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Exploring soft biometric trait with finger vein recognition

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ABSTRACT

Soft biometric trait has been used as ancillary information to enhance the recognition accuracy for face, fingerprint, gait, iris, etc. In this paper, we present a new investigation of soft biometric trait to improve the performance of finger vein recognition. We first propose some extraction criteria of soft biometric trait for comprehensively understanding this kind of ancillary information. And then based on these criteria, the width of phalangeal joint is employed as a novel soft biometric trait, which can be directly extracted from finger vein image. Finally, three frameworks are developed to conduct the combination of the width measurement and finger vein pattern, i.e., the fusion framework, the filter framework and the hybrid framework. We perform rigorous experiments both on the open and self-built finger vein databases, and experimental results illustrate that soft biometric trait can make promising improvement of finger vein recognition performance.

1. Introduction

Biometrics is an automatic user authentication technology, which uses human physiological and/or behavioral characteristics with several desirable properties like universality, distinctiveness, permanence and acceptability. In recent years, there has been an increasing interest in finger vein recognition, which is motivated by the advantages of finger vein in living-body identification, non-invasive and non-contact image capture, and high security over other biometric recognition techniques (e.g., fingerprint, face, iris, voice, gait, etc.) [1].

Many efforts are contributed to develop an effective feature extraction method in finger vein recognition. The related works can be classified into three groups. The methods in the first group were based on the segmentation of finger vein, for example, the repeated line tracking method [2], the maximum curvature point method [3], the mean curvature [4] and the Gabor filter [5]. In these methods, the vein network is segmented firstly, and then the geometric shape or topological structure of the network is extracted for matching. However, the segmentation results of low quality images are often unsatisfying. Principal component analysis (PCA) [6], linear discriminant analysis (LDA) [7] and two-directional and two-dimensional principal component analysis ($(2D)^2$PCA) [8] were used to extract finger vein feature in the second group. These kind of methods were based on the dimensionality reduction technique, which will transform the image matrix to a one-dimensional or two-dimensional feature matrix by a trained projection matrix. But, the more users in database, the more complicated is the training process of projection matrix, which limits the application of these methods. Finger vein texture descriptors based on the binary code were used in last group, which included the local binary pattern (LBP) [9], the local line binary pattern (LLBP) [10], the personalized best bit map (PBBM) [11], etc. These methods are sensitive to the translation and rotation of finger in image. In addition, there are many other problems in finger vein recognition, such as the various qualities of finger vein images affected by user's physiological factor and the imaging conditions, high intra-class variation introduced by unconstrained imaging, low inter-class variation of some users and non-ideal population coverage.

To overcome these problems, a multimodal biometric system was employed, which combined the evidences obtained from finger vein and other traits. Some typical studies on multimodal biometrics are given as examples of recent works. The scores of finger vein, fingerprint and face were fused using weighted sum rule and support vector machines (SVM) in [12]. Unfortunately, the experimental results were from a virtual multimodal database, which combined fingerprint and face images of one person with finger vein image of another person. Hand-based multimodal biometric systems were introduced in the remainder studies. Yang and Zhang proposed the supervised local-preserving canonical correlation analysis method (SLPCCAM) to generate fingerprint-vein feature vectors in feature-level fusion [13]. Finger vein and finger dorsal texture were fused using the proposed holistic fusion and non-linear fusion methods at the score level in [5]. Kang and Park integrated finger vein and finger geometry by means of SVM-based score level fusion [14]. However, along with the higher recognition accuracy, a variety of limitations appear in multimodal

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biometric system, such as, the longer recognition time, the higher cost for multiple high quality sensors and the more inconvenience to user.

A preliminary study about soft biometric trait was presented by Jain et al. [15]. Soft biometric trait was defined as characteristic which provided some information about the individual, but lacked the distinctiveness and permanence to sufficiently differentiate any two individuals, like height, gender and ethnicity. The experimental results suggested that these characteristics can assist user recognition. Inspired by this literature, we think that it may be a good solution to use soft biometric trait to improve the performance of finger vein recognition in a reliable and user-friendly way.

This paper explores the usage of soft biometric trait in finger vein recognition. To deeply understand soft biometric trait and its usage, we firstly summarize and analyze soft biometric trait-related main works. In order to discriminate the dependence of soft biometric trait on primary biometric trait, we classify this kind of ancillary information into three categories. Furthermore, the extraction criteria of the ancillary information are presented to define the applicable soft biometric trait. Based on these criteria and thorough research of finger vein image, we propose a new soft biometric trait, i.e., the width measurement of phalangeal joint, to supplement the primary information of vein pattern. This new soft biometric trait has strong dependence on finger vein, which can be directly extracted from finger vein image.

Last, in order to maximize the recognition performance of soft biometric trait, three frameworks are developed for combining soft biometric trait and primary biometric trait, i.e., the fusion framework, the filter framework and the hybrid framework of filter and fusion. We compare the performance of these frameworks in both the recognition accuracy and speed, and the experimental results display that the hybrid framework outperforms the two other frameworks.

The remainder of this paper is organized as follows. In Section 2, we focus on the introduction of soft biometric trait, including a survey of previous works, the soft biometric trait extraction criteria and the proposed soft biometric trait. Following it, the usages of soft biometric trait in the developed frameworks are presented in detail in Section 3. Section 4 describes the experimental databases and settings, and shows the experimental results and analyses of these results. Last, the key conclusions of this paper are summarized in Section 5.

2. Soft biometric trait

2.1. The related work

In many literatures, the usage of soft biometric trait in biometrics has been investigated, and the promising improvement of recognition performance has been reported. According to the dependence of soft biometric trait on primary biometric trait, we divide this kind of ancillary information into three categories. In the first category, there is no dependence between soft biometric trait and primary biometric trait, in other words, the soft biometric trait needs to be captured by the additional device, such as height in fingerprint recognition. In the second category, the dependence is limited, and soft biometric trait can be derived from primary biometric trait, for example, gender and ethnicity in face recognition. In the last category, soft biometric trait has strong dependence on primary biometric trait, which appears on the image of primary biometric trait, for example, stride length in gait recognition.

About soft biometric trait without dependence on primary biometric trait, three typical literatures are presented. Jain et al. presented a framework for integrating soft biometric trait with the primary biometric by the Bayes formula [16]. An improvement of 5% was obtained for fingerprint recognition performance with the ethnicity, gender and height information. Although fingerprint was used as the primary biometric trait, face image was also captured for estimation of the ethnicity and gender information, which makes inconvenience for user. In addition, the other problem is that the height information, which was randomly drawn from a Gaussian distribution in above literature, is needed to be measured by a specific device in practical application,

Ailisto et al. examined whether fusing weight and fat percentage can improve the fingerprint performance in verification mode [17]. The total error rate (TER) decreased from 3.9% to 1.5%. In their case, the primary biometric trait has no direct relationship with soft biometric traits. Besides, the result for the fat percentage was very poor with minimum TER 35%, which indicated that the fat percentage was questionable in distinctiveness.

