Finger Vein Recognition with Superpixel-based Features

Fei Liu, Yilong Yin*, Gongping Yang, Lumei Dong, and Xiaoming Xi

School of Computer Science and Technology, Shandong University, Jinan 250101, P.R. China

lf_ff@sina.com, ylyin@sdu.edu.cn, gpyang@sdu.edu.cn, dongcomeon@gmail.com, fyzq10@126.com

Abstract

Finger veins based biometrics, as a new approach to personal identification, has received much attention in recent years. The methods based on low level feature, for instance the gray, texture of finger vein, are the mainstream, but they are usually faced with many challenges, such as sensitivity to noise and low local consistency. In fact, finger vein recognition based on high level feature representation has been proved to be a promising way to effectively overcome the above limitations and improve the system performance. Thus, in this paper, we present a novel identification framework, which utilizes superpixel-based features (SPFs) of finger vein for high level feature representation. When comparing two finger veins, the features of each pixel are firstly extracted as base attributes by traditional way. Then, after superpixel over-segmentation, the SPF of each finger vein can be obtained based on its base attributes by some statistical techniques. Lastly, a weighted spatial pyramid matching (WSPM) scheme is utilized to implement matching. Our experiments have yielded some very good results evidenced by an EER of 0.0147 on the benchmark database PolyU.

1. Introduction

The blood vessels transport blood throughout the body to sustain the metabolism, which use a network of arteries, veins, and capillaries [1]. The use of such vascular structures in the palm and finger has been investigated in the biometrics literatures [2-11] with high success. The finger vein is believed to be quite unique, even in the case of identical twins and even between the different fingers of an individual [24] and it is widely considered as a promising biometric pattern for personalized identification.

Currently, personal identification using finger veins has invited a lot of research interest and many methods have been proposed, which can roughly fall into two categories: One is based on the low level feature representation, such as the gray, texture, or shape of finger vein, called low level feature (LLF) based method [1-9]; the other is based on a higher level feature representation, called high level feature (HLF) based method [13,14].

At present, the LLF-based methods are the mainstream. In general, they could be divided into three categories according to their feature extraction rules: ROI-based methods [2-4], network-based methods [1,5-7], and minutiae-based methods [8,9]. For example, many binary local descriptors, such as Local Binary Pattern [2], Local Liner Binary Pattern [3], Local Derivative Pattern [2] and Local Directional Code [4], were presented to extract the binary codes from the whole region of interest (ROI) and usually the similarity between the extracted and enrolled binary codes is measured by Hamming distance. After image segmentation, we can obtain a finger vein network. The biometrics identification from the finger vein network using a repeated line tracking algorithm is detailed in [6] and the robustness in the extraction of finger vein network can be significantly improved with the use of local maximum curvature across the vein images and is detailed in [7] with promising results. In addition, after minutiae extraction, we can discover a finger vein minutia pattern. In [8], the minutiae features were extracted from finger vein patterns and used for geometric representation of the vein patterns' shape for biometrics identification.

Although reasonable experimental results were reported in the literatures [1-14], in practice, the LLF-based methods still have many challenges:

- It is sensitive to pixel noise to implement finger vein recognition with low level feature [14].
- Low level feature could not describe local consistency characteristic of finger vein.
- The distribution information of the vein vessel network will be neglected [13].
- Their matching algorithms (e.g. the Hamming distance) are usually sensitive to the image variation.

Thus, to solve these challenges, two finger vein recognition methods based on high level feature have been proposed in recent years. In particular, Authors in [13] proposed a region-based axis projection (RAP) technique for finger vein recognition. They first divided the vein pattern into small rectangular regions, and then concatenated the projection of the vein distribution curves on the x-axis and y-axis of each region as high level feature for finger vein recognition. Authors in [14] presented a high level feature extraction framework based on a

*Corresponding author

hyperinformation feature (HIF), and under their framework, base attribute is first defined to represent the characteristics of a certain subcategory of a subject. Then, for an image, the correlation coefficient is used for constructing the high level features, which reflects the correlation between this image and all base attributes. Their experimental results demonstrated that utilizing high level feature of finger vein for recognition is a promising way to effectively overcome the limitations of the LLF-based methods and improve their recognition performance.

But, both of them tend to partition finger vein image into rectangular grids, as shown in Figure 1(a). Obviously such windows of fixed size or shape are inconsistent with the vein pattern of images and one window may cover the vein pattern and non-vein pattern, thus it still could not describe the local consistency characteristic of finger vein carefully and could degrade the discriminability of the high level feature.

