attributed to keep as much original unique information as possible [6, 10-15]. Fusion of hand and face biometrics at feature extraction level has been widely investigated in [6, 10-12] in which the feature vectors comprise of different geometric measurements obtained from hand and face are concatenated together. IR-based face recognition together with visible face recognition at feature level is reported [13]. Multiple biometric systems based on the fusion of face features with gait features at feature level is investigated [14].

Statistical test on the uniqueness and persistence of finger vein makes it as a potential candidate for biometric identity authentication recently. In addition, finger vein is a biometrics inside the fingers and can only be captured with special optical devices. It is difficult to forge. Furthermore, pulse information, used for liveness detection, could be obtained while sampling finger vein. Therefore, to authenticate an identity based on fusion of fingerprint and finger vein demonstrate a potential for high level of access control. Finger vein processing, feature extraction and enhancement have been investigated [15, 16]. The fusion of fingerprint and finger vein has been reported [17-19]. In [17], fusion of texture information, rather than minutia-based information, extracted from both fingerprint and finger vein is explored. Local information preservation of finger vein has been investigated for the purpose of keeping the local discrimination [17]. Based on the fact that fingerprint and finger vein are complementary and they can also compensate each other, score-level (matching-level) fusion of fingerprint and finger vein is investigated in [18]. The weighted fusion is applied to the matching results of fingerprint recognition (measured by score) and matching result of finger vein recognition (measured by modified Hausdorff distance). We presented a research result of feature-level fusion of fingerprint and finger vein biometrics in [19]. The features of both fingerprint and finger vein can be represented with minutiae. Therefore, minutia-based feature-level parameters of fingerprint and finger vein are compatible by their nature.

We report a novel approach of dynamic fusion of fingerprint and finger vein biometrics at feature level in this paper. Based on our previous research, the feature-level fusion is realized by concatenating the feature point-sets of minutiae obtained from two sources of fingerprint and finger vein. The concatenated point-set has better discrimination capability than each individual feature vector. The main contribution of this paper includes: i) an effective quality evaluation for fingerprint and finger vein features. ii) the dynamic weighting when fusion of the two groups of minutiae extracted from the two biometric modalities. Experimental results show that the fusion scheme can reduce the uncertainty in biometric images and improve verification performance.

The rest of the paper is organized as follows. Section II discusses feature concatenation from fingerprint and finger vein biometrics. Section III presents the dynamic weighting fusion scheme. Section IV provides performance evaluation. Conclusion is presented in Section V.

2. Concatenation of fingerprint and finger vein features

Fingerprint and finger vein can be represented with the same feature of minutiae. It is easier to concatenate minutiae point-set extracted from fingerprint and finger vein into one feature space. With special designed fusion algorithms, feature-level fusion of minutiae is expected to provide better recognition performance.

2.1 Feature extraction and concatenation

Most of the automatic fingerprint matching systems rely on ridge endings and ridge bifurcations, which are called minutiae as shown in Figure 1. Each minutia has one ridge curve associated with it. A minutia point is usually described by its position (x, y coordinates) and the direction (θ) of the associated ridge curve:

$$m_j = \{(x_j, y_j, \theta_j)\} \quad (0^{\circ} \leq \theta_j < 180^{\circ}) \tag{1}$$

while j=1, 2, …, p is the number of fingerprint minutiae, x_j and y_j indicate the coordinates of row and column of a corresponding minutia, and θ_j indicates the angle of the ridge on which j^{th} minutia resides.

Minutiae-based fingerprint recognition techniques pre-process fingerprint images using Gabor filters, after normalization, binarizing and thinning, minutiae can be extracted. An enhanced method for extracting finger vein features is proposed in [15]. The basic principle is to extract features by detecting concavity in a gray image. The extracted features are filtered, thinned and deblurred, then, as shown in Figure 2, minutiae are extracted:

$$n_k = \{(x_k, y_k, \theta_k)\} \qquad (0^{\circ} \leq \theta_k < 180^{\circ}) \tag{2}$$