Jain and Verma proposed a three-level recognition scheme [18]. In this scheme, if the weight matching was successful in level one, the matching in level two continued by the finger geometry. Otherwise, the claimed identity was seen as “impostor” in level one. Similarly, if the matching was also successful in level two, the fingerprint matching was thirdly performed in last level, and if not, the claimed identity was rejected as “impostor” in level two. Although the finger geometry was extracted while scanning fingerprint, weight need to be measured by an additional device. What is more, the greatest regret is that there was no experiment to verify the effectiveness of the proposed scheme in their work.

In the following literatures, the ancillary information can be derived by a classifier in the machine learning process. Lyle et al. used local appearance features extracted from the periocular region images for gender and ethnicity (i.e., Asian and non-Asian) classification, and further employed the gender and ethnicity information to enhance the periocular recognition [19]. Giot and Rosenberger derived the user gender from keystroke typing pattern using non-linear classifier SVM [20]. The improvement on keystroke dynamics authentication by supplementing gender information through pattern and score fusion was proved. These two works verified that the soft biometric information derived from the primary biometric trait is helpful for identity recognition, but the classification accuracies of ancillary information were limited, with 93% and 91% of the gender and ethnicity [19], and approximate 91% of the gender [20].

Different from the above gender and ethnicity information derived from the primary biometric trait, some ancillary information appear on the image of primary biometric trait, which can be directly extracted from the image. Laplacian-of-Gaussian (LoG) and morphological operators were used to detect facial marks (e.g., freckles, moles and scars) from face image [21]. This work showed three usages of facial marks. (1) To supplement primary features in an existing face matcher. (2) To enable fast retrieval from a large database. (3) To enable matching or retrieval from a partial or profile face image with marks. The rank-1 identification accuracy improved from 92.96% to 93.90% and from 91.88% to 93.14% on FERET and Mugshot images, respectively. Besides, Park and Jain classified facial marks into 10 semantic categories based on morphology and color of the marks [22]. The class label of facial mark was used to supplement the face feature, along with the location, gender and ethnicity information. Facial marks were also used to differentiate identical twins in this work. Jain et al. used facial marks to search a large face database with partial or low-quality face images in forensics applications [23].

Apart from the application of facial marks in face recognition, macro-features on the iris image and user height and stride length on the gait sequence were separately used as soft biometric traits in [24,25]. The visible macro-features, such as, moles, freckles, nevi and melanoma, were used for iris image retrieval, which achieved 92.8% of rank-1 rate [24]. However, the rank-1 rate was achieved on 390 probes, and the remainder 380 images in the database did not have any macro-features. User height and stride length information were utilized in a new probabilistic framework for promoting the gait recognition, and experimental results both in identification and verification modes showed the efficiency of the proposed approach [25].

A survey of previous works on soft biometric trait suggests that, the biometric recognition performance can be improved by supplementing the kind of ancillary information, like user height, gender, age, ethnicity, weight, facial masks, stride length, etc. So developing the appropriate and effective soft biometric trait and employing the trait in finger vein recognition are all worthy to be studied deeply.

2.2. Soft biometric trait extraction criteria

As the soft biometric traits in the first category need to be captured by the additional advice, and the traits in the second category are derived by a classifier in machine learning process, we prefer the traits in last category, which can be directly extracted from the primary biometric trait. In this session, we will present some extraction criteria of this kind of ancillary information to define the applicable soft biometric trait. The criteria are described in detail as follows:

(1) Soft biometric trait must have certain distinctiveness. On one hand, soft biometric trait is used to assist primary biometric trait, so distinctiveness is the most important property of this ancillary information. On other hand, soft biometric trait will not be used to identify an individual independently. So, the ancillary information, with limited distinctiveness between different individuals and impermanence throughout the lifetime of an individual, can be used as soft biometric trait.
(2) The extraction of soft biometric trait should be easier than that of primary biometric trait. As we know, the processing time is one important benchmark for biometrics system in practical application. If the extraction of soft biometric trait is more complicated and takes longer time than that of primary biometric trait, this soft biometric trait is not applicable to a great degree.
(3) Soft biometric trait should be automatically collected with very low cost. As we know, although iris recognition has high universality and promising recognition rate, the expensive acquisition device seriously limits its application. On the contrary, for soft biometric traits like height and body weight, the acquisition devices are familiar in the daily life, and the prices of these devices are very cheap. For other biometric traits like stride length and facial masks, which can be directly extracted from gait sequence and face image, there is no need for the additional acquisition device.
(4) High universality is another necessary property of soft biometric trait. For example, all people have their own gender, age, and ethnicity, but some people may not possess macro-features on the iris image (e.g., moles, freckles, nevi and melanoma).
(5) Soft biometric trait should have high acceptability. The acquisition of soft biometric trait should be performed in unobtrusive, non-invasive and contactless way.

2.3. Soft biometric trait in finger vein

Based on thorough research of finger vein image and comprehensive consideration about extraction criteria of soft biometric trait, we develop a new soft biometric trait, i.e., the width of the distal inter-phalangeal joint in human finger, called the width measurement in the following session of this paper. We accept the fact that the width measurements of two users may be the same, but for a large proportion of users, there are differences in the width measurements. So it is reasonable to think that the width measurement will be useful for the performance improvement of finger vein recognition. Besides, the developed soft biometric trait has high universality and acceptability, and it is not conspicuous without risk of identity theft. More than that, it can be easily and directly extracted from finger vein image, so the additional acquisition device is not necessary.

The extraction of width measurement depends on two main elements, i.e., the finger boundaries and the position of the distal inter-phalangeal joint in finger vein image. We use the Sobel operator in the vertical direction to detect the finger boundaries, and the brighter region with a pixel width in finger vein image is seen as the position of the phalangeal joint. As we know, a phalangeal joint consists of several components, including cartilage, articular cavity filled with synovial fluid, synovium and so on, as shown in Fig. 1(a). As the synovial fluid filling the clearance between two cartilages has lower density than that of bones, more near-infrared lights can penetrate the clearance [26]. Thus a brighter region, corresponding to the distal inter-phalangeal joint, can be found in finger vein image, as shown in Fig. 1(b).

