Feature-Level Fusion of Finger Veins and Finger Dorsal Texture for Personal Authentication Based on Orientation Selection

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SUMMARY This study proposes a feature-level fusion method that uses finger veins (FVs) and finger dorsal texture (FDT) for personal authentication based on orientation selection (OS). The orientation codes obtained by the filters correspond to different parts of an image (foreground or background) and thus different orientations offer different levels of discrimination performance. We have conducted an orientation component analysis on both FVs and FDT. Based on the analysis, an OS scheme is devised which combines the discriminative orientation features of both modalities. Our experiments demonstrate the effectiveness of the proposed method. *key words: feature-level fusion, finger vein, finger dorsal texture, orientation selection*

1. Introduction

LETTER

In recent years, many efforts have been made to increase the authentication of finger-based biometrics authentication. The small size and flexibility of fingers make it easy to capture and process the data required [1]. Among the various finger-based biometrics, finger veins (FVs) and finger dorsal texture (FDT) are two promising modalities. They have unique characteristics in terms of realizing highly secure recognition systems. The FV pattern is underneath the skin and thus extremely difficult to forge [2]. The FDT resists abrasion since people usually hold items with the inner side of the hand [3].

The competitive coding scheme [4] has been widely utilized in the feature extraction of biometrics system. Competitive codes obtained by a bank of Gabor filters represent local dominant orientations, which contain more discriminative power than other features. The results of intuitive visual and quantitative experiments demonstrate that these orientations offer different levels of discrimination performance. Vein blood vessels are mainly spread out along the fingers while dorsal texture and creases exist mostly perpendicular to the direction of the finger. The two modalities have different but complementary orientation features. For this reason, we have designed a strategy called "orientation selection (OS)" to fuse the two modalities at the feature level.

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Compared with existing fusion methods, the OS method has the following advantages. First, OS is a feature-level fusion method which can preserve the discriminability of different modalities as well as eliminate some of the redundant information. Second, OS is based on the orientation codes generated by competitive coding. Therefore, the potential incompatibility of feature spaces does not need to be taken into account [6], [7]. Finally, the most discriminative orientation features are preserved, which can ensure that the overall performance of a recognition system is adequate.

2. Image Acquisition

Figure 1 shows our special imaging device which can simultaneously capture FVs and FDT images. White lightemitting diodes (LEDs) are shone onto the outside of the finger to highlight the dorsal texture. Subsequently, the camera (JSP MODEL: DF-2112) on the top captures the FDT image. As for FVs imaging, transmitted infrared light (wavelength of 890 nm) penetrates both sides of the finger and passes through an infrared high-pass filter (cutoff wavelength of 850 nm). Finally, the camera on the bottom collects the remaining amount of light and records the FVs image. During the imaging period, the volunteer is asked to place his/her finger across the plate hole. Figure 2 shows the captured raw images of FVs and FDT. The size of both images is 720×576 pixels and the resolution is 96 dots per inch (dpi). A database of the raw images can be downloaded from [10].



Fig. 1 Proposed multimodal biometric acquisition device.



Fig. 2 Raw images.

Fig. 3 (a) *FVimage*. (b) *FVcode*. (c) vertical direction of *FVcode*. (d) *FDTimage*. (e) *FDTcode*. (f) horizontal direction of *FDTcode*. (g) *OS code*.

3. Orientation Component Analysis

Figures 3 (a) and (d) are the FVs and FDT images after size and intensity normalization [9]. The size of both images is 200×100 pixels. Figures 3 (b) and (e) show the feature maps after comparative coding while (c) and (f) depict the corresponding dominant directions. The fused feature map after applying the proposed OS scheme is shown in Fig. 3 (g).

A visual inspection shows that the vein vessels are spread out along the finger while the FDT is found across the finger. This indicates that not all of the orientations are equally discriminative. To quantitatively investigate the dominant orientation information, we classified the orientation codes obtained by competitive coding into two categories: vertical and horizontal directions. The orientation codes that range from 0 to 5 represent 6 different orientations. We grouped $\{0, 1, 5\}$ as belonging to the vertical direction and $\{2, 3, 4\}$ as belonging to the horizontal direction.

The vertical direction codes in the feature map of the FVs mainly correspond to the locations where vein vessels exist. On the contrary, the horizontal direction codes of the FVs are mainly caused by background areas, which carry little discriminative information and are susceptible to irregular shading and noise. Similarly, the horizontal direction codes of the FDT image represent the texture and creases while the vertical direction codes are resulted of the background area.

In conclusion, the foreground codes (vertical direction in the FVs and horizontal direction in the FDT image) carry almost all of the discriminative information that can separately indentify individuals. Obviously, we can improve the system performance through the following strategies: maximize the effect of the foreground codes and minimize the effect of the background.

4. Fusion Strategy

From the above analysis, we found that it is fundamental to select and consolidate the discriminative orientation features from the two modalities to perform further recognition. Several advantages contribute to combining the two modalities. First, there is a strong mutual correlation between the FVs and FDT when they come from the same finger. Second, the FDT images are rich in crease and texture, which make them an excellent supplement to line-like features.

The OS scheme is designed to fulfill feature-level fusion. On the one hand, OS retains the vertical components of the FVs image as the dominative feature. On the other hand, it replaces the background areas of the FVs image with the corresponding areas of the FDT image. The details of the OS scheme is shown in Algorithm 1.