where k=1, 2, …, q is the number of finger vein minutiae, x_k and y_k represent the spatial location and θ_k represents the local orientation of corresponding minutia, respectively.
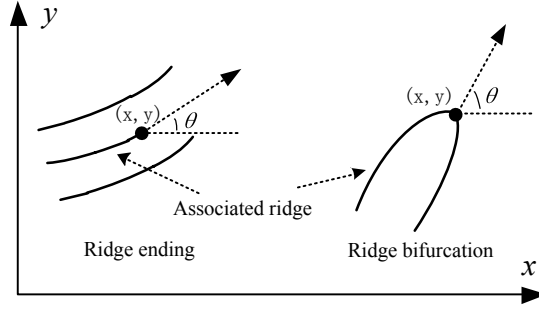
Figure 1. Fingerprint minutiae
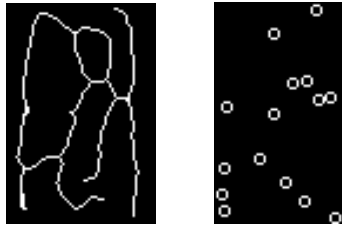
Figure 2. Finger vein and minutiae.

Both m_j and n_k are point-set with coordination and orientation. The concatenated feature point-set of both fingerprint minutiae and finger vein minutiae is expressed as:

$$U = \{m_1, m_2, \dots m_p, \dots , n_1, n_2, \dots n_q\} \tag{3}$$
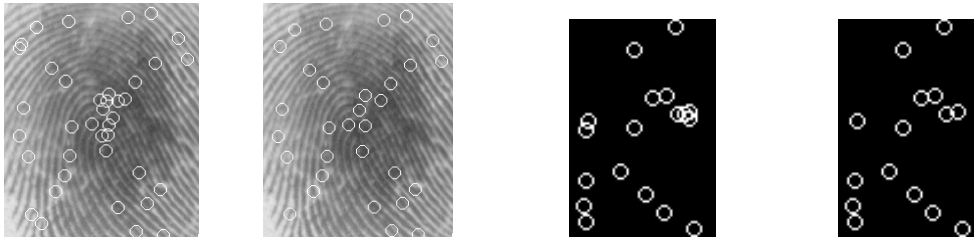
2.2 Redundant point elimination

There is usually redundant area and a number of false minutiae in the acquired fingerprint or finger vein images. The recognition accuracy of the multiple modality fusion system depends heavily on the minutiae extraction of fingerprint and finger vein directly. Redundant feature elimination aims at enhance the reliability of matching while minimize the computational complexity of processing. It includes neighborhood elimination and interested area selection on the feature point-set [16].

Neighborhood elimination technique is employed for the purpose of removing the redundant information while keeping the effective source information for subsequent fusion. The image with redundant points of fingerprint is shown in Figure 3(a), of finger vein is shown in Figure 3(c). For each minutia of fingerprint and finger vein, neighborhood elimination removes those points that lie within a certain radius r around it. For a given minutia (x, y), points satisfy (4) will be eliminated.

$$S_d = \sqrt{(x - x_i)^2 + (y - y_i)^2} \leq r \tag{4}$$

where (x_i, y_i) is a minutia, either from a fingerprint or a finger vein image. r is computed using Euclidean distance.

Based on empirical, $r=10$ pixels is used for fingerprint minutiae elimination, and $r=8$ pixels is applied to finger vein minutiae elimination. After neighborhood redundant point elimination, the reduced fingerprint and finger vein minutiae point-sets are obtained, as shown in Figure 3(b) and (d), respectively.

(a) Fingerprint minutiae. (b) Minutiae after elimination. (c) Finger vein minutiae. (d) Minutiae after elimination.

Figure 3. Effect of neighborhood redundant points elimination.

To locate the interested area on a fingerprint image, the core point of fingerprint is located using a reference point location algorithm discussed in [15, 16]. A radius equal to 40 pixels is set for fingerprint feature point selection as shown in Figure 4(a). Finger vein images capture the infrared picture of two joint bones on finger tips. In order to remove the false minutiae on edges of finger vein images, only the feature point within the region of 70 pixels in width on an image are retained as reduced point-set as shown in Figure 4(b).
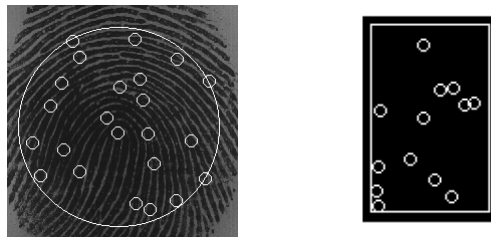
(a) Fingerprint   (b) Finger vein

Figure 4. Selection of interested areas.