The calculation procedure of the width measurement is described in detail. (In the session we will use an image in

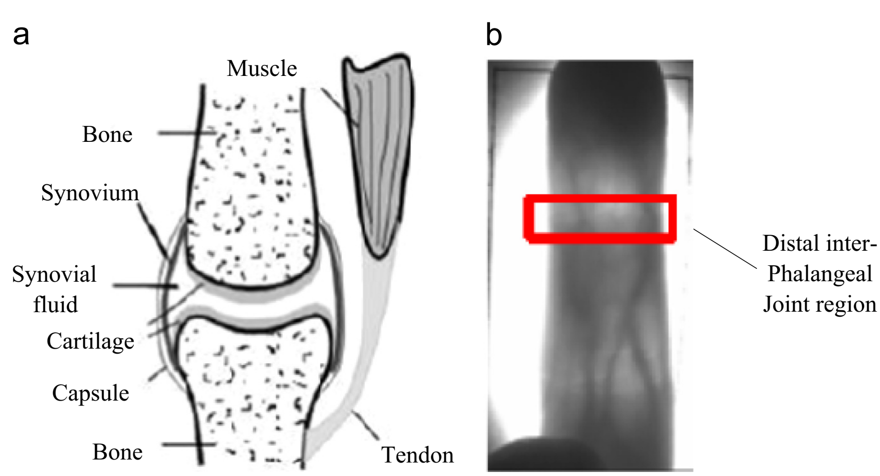

Fig. 1. Phalangeal joint. (a) Structure of a phalangeal joint.; (b) Distal inter-phalangeal joint region in finger vein image.

the open database as an example to describe the calculation procedure.)

(1) Obtain the candidate region. A predefined window with 410×256 pixels is used to crop the original finger vein image to get the candidate region. In this process, we stick to one principle, i.e., removing as much noises and useless informations as possible, at the same time, reserving the right and left boundaries of finger. The red predefined window is shown in Fig. 2(a).
(2) Detect the finger boundaries. The Sobel operator in the vertical direction is applied in the candidate region to detect the finger boundaries. As there are some isolated and loosely connected regions and the broken finger boundaries in the low quality finger vein images from the open database, so denoising and finger boundary estimation are also conducted as [5]. For images in our database, finger boundary estimation can be ignored. The resulting binary finger boundary image is shown in Fig. 2(b).
(3) Detect and correct the rotated images. As imperfect finger placement in image acquisition, there are a number of rotated finger vein images in two databases we used, in which the finger shows a certain tilt angle as shown in Fig. 2(a). Therefore, our former work about rotated image detection and correction [27] is used. Fig. 2(c) shows the corrected finger vein image.
(4) Estimate the position of the distal inter-phalangeal joint. First, we can obtain the key region by cropping the area outside the internal tangents of finger boundaries. In Fig. 2(d), the red lines are the internal tangents of finger boundaries, and the region between two red lines denotes the key region. Then, the sum of pixel value at each row is calculated in the key region by the following equation:

$$S_i = \sum_{j=1}^{w} I(i,j) \quad i = 1, 2, \ldots, h \tag{1}$$

where w and h respectively represent the width and the height of the key region. Last we use Eq. (2) to determine the position of the distal inter-phalangeal joint, which is denoted by r and shown in Fig. 2(e).

$$r = \arg\max(S_i) \quad i = 1, 2, \ldots, h \tag{2}$$

(5) Calculate the width of the distal inter-phalangeal joint. We search the rth row in the corrected finger boundaries image to find two points with pixel value 1, and the width measurement is equal to the horizontal distance between the two points.

3. Finger vein recognition frameworks with soft biometric trait

The survey in session 2.1 suggests that, there are two main usages of soft biometric trait. On one hand, soft biometric trait can be fused with the primary biometric trait to promote the recognition performance. On other hand, the retrieval performance can be also promoted by soft biometric trait. Besides, Wayman proposed other usages of soft biometric traits like gender and age, i.e., filtering a large biometrics database, in which filtering implied using these characteristics of the interacting user to limit the number of matching in recognition [28]. For example, if the user can somehow be identified as a young female, only the enrolled users with this profile will be matched. As users with different profiles can be confidently rejected, filtering has great advantage in the improvement of matching speed.

In this paper, we propose three frameworks to explore the usages of soft biometric trait in finger vein recognition, i.e., the fusion framework, the filter framework and the hybrid framework of filter and fusion. In fusion framework, the simple and effective weighted sum rule-based score level fusion is used to integrate soft biometric trait with finger vein pattern. However, in filter framework, soft biometric trait is employed to filter the specific imposter user, whose soft biometric trait has big difference with that of the enrolled user. We combine filter framework and fusion framework in hybrid framework. In above frameworks, the width measurement is used as soft biometric trait to supplement finger vein pattern. Although we show the frameworks only in the case of one soft biometric trait, it can be easily generalized to other soft biometric traits.

The first described framework is associated with fusion, which is shown in Fig. 3. In this framework, soft biometric trait and primary biometric trait are both first extracted for an image, and then the width measurement matching score and finger vein matching score are separately calculated. Last we use the weighted

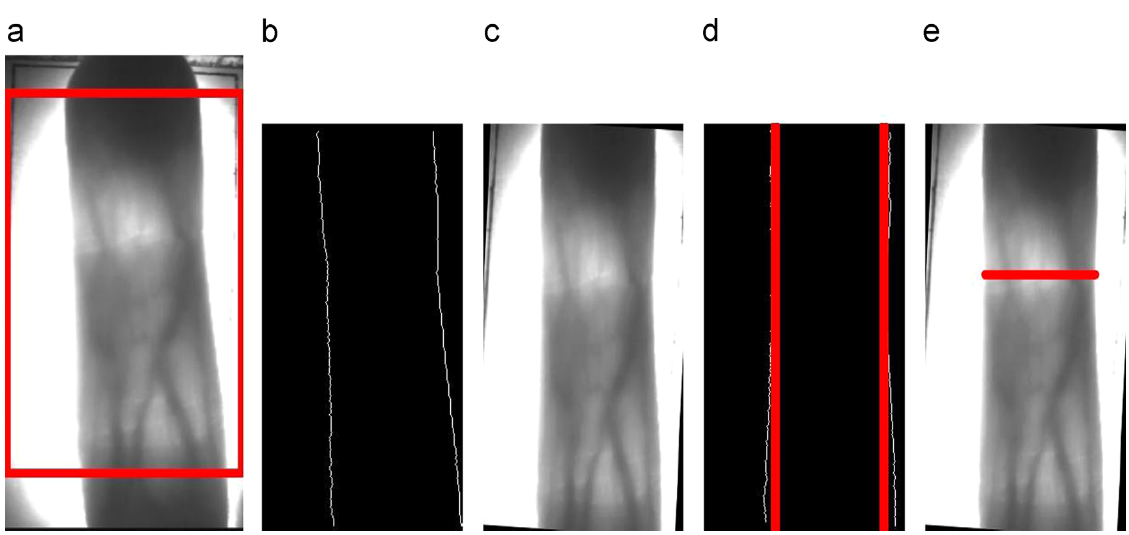

Fig. 2. Extraction of the width measurement. (a) Candidate region in red window; (b) finger boundaries; (c) corrected images; (d) corrected finger boundaries with internal tangents; and (e) position of the distal inter-phalangeal joint. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

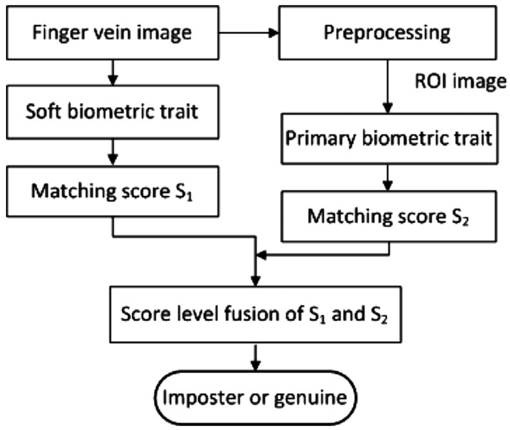

Fig. 3. Fusion framework.