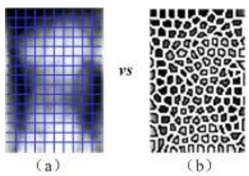

Figure 1: (a) Rectangular grid based partition vs (b) Superpixel based partition.

Recent studies showed that superpixel, as shown in Figure 1(b), has superior performance to rectangular image window for localized image processing [15,16,17]. Superpixel is a natural form of enforcing local consistency and is obtained by grouping nearby pixels. Comparing to pixel, superpixel is a bigger granularity representation of the image and can be robust to the noise in pixel level. In addition, it is high efficiency, homogeneity, and local image consistency, which can describe local consistency characteristic of images effectively. It is against this background that in this paper, we utilize superpixel-based features (SPFs) to implement the high level feature representation for finger vein recognition.

From Figure 1 we can see that, different from rectangular grid with fixed size and shape, the size and shape of the superpixel are various, which could led to the difficulty to establish the feature correspondence across pairs of images in the matching process. Therefore, it is necessary to investigate an effective matching method for SPFs. For this purpose, a weighted spatial pyramid matching scheme (WSPM), which adapted from spatial pyramid matching (SPM) scheme of Lazebnik et al. [18], was proposed. The SPM works by representing each image as a set 0of spatial pyramid histograms and using a pyramid match kernel to determine the matching score. In order to make use of the distribution information of the vein vessel network, in this paper, we made improvement of the SPM scheme by adding a weight, which is the similarity degree of the superpixel distribution features across pairs of images, to the pyramid match kernel.

In conclusion, this paper proposed a novel finger vein recognition framework that utilizes SPF based on WSPM scheme. Under this framework, when comparing the input and template finger veins, the features of each pixel are firstly extracted by traditional way as their base attributes. Then superpixel over-segmentation is implemented to generate superpixels for each finger vein. After that, the SPFs, including superpixel histogram feature and superpixel distribution feature, can be obtained based on their base attributes by using some statistical techniques. Finally, WSPM is utilized to implement image matching by representing each finger vein as a set of spatial pyramid histograms and measuring their matching score by using a weighted pyramid match kernel.

In order to demonstrate the potential of the proposed framework, we provide a case study by choosing the local descriptor LBP [2] as the corresponding base attributes. Experimental results demonstrate that the proposed framework has yielded an Equal Error Rate (EER) of just 0.0147 on the benchmark database PolyU, which not only less than the corresponding LLF-based method and most of the benchmark LLF-based methods, but also less than the existing HLF-based methods in the literatures.

2. Our method

The novel finger vein recognition framework based upon SPF is provided in the beginning of this section.

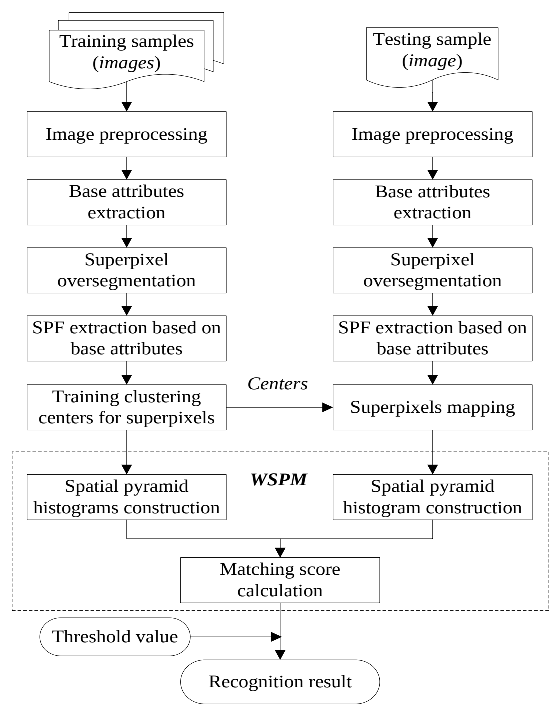

Figure 2: Overview of our finger vein recognition framework.