After removing the neighborhood redundant point, only the highly distinctive points inside the interested regions are kept.

3. Dynamic weighting for effective fusion

The concatenated feature in (3) consists of minutiae of both fingerprint and finger vein. The quality of source images has significant influence on the minutiae extracted. There are usually quite a number of false feature points, particularly in low quality images. We propose to evaluate the feature point-set of both fingerprint and finger vein prior to the concatenation of feature. Then a dynamic weight is assigned to the feature point-set of fingerprint and finger vein based on their quality levels of the source images for fusion and subsequent matching.
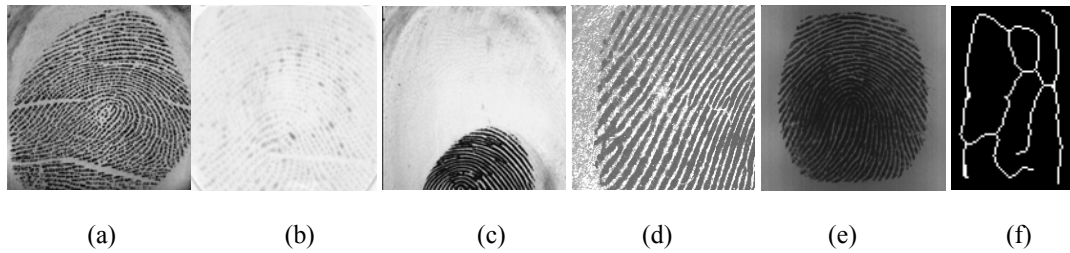
3.1 Quality evaluation

Quality evaluation of both fingerprint and finger vein images are critical to the reliable matching. For quality evaluation of an input sample, a template is used as a reference. After evaluation, the quality of each input sample is divided into either excellent or poor. The corresponding evaluation component is determined by the constraints in the following [14]:
- whether the number of minutiae extracted is within a certain range from the input sample;
- the variation of minutiae number before and after redundant feature elimination from the input sample;

- the ratio of minutiae number after elimination to those on reference template;
- the proportion of interested area on the source image;
- the deviation of core point from the centre of interested area.

All the five factors mentioned above are used for fingerprint evaluation. The first three factors are used for finger vein evaluation.

Five typical fingerprint images and one finger vein image are shown in Figure 5. Among them figures (a)-(d) are classified as poor quality, figures (e) and (f) are classified as excellent quality. The feature quality of the sampled images is evaluated by the proposed method in this section. The performance of evaluation is shown in Table 1. The image quality evaluation matches the human perception.

(a)   (b)   (c)   (d)   (e)   (f)

Figure 5. Sample images to be evaluated. (a)-(d) Poor quality fingerprints. (e) Excellent quality fingerprint. (f) Excellent quality finger vein.

Table 1. Performance of the evaluation

Sample image	Quality	Reason
Figure 5 (a)	Poor	No region for effective feature extraction
Figure 5 (b)	Poor	Obvious scars and many false minutiae
Figure 5 (c)	Poor	Center deviation, small effective region
Figure 5 (d)	Poor	Center deviation
Figure 5 (e)	Excellent	Excellent quality
Figure 5 (f)	Excellent	Excellent quality

3.2 Predictive dynamic weighing

According to the result of image quality evaluation, a dynamic weighting strategy is employed for the fusion of fingerprint and finger vein biometrics. A high weight value is assigned to the feature point-set corresponds to an excellent quality source image while a low weight is assigned to the feature point-set corresponds to a poor quality source image. The fusion algorithm is described as follows:

Step1: Extract the feature point-sets (minutiae) from fingerprint and finger vein images, as expressed in (1) and (2), each feature point-set consists of the spatial location (x, y) and the local orientation θ.

Step2: Apply the redundant feature elimination techniques to reduce the points in the feature point-set, record the centre of image, and concatenate both features from fingerprint and finger vein as expressed in (3).