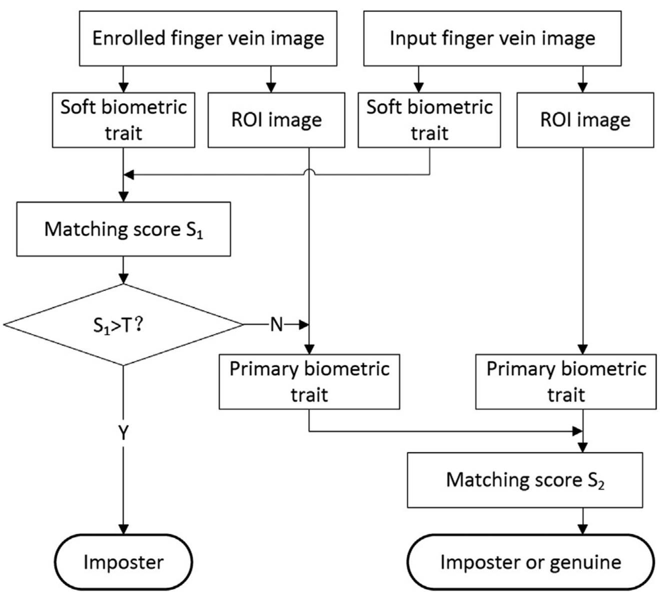

Fig. 4. Filter framework.

sum rule to fuse two matching scores. The score level fusion is chosen since the superiorities of score level fusion is easily available for matching scores and has sufficient information to discriminate genuine and imposter users. Besides, the weighted sum rule is used frequently in literatures and can achieve good performance in general.

Next, the filter framework is presented in detail, illustrated in Fig. 4. Filter implies that the number of searched entries in database will be restricted based on soft biometric trait of the interacting user. More specifically, in our filter framework, if the width measurement matching score is greater than the predefined threshold, the interacting user will be rejected as an imposter user, and identity recognition comes to an end. Otherwise, it is not clear whether the user is an imposter or a genuine user, so identity recognition will be continued using primary biometric trait, i.e., finger vein pattern. We define the max intra-class score of width measurement matching as the filter threshold. So the filter will not cause the false rejection for genuine users, at the same time, for imposter users with matching score more than the threshold, we can confidently reject them to end the recognition. There are two benefits of this framework. (1) Facilitating a fast recognition process by narrowing down the identity-related search space. (2) To some extent, enhancing the recognition accuracy by reducing the false acceptance rate.

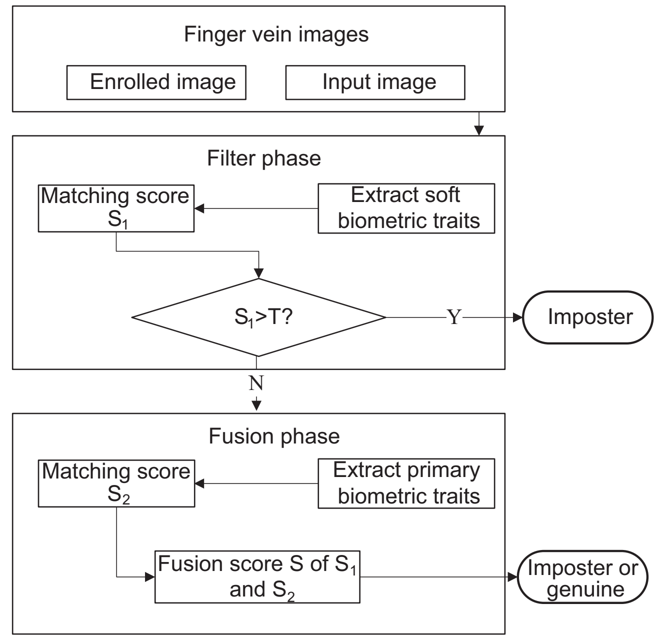

Fig. 5. Hybrid framework.

Last, the most important framework is shown in this session, which is the hybrid framework, including two phases, i.e., filter and fusion phases, illustrated in Fig. 5. In the first phase of hybrid framework, we see the user with width measurement matching score greater than the predefined threshold as an imposter user, which is the same as filter framework. Although the filter framework has advantages in the recognition speed and accuracy, it is a pity that the width measurement matching scores are only used to determine whether a user is an imposter user. Based on filter, we further develop another usage of soft biometric trait, i.e., fusion, in the hybrid framework. It should be noted that fusion in hybrid framework has a difference in the number of involved users within the fusion framework. In detail, in fusion framework, fusion is performed for all users; however, only for the remainder users after filter, we perform fusion in the second phase of the hybrid framework.

In these frameworks, the width measurement is extracted by the approach presented in session 2.3, and the corresponding matching score consists in the normalized absolute difference between the enrolled width measurement and the extracted one. Here, the well-known min–max normalization method is used to map the raw matching scores to the interval [0, 1]. For finger vein pattern, we first perform preprocessing for finger vein image, which mainly covers finger boundary detection, skewed image detection and correction, region of interest (ROI) segmentation and image size normalization [11,27]. And then finger vein feature is extracted from the preprocessed ROI image by LBP operator. Last, the finger vein matching score is calculated by the hamming distance (HD) between the enrolled and extracted codes. As the HD is in the interval [0, 1], we do not perform normalization for the finger vein matching scores.