The overview of our framework is provided in Figure 2. It mainly involves two stages: training stage and recognition stage. The training stage aims to obtain superpixel clustering centers and generate spatial pyramid histograms for each class template. On the whole, the framework mainly includes the following procedures:

- Image preprocessing: it mainly refers to image alignment, ROI extraction, image normalization [20], and image enhancement with histogram equalization that is employed to reduce the noise and make the image intensity more uniform.
- Base attributes extraction: features of each pixel are extracted by traditional way as the base attributes for SPF extraction.
- *Superpixel over-segmentation:* Simple Linear Iterative Clustering (SLIC) method [21] is utilized to generate superpixel.
- *SPF extraction:* superpixel histogram feature and superpixel distribution feature of each finger vein image are extracted respectively based on its base attributes by some statistical techniques.
- Training clustering centers for superpixels: based on the superpixel histogram features, all the superpixels of train images are clustered into M classes by using k-means clustering algorithm so as to get clustering centers.
- Superpixels mapping: each superpixel of the test image is mapped to a closest class according to the similarity between its superpixel histogram feature and the clustering centers. Euclidean distance is used as the similarity measure.
- *Spatial pyramid histogram construction:* spatial pyramid scheme proposed in [18] is applied to represent the finger vein image as a spatial pyramid histogram.
- *Matching score calculation:* a weighted pyramid match kernel is proposed to determine the matching score based on the spatial pyramid histograms and superpixel distribution features of the input and template finger vein images.

In the following sections, four important steps in the Italic font: *superpixel over-segmentation, SPF extraction, spatial pyramid histogram construction and matching score calculating*, are descripted respectively.

2.1. Superpixel over-segmentation

Superpixel over-segmentation is a usual way to obtain superpixels. In this work, we utilize the Simple Linear Iterative Clustering (SLIC) method [21], to implement finger vein image over-segmentation so as to generate superpixel. SLIC divides an image into small patches by integrating the local intensity and position information. It only need specify one parameter of the desired number of superpixels and has low computation complexity. In practice, SLIC is an adaptation of k-means for superpixel generation with two important distinctions [21]:

- The number of distance calculations in the optimization is dramatically reduced by limiting the search space to a region proportional to the superpixel size. This reduces the complexity to be linear in the number of pixels and independent of the number of superpixels.
- A weighted distance measure combines color and spatial proximity while simultaneously providing control over the size and compactness of the superpixels.

In particular, suppose is the number of pixels in an image, and S is the desired number of superpixels. SLIC will search a limited region proportion to the superpixel size $\sqrt{S}$, where is the grid interval, a superpixel is a region of approximate size . Essentially, SLIC clusters pixels in the combined color space and image plane space based on the weighted distance measure , which is shown in eq. (1), to efficiently generate compact, nearly uniform superpixels.

where denotes color space in grayscale images and denotes the pixel's position, denotes cluster center, is the color proximity, is the space proximity, and , are the normalized factors.

The complexity of SLIC is linear in the number of pixels in the image O (n). This is because SLIC only computes distances from each cluster center to pixels within a region. This approach not only reduces distance computations but also makes complexity independent of the number of superpixels.

2.2. SPF extraction

From the perspective of collection, we view each superpixel as a set of local nearby homogenous pixels. In this section, based on the base attributes of each finger vein image, we can use SPF to implement their high level feature representation by using some statistical techniques in consideration of the following advantages:

- Many statistical techniques such as mean, variance, histogram, are simple and efficient.
- Using statistical techniques for feature extraction greatly enriches the representations of superpixel.

Based on this knowledge, in this paper, we extracted two categories of superpixel-based features: the superpixel histogram feature and the superpixel distribution feature. Their extraction process will be described respectively as follows:

At first, for each superpixel in a finger vein image, by making it as a unit, we can choose to utilize the simply histogram statistical technique to get the superpixel histogram feature based on its base attributes. An example of a 16-dimension superpixel histogram feature is shown in Figure 3.

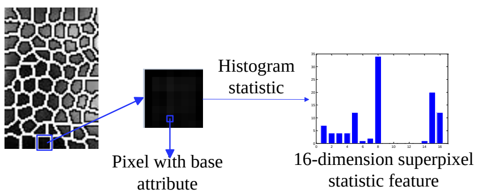

Figure 3: Example of superpixel histogram feature.

Then instead of simply making the superpixel as an independent unit, we can utilize the context information among multi superpixels to get the superpixel distribution feature in an image. In this paper, we chose to utilize the intensity variance of neighboring superpixels to represent the distribution information of the vein vessel network. The superpixel distribution feature will be used as a weight to the pyramid match kernel in the matching process.