Step3: Evaluate the quality of source images. According to the quality evaluation result of either excellent or poor quality, a modified weight is assigned to fingerprint and finger vein, respectively.

Step4: Set the fusion weight, λ_m and λ_n, to the fingerprint and finger vein features based on Table 2.

Table 2. Fusion factors for fingerprint and finger vein

λ_m	λ_n	Condition
1	2	Initial values
1	2	Both fingerprint and finger vein are excellent or poor
2	2	Fingerprint is excellent, finger vein is poor
1	4	Fingerprint is poor, finger vein is excellent

where *m* and *n* correspond to fingerprint and finger vein features, respectively.

Remark: There are usually less number of minutiae on finger vein, and the finger vein feature is relatively stable, therefore, the initial values are set for $\lambda_m=1$ and $\lambda_n=2$, which means to adjust the contribution of finger vein in matching. The final fusion weights are determined by the result of image quality evaluation shown in Table 2.

3.3 Matching based on the weighted fusion

Matching is the process of comparing the concatenated feature point-set generated from the query samples with the reference template. The proposed evaluation factor above is considered in the matching algorithm, the details are:

a) *Check the matched minutiae pair.*

Two minutiae, one in the reference template, the other in a query sample, are considered as a matched pair only if both the spatial distance (6) and the direction distance (7) are within pre-determined thresholds. The query images are preprocessed, such as alignment, rotation and translation, etc., before comparison.

$$\Delta_d = \sqrt{(x'-x)^2 + (y'-y)^2} \le r_0 \tag{6}$$

$$\Delta\theta = \min\left(|\theta'-\theta|, 360^0 - |\theta'-\theta|\right) \le \theta_0 \tag{7}$$

where (x, y, θ) and (x', y', θ') represent the minutia in a reference template and an input query sample, respectively. Based on emprical, $r_0 = 4$ pixels, $\theta_0 = 5°$.

Note that if more than one minutia satisfy (6) and (7), then the minutia has an average minimum distance is selected as the candidate of matched pair. The alignment of query sample with template is performed in image pre-processing. The fusion of feature point-sets does not affected by rotation and translation as well as other parameter variation.

b) *Compute the matching score.*

The matching score is calculated using (8) based on the contribution of fingerprint and finger vein:

$$S = \frac{\lambda_m \cdot M' + \lambda_n \cdot N'}{\lambda_m \cdot M_T + \lambda_n \cdot N_T}, \tag{8}$$

where M' and N' represent matched pairs of fingerprint and finger vein minutiae, respectively. $M_T = \max(M, M')$ and $N_T = \max(N, N')$ stand for the maximum number of feature points found in the reference template and the query sample, of fingerprint and finger vein respectively. The basic flowchart of dynamic weighting fusion algorithm is shown in Figure 6.

In Figure 6, *p* and *q* are the minutiae number after redundant feature elimination from total minutiae on fingerprint and finger vein, respectively, therefore, $p<j$, $q<k$, where *j* and *k* are minutiae number on input query samples of fingerprint and finger vein, respectively. If images quality evaluation is not considered, then the default value used for matching is the initial weight $\lambda_m=1$ and $\lambda_n=2$.
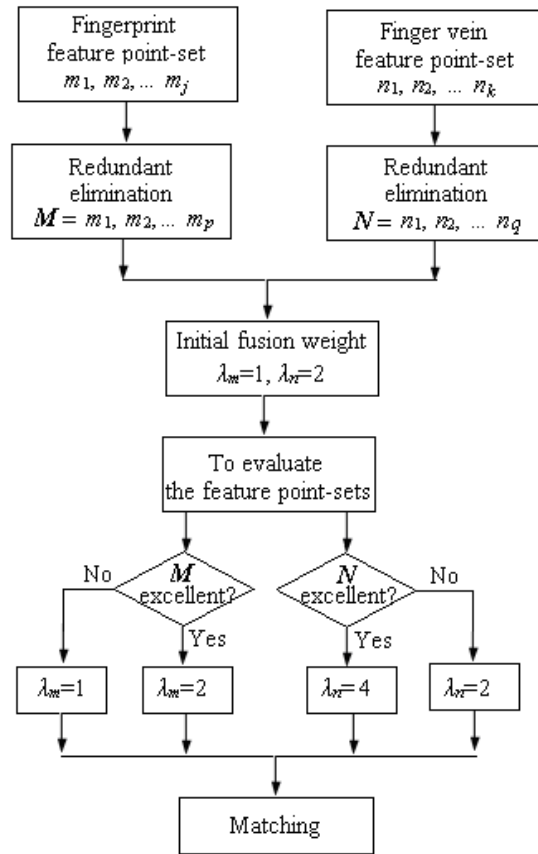
Figure 6. Block diagram of dynamic weighting fusion matching