4. Databases and experiments

4.1. The experimental databases

We use the open finger vein database [5] and our self-built finger vein database to comprehensively evaluate the proposed frameworks. The open database consists of 3132 finger vein

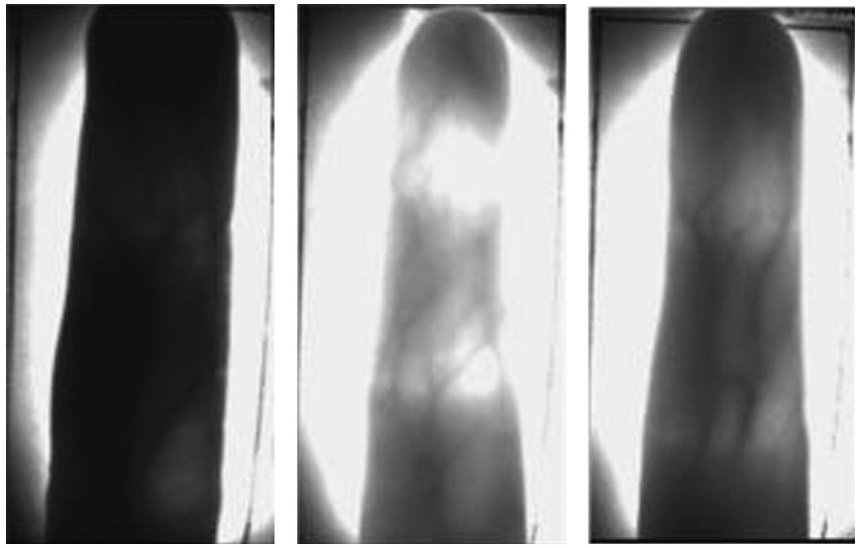

Fig. 6. Typical finger vein images in the open database.

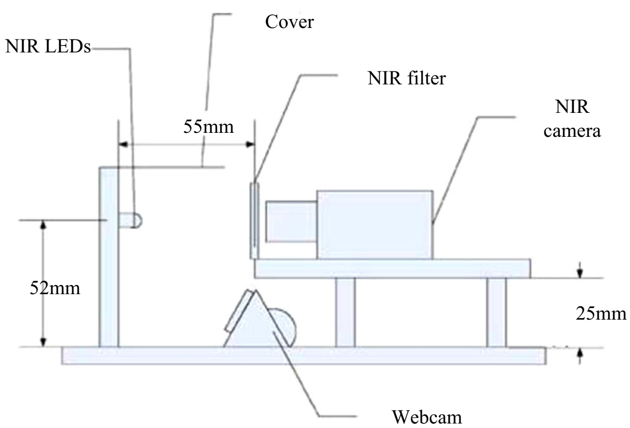

Fig. 7. Imaging device of the open database.

images taken from 156 volunteers in two separate sessions with the average interval of 66.8 days. For each subject, six finger vein images and six finger texture images are captured from the index and middle fingers of the left hand in each session. The typical finger vein images are shown in Fig. 6, and the imaging device is shown in Fig. 7. Finger vein image and finger texture image can be captured simultaneously by the device, but we only use finger vein image. As only 105 volunteers turned up for the imaging during the second session, for each of these volunteers there are 12 images of each finger, but for the others, there are only six images of each finger. So, in our experiment, we use 1872 images from all volunteers with six images of each finger.

There are 2720 finger vein images in our self-built finger vein database, which are collected from 34 volunteers, including 20 males and 14 females, in two separate sessions with the interval of 20 days. Each volunteer is asked to provide 20 images for each of the index and middle fingers on the both hands. Some typical images are shown in Fig. 8. The finger vein images are captured by a device manufactured by the Joint Lab for Intelligent Computing and Intelligent System of Wuhan University, China, which mainly consists of a near-infrared light source, lens, light filter, and image capture equipment, as shown in Fig. 9.

Three experiments are performed on two databases to evaluate the effectiveness of the proposed frameworks. The distinctiveness of soft biometric trait we used is analyzed in the first experiment in session 4.2. The second experiment in session 4.3 is designed to verify the enhanced finger vein recognition performance of the proposed frameworks, and compare the performance of three frameworks to determine the best one. In the last experiment in session 4.4, we discuss the effect of variation in filter threshold on the performance of the filter and hybrid frameworks.

In order to reduce the difference in the numbers of intra-class and inter-class matchings, all six images per finger in the open database are used for intra-class matching and the first two images per finger are used for inter-class matching in three experiments, totally including 4680 $(312 \times 6 \times 5/2)$ intra-class matchings and 194,064 $(312 \times 311 \times 2)$ inter-class matchings. In the self-built database, we separately use first 12 images per finger and first four images for intra-class and inter-class matchings, totally including 8976 $(136 \times 12 \times 11/2)$ intra-class matchings and 146,880 $((136 \times 135/2) \times 4 \times 4)$ inter-class matchings. The equal error rate (EER), false acceptance rate (FAR) and false rejection rate (FRR) are used to evaluate the performance of the recognition system, which are the most common benchmarks in biometrics. In addition, it is important to note that we regard one finger as a single user to perform experiments. For example, there are 136 fingers of 34 volunteers in the self-built database, but 136 fingers are seen as 136 different users in our experiments.

4.2. Performance of soft biometric trait

As we know, although the soft biometric trait cannot be individually used to perform identity recognition, it should have certain distinctiveness to support primary biometric recognition. In this experiment, the distinctiveness of the width measurement will be tested on two databases. Some typical finger vein images with different width measurements are first shown in Fig. 10, in which the red line marks the position of the distal inter-phalangeal joint. The ROC curves are then shown in Fig. 11, and the corresponding EERs, FRRs with different FARs are listed in Table 1. The max raw intra-class scores of width measurement matchings (the following abbreviations for Max Score), i.e., 13 on the open database and 8 on the self-built database, will be used as the filter threshold in the next two experiments.

From Fig. 10, we can see that, the width measurements are obviously different in these typical images. From the experimental results in Fig. 11 and Table 1, we can see that the EERs of 10.34% and 16.50% are achieved by the width measurement on the self-

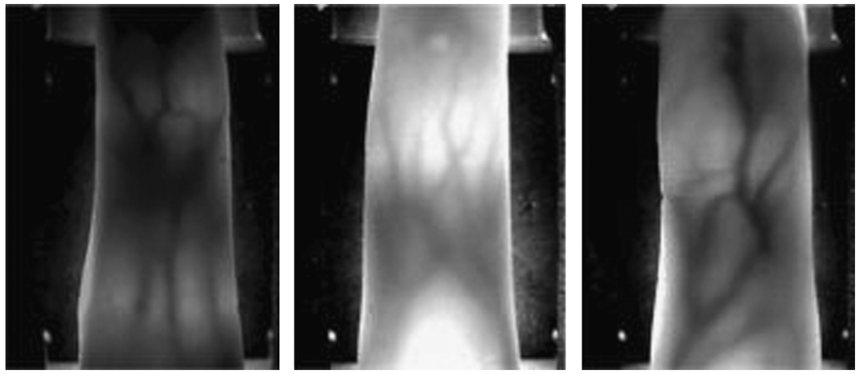

Fig. 8. Typical finger vein images in the self-built database.