2.3. Spatial pyramid histogram construction

In this section, we introduce the construction of the spatial pyramid histogram for each finger vein image based on its superpixels. The construction process involves partitioning the image into increasingly fine sub-regions to construct "spatial pyramid" and computing histograms of the superpixel clustering categories found inside each sub-region. In our work, we construct three-level spatial pyramid, level 0 to level 2, as shown in Figure 4.

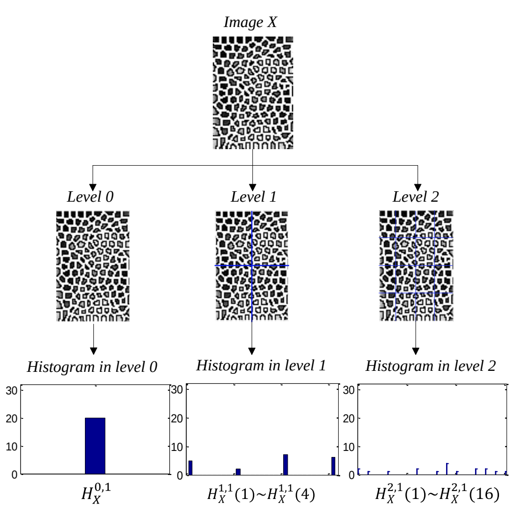

Figure 4: Example of spatial pyramid histogram construction at class 1.

Suppose X and Y are the input and template finger vein images. L is the spatial pyramid level, where in level *l*, the image is divided into T T sub-regions. For each image, after image mapping, all the superpixels were mapped into M classes. Hence, for each level and each class, we count the superpixels that fall in each spatial bin as the histograms.

Particularly, let T and T denote the numbers of superpixels of class *m* that fall into the *i*th sub-region at level *l*, so that T and T are the histograms of class *m* at level *l* in image X and Y. Obviously, for the respective images, each class gives us three spatial pyramid histograms, and all of them will be used for the matching score calculating. Figure 4 shows an example of spatial pyramid histograms construction at class 1.

2.4. Matching score calculation

In this section, we introduce the matching score calculating process using a weighted pyramid match kernel based on the spatial pyramid histograms and superpixel distribution features of the input and template finger vein images.

With an assumption that the superpixels of the same class can be matched to one another, firstly, the number of matches of superpixels of class *m* at level *l* between X and Y can be given by the histogram intersection function [19]:

$$T \quad T \qquad\qquad T \qquad T \tag{4}$$

In the following, we will abbreviate T T as T. Let and be the superpixels in X and Y with class *m*. Then, we can get the separate pyramid match kernel of class *m* by weighting each spatial pyramid histogram according to eq. (5) as follows:

$$T \quad T \quad T \tag{5}$$

In the SPM scheme [17], the final pyramid match kernel is defined as the sum of the separate class kernels as follows:

$$\tag{6}$$

In our work, in order to specifically cater for our work and make use of the discriminative distribution information of the vein vessel network, we make improvement of SPM scheme by adding a weight, which express the similarity of the superpixel distribution features across pairs of images, to the final pyramid match kernel (see eq. 6), which aims to increase the class separation distance and improve the recognition performance.

Hence, in this paper, the final pyramid match kernel between the input and template images, called matching Score *MS*, will be defined by:

$$M^{L} \tag{7}$$

where is the separate pyramid match kernel of class *m*, denotes the Euclidean distances of the superpixel distribution feature between X and Y.

3. Experiments and results

In this section, we provide a case study by choosing the local descriptor LBP [2] as the base attribute to ascertain the performance of the proposed framework. LBP is an effective local texture descriptor and has received lots of research interest and applications in biometric recognition field [2,22-24]. It uses a nonparametric kernel and compares the gray values of the center pixel with its 8-neighboring pixels, as shown in Figure 5. The binary sequence on the block is defined clockwise from the top-left as 01001100.

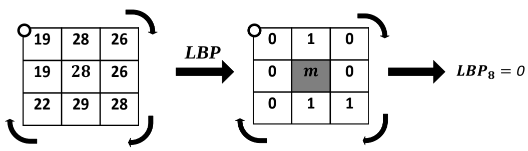

Figure 5: The LBP descriptor.

All the experiments were performed on the benchmark database PolyU [1] constructed by Hong Kong Polytechnic University. Several finger vein images in the database are shown in Figure 6, and the images in each row are from the same subject.