4. Simulations

The proposed approach has been tested on public-domain fingerprint database (FVC2000_DB1_B-DB4_B) and self-constructed finger vein database. Fingerprint database consists of fingerprints captured from 40 persons; there are 8 images from the same finger of each person. Finger vein database consists of finger vein images captured from 40 individuals; there are 8 images from the same finger of each person. The finger vein images are acquired under different illumination using a commercial infrared sensor. All fingers are vertical upward when sample the finger vein images. The grayscale and size of acquired finger vein images are 256 and 135×235 pixels.

Preprocessing of fingerprint and finger vein images is necessary [18]. The preprocessing includes filtering, enhancement, gray-scale normalization, alignment, etc. [19, 20]. After preprocessing, the 128×128 pixel fingerprint images and 80×120 pixel (extension size is 128×128 pixel) finger vein images are obtained respectively.

4.1. Quality evaluation of fingerprint images

The fingerprint images are evaluation based on the following factor:

i) The proportion of the effective area (interested area compared with that of total area).

ii) The number of minutiae extracted before and after redundant feature elimination.

iii) The variation of minutiae number extracted from an input sample before and after redundant feature elimination.

The number of minutiae before and after redundant feature elimination is shown in Figure 7(a). The minimum number for excellent quality after redundant feature elimination is 15. The maximum number before redundant feature elimination is 55. The variation of minutiae number extracted from an input sample before and after redundant feature elimination is shown in Figure 7(b). The parameter for excellent quality is empirically set as 0.5.
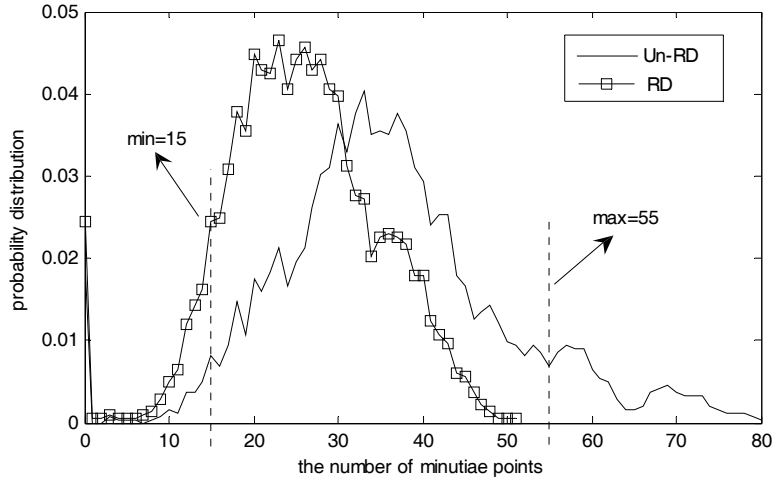
(a)
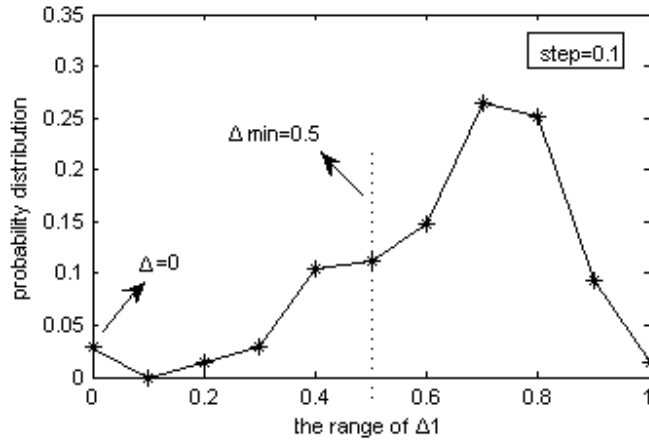
(b)

Figure 7. Statistical of the minutiae number in FVC2000. (a) The probability distribution of minutiae before (Un-RD) and after (RD) redundant deduction. (b) The probability distribution of minutiae number variation before and after redundant feature elimination.