Fig. 9. Imaging device of the self-built database.

built and open databases, respectively. As FAR increases from 1% to 10%, the FRR sharply descends. When the FAR is equal to 10%, we can obtain the FRRs of 7.64% and 25.31%. Besides, the width measurement performs better on the self-built database than on the open database. The main reason is that large intra-class variation of finger vein image in the open database deteriorates the performance of the width measurement. Nevertheless, it can be concluded that (1) the recognition system only using soft biometric trait cannot be used in practical application; and (2) the width measurement possesses some distinctiveness, and can be used as soft biometric trait to assist finger vein recognition.

4.3. *Performance of frameworks*

In this experiment, we will verify whether the width measurement can enhance the finger vein recognition performance, and discuss how the width measurement assist finger vein in the proposed frameworks. Besides, we will comprehensively analyze the performance of the proposed frameworks to determine which framework outperforms best in recognition accuracy and speed. The set of weights in fusion is chosen with the best performance of system, which is listed in Table 2. The filter thresholds on the open and self-built databases respectively are 13 and 8, which will be used in the filter and hybrid frameworks. The performance of framework is compared with that of finger vein in Figs. 12 and 13, which are respectively from the open and self-built databases. The corresponding EERs and FRRs with different FARs are listed in Tables 3 and 4.

As can be seen from the experimental results, all three frameworks perform better than separate finger vein, which suggests the advantage of the width measurement in enhancing the finger vein recognition performance. In fusion framework, as finger vein pattern and the width measurement are fused for all users, the distinctiveness of each use is improved, which makes the performance of this framework better. However, the reason of achieving better performance in filter framework is different from it in the fusion framework. As there is no ancillary information added to finger vein, the distinctiveness of each user is unchanged in filter framework. The main reason lies in the fact that filter framework reduce the FAR to further improve the overall performance. In detail, user with the width measurement matching score greater than the predefined threshold will be rejected as imposter user in filter framework, so this kind of user will not be falsely accepted even if they have similar finger vein pattern with the enrolled user. For the hybrid framework, filter in first phase decreases the FAR by rejecting a portion of imposter users like the filter framework, and fusion in second phase supplements the ancillary information for the remainder users like the fusion framework, which are two main factors of better experimental results.

The experimental results also imply that the hybrid framework achieves best performance in all three frameworks. Compared with the filter framework, the preferable performance of the hybrid framework can be mainly attributed to the fact that fusion enriches user′s information in second phase, as filter in the first phase of the hybrid framework is the same as it in the filter framework. In addition, compared with the fusion framework, the filter framework also does not perform well in the EERs, but the filter framework has advantage in the recognition speed. By filtering, there are 102,047 inter-class matchings to be reduced in finger vein recognition on the open database, which holds approximately 52.58% of all inter-class matchings. Correspondingly, the number and ratio are respectively 84,582 and 57.59% on the self-built database. The hybrid framework achieves nearly identical performance with the fusion framework in the EERs, but the same as the filter framework, filter in the hybrid framework also avoids a large number of inter-class matchings, which facilitates a fast recognition process. In one word, the hybrid framework can enhance the recognition performance, at the same time, improve the recognition speed.

Like the first experiment, the overall performance on the open database is also worse than it on the self-built database in this experiment. It is potentially caused by the relatively larger intra-class variations in unstrained imaging for the open database. It can be seen that there is a groove in our imaging device in Fig. 9, which is a guide for finger placement. Fig. 14 shows some typical images with large intra-class variation in the open database. Besides, we do not perform additional image enhancement processing for images from the open database. However, the relatively larger intra-class does not influence the assistant function of soft

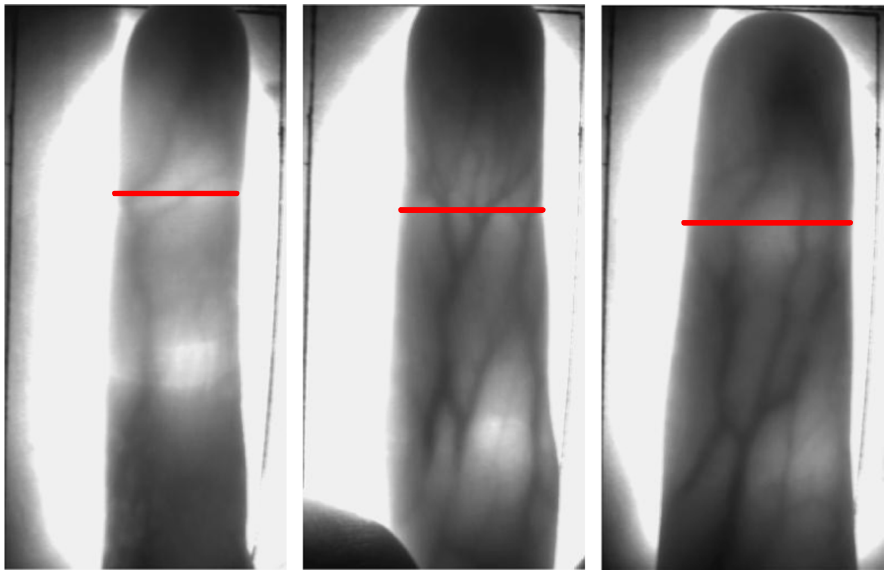

Fig. 10. Typical finger vein images with different width measurements from the open database. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

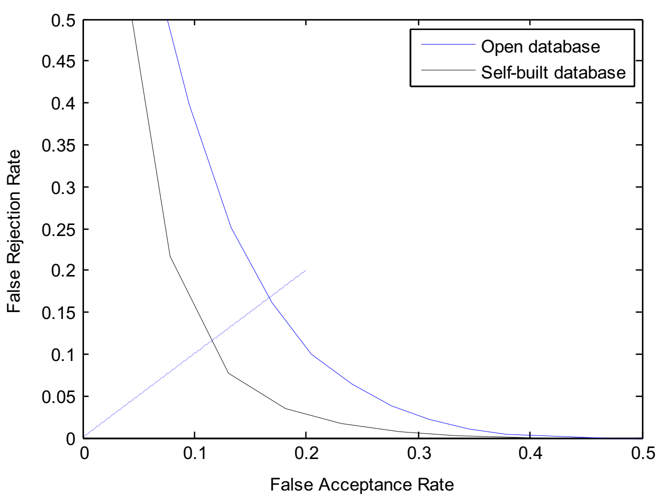

Fig. 11. ROC curves of the width measurement on two databases.