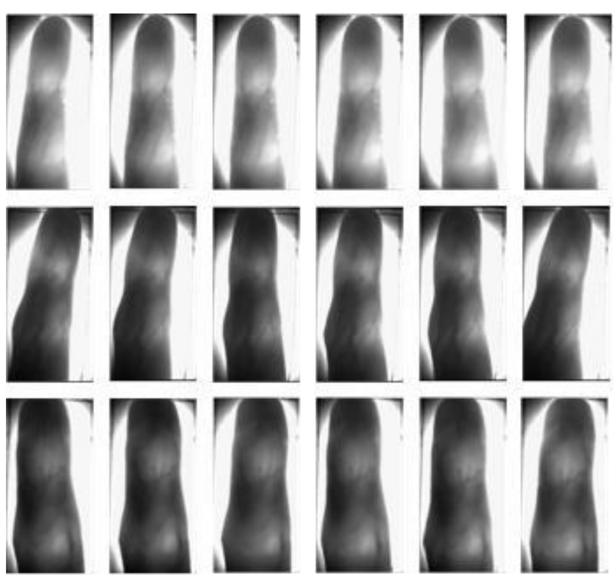

Figure 6: Example images from PolyU finger vein database. The images in each row are from the same subject.

PolyU database was acquired from 156 volunteers over a period of eleven months and each of the subjects provided six image samples from the index finger to the middle finger, respectively. In our experiments, we employed all the finger vein images acquired in the first session, i.e., 156 subjects with 12 images per subject. Since the finger veins are believed to be quite unique between the different fingers of an individual [25], different finger vein images from the same subject were regarded as belonging to different class, i.e., 312 classes with 6 samples per class. The performance was evaluated using sixfold cross validation, thus the total number of genuine and imposter scores are 1872 (6×312) and 582192 ($312\times311\times6$), respectively.

In these experiments, the performance of a system is evaluated by the equal error rate (EER), the false rejection rate (FRR) at zero false acceptance rate (FAR), the FAR at zero FRR and the statistical hypothesis *t-test*. *t-test* is a statistical hypothesis testing technique which is usually utilized to ascertain whether the difference between two methods is statistically significant, where *H* is the indicator of significance. H=1(−1) indicates that the method is significantly better (worse) than its corresponding method, and H=0 means that there is no significant difference. P is the probability for rejecting the hypothesis that ‘The method outperforms its corresponding method.’

3.1. Performance evaluation in two modes

The key objective in this set of experiments is to evaluate the identification performance of SPF by comparing with its corresponding LLF (LBP [2]) in verification and identification modes, respectively.

The experimental results from Table 1 and Figure 7 suggest significant improvement in the performance by using SPF. Particularly, the EER of the LLF-based method is 0.0690 while it is decreased to 0.0147 with SPF-based method. In addition, the results of the *t-test* show that the superiority of the SPF is significant.

In the identification mode, we don’t know the classes of the input finger vein images and want to identify which class it belongs to. For each probe, there is a corresponding gallery of the same person, where the gallery is sorted by decreasing similarity for each probe. The probe is said to be correctly recognized at rank k if the gallery of the same person is among the first k images in the sorted gallery.

The rank-one recognition rate and the lowest rank of perfect recognition are reported in Table 2. It can see that the identification performances of SPF-based method are much better than the LLF-based method. This experimental result is quite consistent with the result from the verification mode. In addition, the rank one recognition rates of our work are close to 98%, which indicates that most of the probes are identified correctly.

Table 1: Verification performance with different level features.

Level	EER	FRR at-zero-FAR	FAR at-zero-FRR	*t-test*	
				H	*P*
LLF (LBP)[2]	0.0690	0.4193	0.6748	1	9.79e-05
SPF	**0.0147**	**0.1891**	**0.1908**	--	--

Table 2: Identification performance with different level features.

Level	Rank-one recognition rate	Lowest rank of perfect recognition
LLF (LBP)[2]	85.84%	251
SPF	**97.92%**	**73**

Table 3: Performance with different categories of methods.