Algorithm 1 OS fusion scheme.
Input FVimage,FDTimage
Output OS code
for all $FVcode(x, y)$, $FDTcode(x, y)$ do
$FVcode(x, y) = \arg\min_{i} \{FVimage(x, y) * G(x, y, \theta_j)\};$
$FDTcode(x, y) = \arg\min_{i} \{FDTimage(x, y) * G(x, y, \theta_j)\};$
% G : Gabor filter [8]
$\% \theta$: orientation parameter, $\theta = j\pi/6$, $j = \{0, \dots, 5\}$
end for
for all $OS code(x, y)$ do
if $FVcode(x, y) \in \{0, 1, 5\}$ then
OS code(x, y) = FV code(x, y);
else
OS code(x, y) = FDT code(x, y);
end if
end for

5. Matching

Suppose *P* and *Q* are the registered and input fused feature maps respectively. The ratio R(P, Q) is defined as the similarity between *P* and *Q*. P(x, y) and Q(x, y) are assumed to match if they are equal. *R* represents the ratio of the matched pixels to the total pixels in the fused feature map.

$$R(P,Q) = \frac{\sum_{x=1}^{m} \sum_{y=1}^{n} \phi(P(x,y), Q(x,y))}{S}$$
(1)

where $S = m \times n$ denotes the area of the code map, and m and n represent the width and height of the fused feature map, respectively.

$$\phi(P(x,y),Q(x,y)) = \begin{cases} 1 & if \ P(x,y) = Q(x,y) \\ 0 & otherwise. \end{cases}$$
(2)

In taking into account the possible displacement between P and Q, translation and rotation adjustments were performed. The horizontal and the vertical translations were set as -15

Table 1EER comparison.





Fig. 4 ROC curves of different methods.

to 15 pixels. The range of the rotation adjustment was -5° to 5° . After obtaining multiple similarities for the above adjustments, we chose the largest one as the final result.

6. Experimental Results

To evaluate the proposed fusion method, we extended the database from our previous work [9]. The database can be downloaded from [10] for academic purposes. The contents of the database were collected from 220 volunteers in two separate sessions with an interval of about dozens of seconds. In each session, each subject was asked to provide 1 *FVs* image and 1 *FDT* image of the same finger. In this way, the numbers of genuine and imposter matchings are 220 and 48,180 (220×219) respectively.

The proposed fusion scheme was compared with single modality methods, *FVcode* and *FDTcode*, as well as fusion methods, such as that in our previous work (Yang [9]), and sum fusion (score-level fusion). The equal error rate (EERs) for each method are presented in Table 1 for comparison purposes. Furthermore, the receiver operating characteristic (ROC) curves are shown in Fig. 4 which were used to evaluate the verification accuracy.

The results in Table 1 and Fig. 4 demonstrate that the OS fusion method outperforms the other methods. By replacing the background in the FVs with the informative area in the FDT image, OS can improve the performance of a recognition system.

7. Conclusion

In this paper, we present a new feature-level fusion method based on OS. The OS method is inspired by the orientation characteristics of FVs and FDT images. We have designed our fusion method based on the orientation code maps obtained by the competitive coding scheme. The OS method can combine the discriminative orientation information from two modalities into one code map. The experimental results show that the OS fusion method can achieve higher recognition rates and lower EERs.

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References

- A. Kumar and Y. Zhou, "Human identification using finger images," IEEE Trans. Image Process., vol.21, no.4, pp.2228–2244, 2012.
- [2] N. Miura, A. Nagasaka, and T. Miyatake, "Feature extraction of finger vein patterns based on repeated line tracking and its application to personal identification," Mach. Vis. Appl., vol.15, no.4, pp.194– 203, 2004.
- [3] L. Zhang, L. Zhang, D. Zhang, and H. Zhu, "Online finger-knuckleprint verification for personal authentication," Pattern Recognit., vol.43, no.7, pp.2560–2571, 2010.
- [4] A.W.K. Kong and D. Zhang, "Competitive coding scheme for palmprint verification," Proc. Int. Conf. on Pattern Recognition, vol.1, pp.520–523, 2004.
- [5] A. Ross and A. Jain, "Information fusion in biometrics," Pattern Recognit. Lett., vol.24, no.13, pp.2115–2125, 2003.
- [6] J. Yang and X. Zhang, "Feature-level fusion of fingerprint and finger-vein for personal identification," Pattern Recognit. Lett., vol.33, no.5, pp.623–628, 2012.
- [7] J. Wang, W. Yau, A. Suwandy, and E. Sung, "Person recognition by fusing palmprint and palm vein images based on Laplacianpalm representation," Pattern Recognit., vol.41, pp.1514–1527, 2008.
- [8] Lee, Tai Sing, "Image representation using 2D Gabor wavelets," IEEE Trans. Pattern Anal. Mach. Intell., vol.18, no.10, pp.959–971, 1996.
- [9] W. Yang, X. Yu, and Q. Liao, "Personal authentication using finger vein pattern and finger-dorsa texture fusion," ACM Int. Conf. on Multimedia (ACM Multimedia'09), pp.905–908, Oct. 2009.
- [10] Tsinghua finger-vein finger-dorsal image database, "http://www.sz. tsinghua.edu.cn/labs/vipl/thu-fvfdt.html."