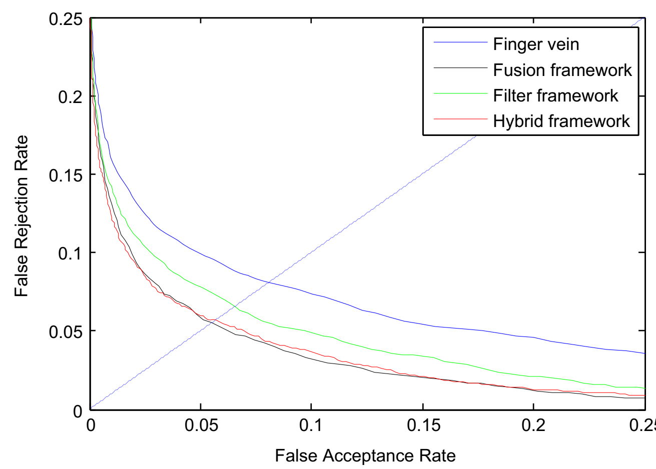

Fig. 12. ROC curves of finger vein and frameworks on the open database.

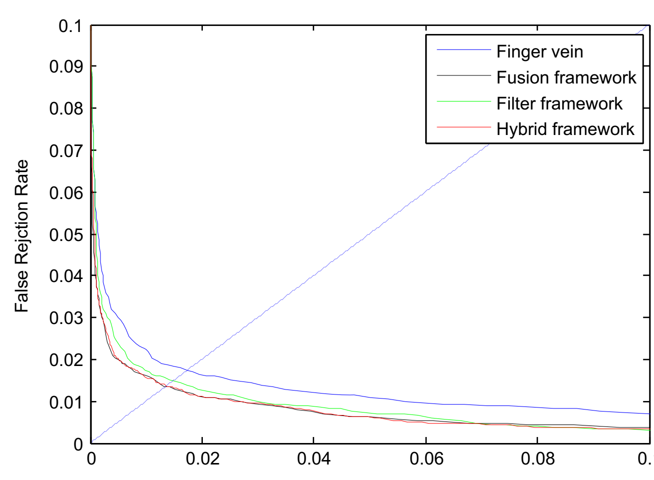

Fig. 13. ROC curves of finger vein and frameworks on the self-built database.

Table 1
Verification performance of the width measurement on two databases.

Database	EER (%)	FRR (FAR = 1%) (%)	FRR (FAR = 10%) (%)
The open	16.50	86.50%	25.31%
The self-built	10.34	64.38%	7.64%

Table 2
Weight values in fusion.

Database	Fusion framework		Hybrid framework	
	Weight of vein	Weight of width	Weight of vein	Weight of width
The open	0.65	0.35	0.9	0.1
The self-built	0.8	0.2	0.95	0.05

biometric trait, and the recognition performance on the open database is enhanced in the proposed frameworks, which is the same as the self-built database.

4.4. Performance of different filter thresholds

In the proposed frameworks, there are two varying influence factors: the fusion weight and the filter threshold. As it is common that the weight is set as the empirical value like [22], we empirically set the weight in fusion to obtain the best recognition performance in frameworks. In this experiment, we will especially focus on the setting of the filter threshold. Taking it into consideration that the main purpose of filter is to confidently reject the imposter to narrow down the number of matching, the Max Score is used as the filter threshold in Experiment 4.3. In order to discuss the effect of filter threshold variation on the recognition performance, we try some other typical filter thresholds, which are more or less than the Max Score. The experimental results of different thresholds on two databases are respectively presented in Tables 5 and 6, and Figs. 15 and 16 illustrate the corresponding variation trend of EERs. Although the width measurement matching scores are normalized into [0, 1] in fusion, in order to intuitively display the width difference, the filter threshold we used is the raw score in width measurement matching.

The experimental results summarized in Tables 5 and 6 and Figs. 15 and 16 suggest that, when the Max Score is set as the filter threshold, the EER value is lower than those of other thresholds on the whole, and the number of reduced matchings is very impressive. If the filter threshold is less than the Max Score, more imposter users will be rejected by filter, but it is inevitable that some genuine users will be falsely rejected. It means that filter not only reduces the FAR, but also increases the FRR. In contrast, when the filter threshold is more than the Max Score, less imposter users will be rejected, and there is no effect on the genuine users. In other word, only the FAR will be reduced by filter. And the performance of hybrid framework is persistently better than it of the filter framework, which shows the advantage of hybrid framework in recognition performance. In addition, a large part of intra-class scores are less than 5 in width measurement matching, but the Max Score of two databases are 13 and 8 respectively. The main reason of this phenomenon is the variations in capturing distance, finger rotation and blending in image acquisition, which can lead to different widths of phalangeal joint in different images of one user.

Table 3
Verification performance of finger vein and frameworks on the open database.

Framework	EER (%)	FRR (FAR=0.1%)	FRR (FAR=1%)	FRR (FAR=10%)
Finger vein	8.08	24.42%	15.64%	7.35%
Fusion	5.53	22.71%	12.50%	3.16%
Filter	6.56	23.23%	13.76%	4.89%
Hybrid	5.66	21.82%	12.07%	3.61%

Table 4
Verification performance of finger vein and frameworks on the self-built database.

Framework	EER (%)	FRR (FAR=0.1%)	FRR (FAR=1%)	FRR (FAR=10%)
Finger vein	1.74	5.51%	2.18%	0.71%
Fusion	1.35	3.89%	1.56%	0.38%
Filter	1.49	5.05%	1.72%	0.32%
Hybrid	1.37	4.03%	1.55%	0.33%

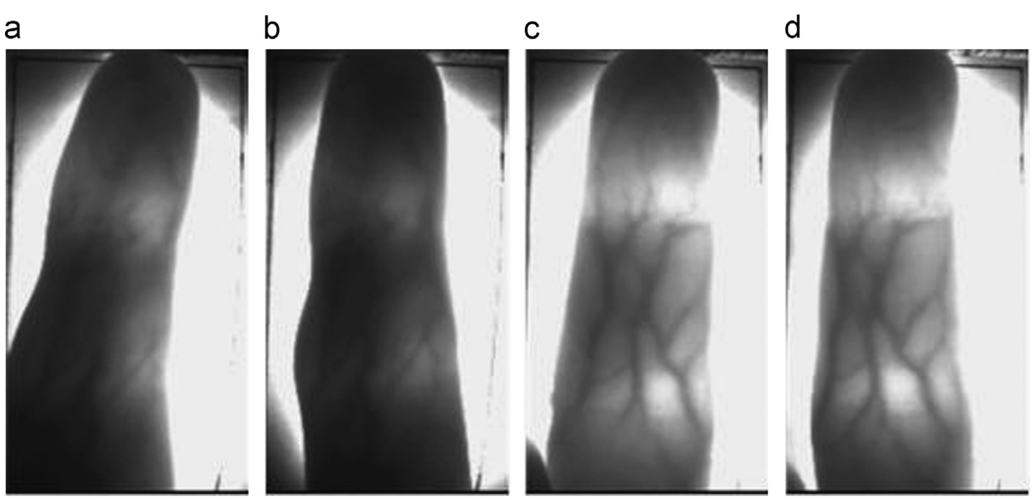

Fig. 14. Images with large intra-class variation from the open database. The first two images are from one user, and the last two images are from another user.