Category		Method	EER	*t-test*	
				H	*P*
LLF-based method	ROI-based method	LLBP [3]	0.0427	1	0.0025
		LDP [2]	0.2241	1	2.36e-07
		LDC [4]	0.0359	1	0.0187
	Network-based method	MeanC [5]	0.1064	1	3.51e-04
		MaxiC [7]	0.0265	--	--
		RLT [6]	0.0825	--	--
		EGM [1]	0.0065	--	--
	Minutiae-based method	SIFT [9]	0.0472	1	7.49e-04
		MHD [8]	0.2168	1	4.90e-05
HLF-based method		**SPF**	**0.0147**	--	--

The experimental results presented in two modes consistently suggest the significant improvement in the identification performance by using SPF. The inferior performance of LLF (LBP) may be attributed to its sensitivity to noise and low local consistency while SPF is robust to the noise in pixel level and can describe local consistency characteristic of images. In addition, the using of the WSPM made good use of the distribution information of the vein vessel network as well as ensured the rough geometric correspondence on a global scale across pairs of finger veins.

3.2. Comparison with LLF-based methods

The key objective of this set of experiments is to evaluate the finger vein recognition performance of the SPF-based method in comparison with different categories of benchmark LLF-based methods.

The comparison partners include:

- ROI-based methods: Local Liner Binary Pattern (LLBP) [3], Local Derivative Pattern (LDP) [2] and Local Directional Code (LDC) [4].
- Network-based methods: Mean Curvature (MeanC) [5], Repeated Line Tracking (RLT) [6], Maximum Curvature (MaxC) [7] and Even Gabor with Morphological (EGM) [1].
- Minutiae-based method: Scale-Invariant Feature Transform (SIFT) [9] and Modified Hausdorff Distance (MHD) [8].

The ROCs for the corresponding performances are illustrated in Figure 7 and the experimental results are shown in Table 3, where we directly use the results of RLT, MaxC and EGM reported in the Experiment B of [1]. Table 3 indicates that our SPF-based method outperforms almost all comparison LLF-based methods, and the results of the *t-test* show that the superiority of our work is significant.

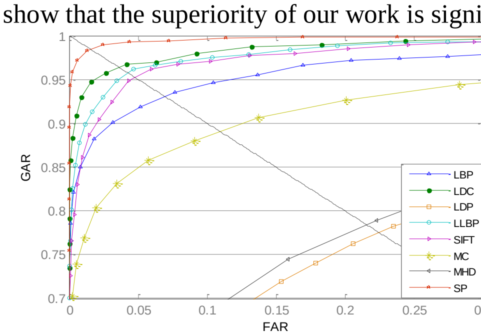

Figure 7: ROCs with different categories of methods.

The reason for such performance lies in five aspects: (i) the finger vein images are usually noisy from unconstrained imaging and so on, while SPF is more robust against pixel noisy and image variations than low level features; (ii) SPF can describe local consistency characteristic of finger vein images; (iii) the statistical techniques used for SPF extraction greatly enrich the representations of the finger vein image; (iv) the rough geometric correspondence between two images was established by utilizing the spatial pyramid scheme; (v) the distribution information of the vein vessel network was utilized by adding a weight to the traditional spatial pyramid kernel.

Table 3 shows that EGM [1] is comparatively better than our method. The reasons are as follows: EGM devoted to investigate the whole procedures of finger vein recognition, including image capturing, preprocessing, feature extraction and matching, and in each procedure. They made many efforts to improve their recognition performance. Specially, their preprocessing procedure contains localization, segmentation, alignment, and image enhancement, in which, the image enhancement are highly effective in achieving its robust performance [1], while our preprocessing only includes localization, segmentation alignment, and histogram equalization without too much enhancement to the acquired images. The low contrast and uneven illumination of our images seriously affect the recognition performance.

Therefore, combining the above experiments, we can draw a conclusion that our framework performs better than almost all the LLF-based methods in the literatures.

3.3. Comparison with HLF-based methods

The key objective of this set of experiments is to evaluate the finger vein recognition performance of the SPF-based method in comparison with the existing HLF-based methods in the literatures, which includes the RAP-based method proposed by Xiao et al. [13], the HIF-based method proposed by Xi et al. [14] and the PSPFS-based method presented by Liu et al. [17]. They both used rectangular grid for localized image processing.

Table 4: Performance with different HLF-based methods.

Method	EER	*t-test*	
		H	*P*
RAP [13]	0.0450	1	7.25e-05
HIF [14]	0.0278	1	0.0112
PSPFS [17]	0.0391	1	0.0076
SPF	**0.0147**	--	--

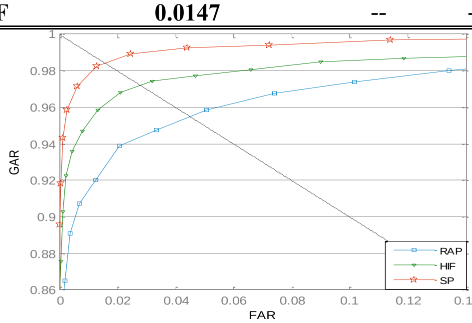

Figure 8: ROCs with different HLF-based methods.