The single fingerprint and single finger vein recognition are tested before and after redundant deduction (*RD*), respectively. The matching scores are computed using point pattern matching for fingerprint and finger vein independently. The False Acceptance Rate (FAR), False Rejection Rate (FRR) and accuracy are compared. The individual system performances are recorded and the results are computed for each modality as shown in Table 3.

Table 3. Point pattern matching performance of single biometrics

Algorithm		FRR (%)	FAR (%)	Accuracy (%)
Un-RD	Fingerprint	6.07	9.56	90.83
	Finger vein	5.36	11.33	88.93
RD	Fingerprint	4.29	7.95	92.31
	Finger vein	5.38	9.60	89.29

From the Table 3, it can be seen that with the reduction of the redundant features, the recognition accuracy increased by 1.48% for fingerprint and 0.36% for finger vein.

4.2. Predictive weighing for fusion

Fusion of both fingerprint and finger vein features is tested on the multimodal databases acquired by the authors. The database has 40 pairs of images that composed of a fingerprint sample and finger vein sample for each person. For comparison, the performances for multimodal fusion at matching score and feature extraction level are computed as shown in Table 4. For feature level matching, both unweighted fusion and dynamic weighting fusion algorithms are calculated. The results show that the proposed dynamic weighting fusion scheme achieves 98.9% recognition accuracy, compared with fingerprint and finger vein modalities (shown in Table 3, after redundant deduction) increased by 6.6% and 9.6%, respectively. Compared with fusion recognition at matching score level, the recognition rate of feature level fusion is increased by 5.4%. Moreover, compared with the unweighted feature level fusion, the dynamic weighting fusion enhanced the recognition rate by 3.1%.

**Table 4.** Performance comparison of the fingerprint and finger vein fusion

Algorithm	FRR (%)	FAR (%)	Accuracy (%)
Matching score level fusion	6.92	5.33	93.50
Unweighted feature fusion	6.78	2.52	95.81
Dynamic weighting fusion	1.85	0.97	98.93

Further test is conducted on two databases Database 1 comprises *FVC2002_DB1_A* and self-constructed finger vein database; Database 2 comprises *FVC2004_DB1_A* and self-constructed finger vein database. Each database contains fingerprint from one finger and finger vein of 40 persons. There are 8 images captured for each finger and finger vein.

A total of 320 (40×8) combinations of fingerprint and finger vein in each bimodal database. Each combination of fingerprint and vein in the test set was matched with the other combinations in the set. A total of 102080 (320×319) matches have been performed on test Database 1 and Database 2 respectively. The times of Genuine and Impostor matches are 2240 (40×7×8) and 99840 (40×312×8) on each test database.

For comparison, the performances for multimodal fusion are computed as shown in Fig. 8. Experimental results show that Dynamic weighting fusion algorithm achieves 1.19% and 1.78% EER (Equal Error Rate) on Database 1 and Database 2 respectively.