Table 5
Verification performance of different thresholds on the open database.

Threshold	EER		Number of reduced matching (ratio)	
	Filter framework (%)	Hybrid framework (%)	Intra-class	Inter-class
7	7.49	7.36	182 (3.89%)	140,562 (72.43%)
9	6.31	5.97	50 (1.07%)	127,084 (65.49%)
11	6.27	5.70	9 (0.19%)	114,175 (58.83%)
13[a]	6.56	5.66	0 (0)	102,047 (52.58%)
15	6.92	5.70	0 (0)	90,646 (46.71%)
17	7.19	5.80	0 (0)	79,929 (41.19%)

[a] The threshold 13 is the Max Score.

Table 6
Verification performance of different thresholds on the self-built database.

Threshold	EER		Number of reduced matching (ratio)	
	Filter framework (%)	Hybrid framework (%)	Intra-class	Inter-class
4	2.28	2.27	154 (1.72%)	112,900 (76.87%)
6	1.54	1.46	19 (0.21%)	97,782 (66.57%)
8[a]	1.49	1.37	0 (0)	84,582 (57.59%)
10	1.54	1.41	0 (0)	72,290 (49.22%)
12	1.59	1.44	0 (0)	60,400 (41.12%)
14	1.62	1.45	0 (0)	50,532 (34.40%)

[a] The threshold 8 is the Max Score.

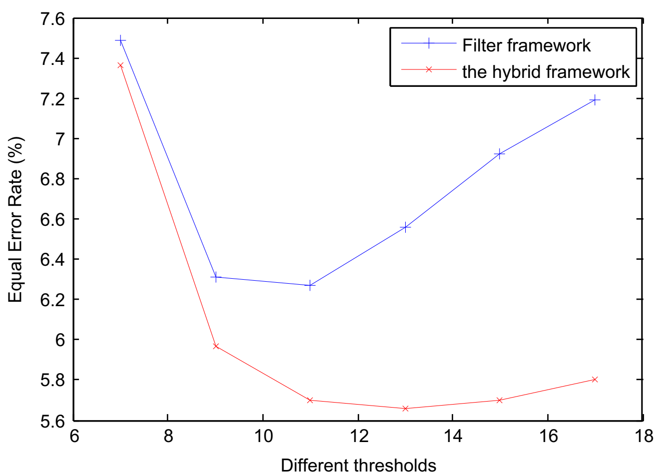

Fig. 15. EER values of different thresholds on the open database.

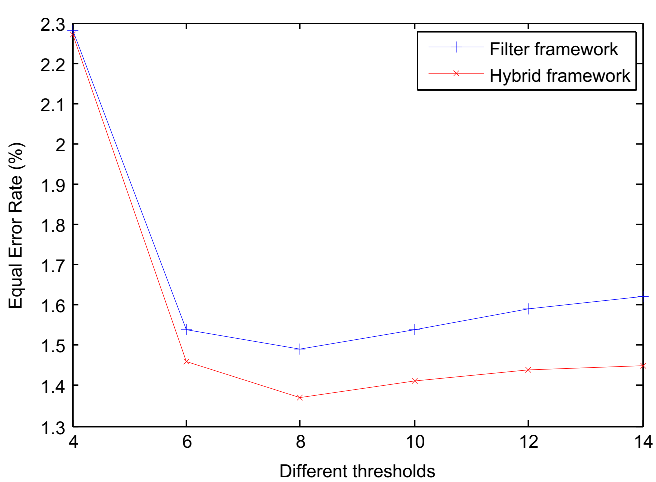

Fig. 16. EER values of different thresholds on the self-built database.

Taking a good look at Table 5 and Fig. 15, when we use 9 and 11 as the filter thresholds, the system performance is a little better than the filter threshold of 13. With the filter threshold of 13, only the number of inter-class matchings will be decreased in finger vein recognition, and there is no effect on intra-class matching. When we choose 9 and 11 as the filter thresholds, some genuine users are falsely rejected as imposter users, but compared with the falsely rejected genuine users, there are more correctly filtered imposter users. That is to say, the increase range of FRR is smaller than the decrease range of FAR. So the overall performance is slightly improved.

Besides, from Table 5 and Fig. 15, we also perceive that the performance variation trends of the two frameworks are different, i.e., the best performance of the filter framework is achieved with the filter threshold of 11, but the corresponding filter threshold of the hybrid framework is 13. It is possibly because that the performance of the hybrid framework does not depend on the filter phase merely, but depends on the combination of filter and fusion phases. As the increase of the filter threshold in the hybrid framework, more users will be involved into the fusion phase, at the same time less users will be rejected as imposters in filter phase. In hybrid framework, compared with 11, when 13 is set as the filter threshold, more users will be involved into the fusion phase, and the better performance is achieved, which indicates that fusion contributes more to the performance than filter in this case. Based on these analyses, it is normal that the best performance of the filter and hybrid framework will be achieved at different filter thresholds.

The two above observations from Table 5 and Fig. 15 show that, the performance of two frameworks fluctuates in local scale. However, in this paper, we prefer the max intra-class score in width measurement matching as the filter threshold rejects the imposter users with absolute certainty.

5. Conclusion

To the best of our knowledge, this paper presents the first study on the usage of soft biometric trait in finger vein recognition. The main works of this paper are the following: First, we classify soft biometric traits into three categories based on the dependence of these traits on primary biometric traits. Second, some extraction criteria of soft biometric trait are presented to define the good soft biometric trait, which can easily be extracted and effectively assist primary biometric trait. Third, based on comprehensive analysis of the presented criteria and thorough research of finger vein image, the width of phalangeal joint in finger is used as soft biometric trait to assist finger vein recognition. Finally, in order to effectively use the proposed soft biometric trait, three frameworks are developed to incorporate the soft biometric trait with finger vein, which can be easily generalized to other biometrics such as face, fingerprint, etc.. The experimental results show that all three frameworks outperform separate finger vein trait, and the hybrid framework performs best.

However, the stability of soft biometric trait extracted directly from images should be explored further, as the measurement of soft biometric trait depends on the scale of the image, which is related to image acquisition device. The width of phalangeal joint we used also depends on the scale of the image. But considering that each existing finger vein database is captured by single device, and the scale of images in one database is uniform, we use the width of phalangeal as soft biometric trait in this paper and experiments prove its effectiveness.

Besides, soft biometric trait in the proposed frameworks is only exemplified by the width measurement. In the future, we will focus on the design of more effective soft biometric traits. As focusing on the soft biometric trait, LBP operator is used to extract finger vein feature, the combination of soft biometric trait and other finger vein feature is another future research work.

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