The experimental results from various methods are shown in Table 4 and the ROCs for the corresponding performances are illustrated in Figure 8. They indicate that our SPF-based method outperforms the RAP-based and HIF-based method and the results of the *t-test* show that the superiority is significant. This experiment verified that superpixel has superior performance to rectangular grid for high level features extraction.

3.4. Comparison with SPM scheme

In our work, we make improvement of SPM scheme [18] by adding a weight to the final pyramid match kernel. The key objective of this experiment is to verify the matching performance of the WSPM scheme in comparison with the SPM scheme [18].

Table 5: Performance with different schemes.

Method	EER	*t-test*	
		H	*P*
SPM [18]	0.0164	0	0.6893
WSPM	**0.0147**	--	--

The experimental results from various schemes are shown in Table 5. It suggests the improvement in the performance by adding the weight. This can be explained by the using of the distribution information of the vein vessel network, which increased the class separation distance and improved the recognition performance.

3.5. Selection of the number of superpixels

In this section, we discuss the influences of the number of superpixels in each finger vein image on the recognition performance. We use EER as the performance measure and the experimental results when varying the superpixel number k are given in Figure 9.

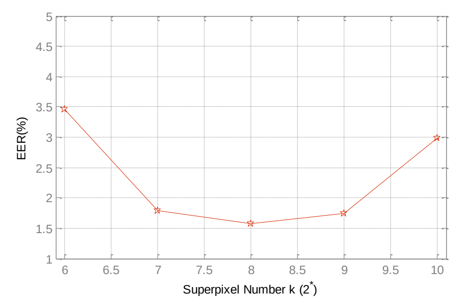

Figure 9: The effects of the number of superpixels.

It can be concluded that, when the number of superpixels is set to , we can achieve a comparatively best performance. Moreover, it shows that k can vary within a relative large range without affecting recognition performance too much.

4. Conclusions and future works

This paper proposes a novel identification framework for finger vein recognition with superpixel-based features (SPFs). We employ two simple statistical techniques to extract SPF and present a weighted SPM scheme (WSPM) to implement the image matching. Experimental results demonstrate that the proposed framework has yielded an EER of 0.0147 with the base attribute LBP on the benchmark database PolyU, which not only less than the corresponding LBP-based method and almost all the benchmark LLF-based methods, but also less than the existing HLF-based methods in the literatures.

The proposed framework has the following unique characteristics: (i) it utilizes SPF to implement the high level feature representation for finger vein. To the best of our knowledge, it is the first time to introduce SPF to the feature representation of finger vein; (ii) it makes improvement of SPM method by adding a weight to the final pyramid match kernel so as to make good use of the distribution information of the vein vessel network; (iii) it proposes a novel framework for finger vein recognition and achieves an inspiring recognition performance

Future works will focus on two directions: one is to improve the quality of the finger vein images by using some image enhancement techniques; the other is to find more discriminative feature representation for superpixel.

5. Acknowledgements

The authors would particularly like to thank the anonymous reviewers for their helpful suggestions. The work is supported by National Science Foundation of China under Grant No. 61173069, 61472226 and Shandong Natural Science Funds for Distinguished Young Scholar under Grant No. JQ201316.

References

[1] A. Kumar, and Y. Zhou. Human identification using finger images. IEEE Trans. Image Processing, 21(4):2228–2244, 2012.

[2] E.C. Lee, H. Jung, and D. Kim. New Finger Biometric Method Using Near Infrared Imaging. Sensors, 11(3):2319–2333, 2011.

[3] B.A. Rosdi, C.W. Shing, and S.A. Suandi. Finger vein recognition using local line binary pattern. Sensors, 11(12):11357–11371, 2011..

[4] X.J. Meng, G.P. Yang, Y.L. Yin, and R.Y. Xiao. Finger vein recognition based on local directional code. Sensors, 12(11):14937–14952, 2012.

[5] W. Song, T. Kim, H.C. Kim, J.H. Choi, H.J. Kong, and S.R. Lee. A finger-vein verification system using mean curvature. Pattern Recognition Letters, 32(11):1541–1547, 2011.