Table 5 shows the EER results for the different algorithms of fingerprint, finger vein, matching level fusion (the excellent results of sum-based fusion) and the proposed dynamic weighting fusion in this paper. It can be seen that the proposed dynamic weighting fusion scheme achieves 1.485% average EER, compared with fingerprint and finger vein modalities reduced by 75.64% and 80.86% respectively. Moreover, compared with fusion recognition at matching score level, the EER of feature level fusion is reduced by 53.81%. This indicates that our algorithm is capable of improving the matching performance by the weighting fusion of fingerprint and finger vein at the feature extraction level.
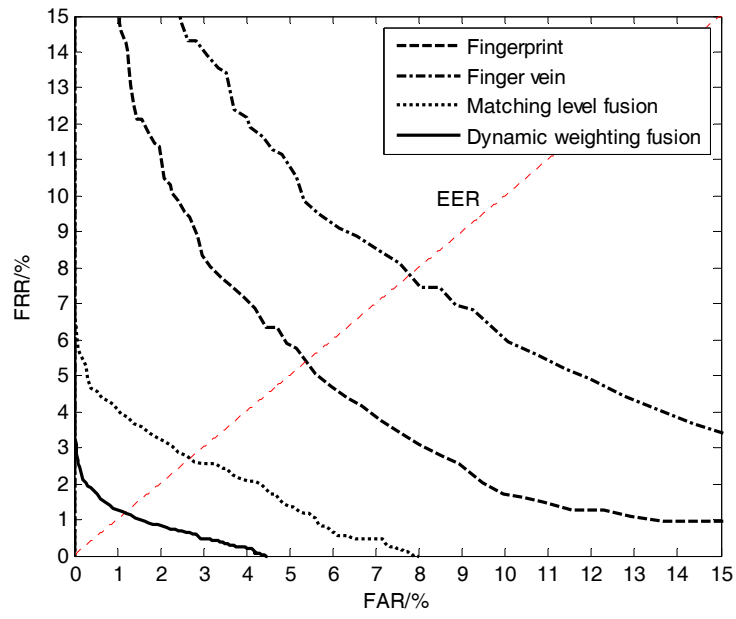
(a)
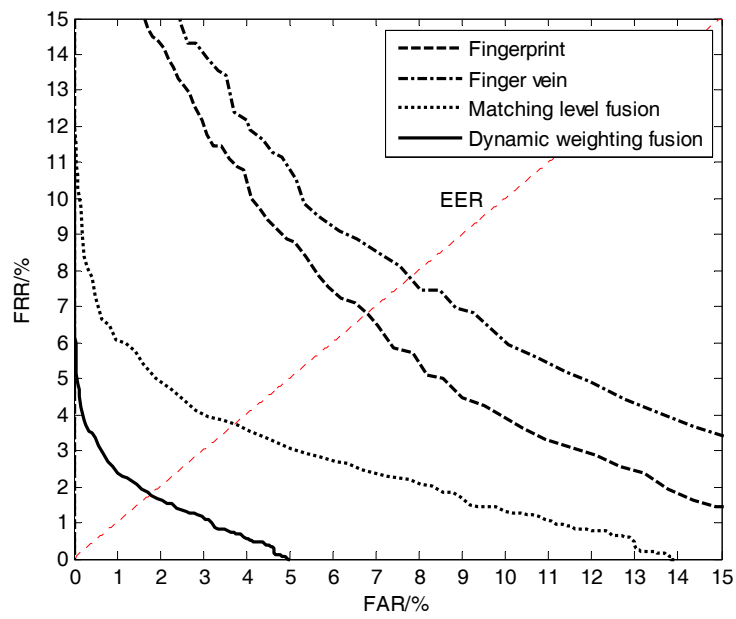
(b)

Figure.8 Performance of Dynamic weighting fusion algorithm on the test Databases. (a) ROC curves for experimental database 1 (EER=1.19%). (b) ROC curves for experimental database 2 (EER=1.78%)

Table 5 Statistical EER results for the different algorithms

Algorithm	EER (%)		Average EER (%)	Performance Improvements
	Database 1	Database 2		
Fingerprint	5.40	6.79	6.095	75.64%
Finger Vein	7.76	7.76	7.760	80.86%
Matching level fusion	2.69	3.74	3.215	53.81%
Dynamic weighting fusion	1.19	1.78	1.485	—

Note that, the images in database 2 is collected in order to accommodate deform of fingerprint images. In this case, the performance of dynamic fusion is not as good as those of database 1. However, a 1.78% EER is achieved due to the low weighting is allocated to the poor quality fingerprint. This fact strongly support that our fusion algorithm perform much better.

5. Conclusion

A multimodal biometric identification system based on the fusion of fingerprint and finger vein traits at feature level has been proposed. To achieve the effective fusion, the quality of input query samples is evaluated. A dynamic weighting fusion algorithm based on quality evaluation of interest features is proposed. By evaluating the quality of source features and allocating different weight corresponds to the quality level, the matching performance has been improved significantly.

Future work will focus on the selection of optimal fusion parameters.

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