[6] N. Miura, and A. Nagasaka. Feature extraction of finger-vein pattern based on repeated line tracking and its application to personal identification. Machine Vision and Applications, 15(4):194–203, 2004.

[7] N. Miura, A. Nagasaka, and T. Miyatake. Extraction of finger-vein patterns using maximum curvature points in image profiles. IEICE transactions on information and systems. E90-D(8):1185–1194, 2007.

[8] C.B. Yu, H.F. Qin, Y.Z. Cui, and L. Zhang. Finger-vein image recognition combining modified Hausdorff Distance with minutiae feature matching, Interdisciplinary Sciences: Computational Life Sciences, 1(4):280–289, 2009.

[9] S.H. Pang, Y.L. Yin, G.P. Yang, and Y.N. Li. Rotation invariant finger vein recognition, in Proceedings of the 7th Chinese Conference on Biometric Recognition (CCBR). Guangzhou, China. 151–156, 2012.

[10] L. Wang, G. Leedham, and S.Y. Cho. Minutiae feature analysis for infrared hand vein pattern biometrics, Pattern Recognition, 41(3):920–929, 2008.

[11] A. Kumar, and K.V. Prathyusha. Personal authentication using hand vein triangulation and knuckle shape, IEEE Trans. Image Processing. 18(9):2127–2136, 2009.

[12] J.G. Wang, W.Y. Yau, A. Suwandy, and E. Sung. Person recognition by palmprint and palm vein images based on "Laplacianpalm" representation. Pattern Recognition, 41(5):1531–1544, 2008.

[13] R.Y. Xiao, G.P. Yang Y.L. Yin, and L. Yang. A Novel Matching Strategy for Finger Vein Recognition. Intelligent Science and Intelligent Data Engineering (IScIDE). NanJing, China. 364–371, 2012.

[14] X.M. Xi, G.P. Yang, Y.L. Yin, and L. Yang. Finger vein recognition based on the hyperinformation feature. Optical Engineering, 53(1):013108, 2014.

[15] D. Kim, S. Oh, and J. Rehg. Traversability classification for ugv navigation: A comparison of patch and superpixel representations. Intelligent Robots and Systems, 3166–3173, 2007.

[16] A. Hammoudi, F. Li, L. Gao, Z. Wang, M. Thrall, Y. Massoud, and S. Wong. Automated nuclear segmentation of coherent anti-stokes Raman scattering microscopy images by coupling superpixel context information with artificial neural networks. Machine Learning in Medical Imaging, 7009:317–325, 2001.

[17] F. Liu, G.P. Yang, Y.L Yin, and X.M Xi. Finger-vein Recognition Based on Fusion of Pixel Level Feature and Super-pixel Level Feature, Chinese Conference on Biometric Recognition (CCBR), 274-281, 2013.

[18] S. Lazebnik, C. Schmid, and J. Ponce. Beyond bags of features: spatial pyramid matching for recognizing natural scene categories. IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR). New York, USA. 17–22, 2006.

[19] M. Swain and D. Ballard. Color indexing. International Journal of Computer Vision, 7(1):11–32, 1991.

[20] L. Yang, G.P. Yang, Y.L. Yin, and R.Y. Xiao. Sliding window-based region of interest extraction for finger vein images. Sensors, 13(3):3799–3815, 2013.

[21] R. Achanta, A. Shaji, K. Smith, A. Luchi, P. Fua, and S. Ssstrunk. Slic superpixels compared to state-of-the-art superpixel methods. IEEE Trans. Pattern Analysis and Machine Intelligence, 34(11):2274–2282, 2012.

[22] T. Ahonen, A. Hadid and M. Pietikainen. Face description with local binary patterns: application to face recognition. IEEE Trans. Pattern Analysis and Machine Intelligence, 28(12):2037–2041, 2006.

[23] T. Ojala, M. Pietikainen, and T. Maenpaa. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Trans. Pattern Analysis and Machine Intelligence, 24(7): 971–987, 2002.

[24] X. Wang, H. Gong, H. Zhang, B. Li, and Z. Zhuang. Palmprint identification using boosting local binary pattern. International Conference on Pattern Recognition (ICPR). 503–506, 2006.

[25] T. Yanagawa, S. Aoki, and T. Ohyama. Human finger vein images are diverse and its patterns are useful for personal identification. MHF Prepr. Ser. 1–7, 2007.