# DFVR: DEFORMABLE FINGER VEIN RECOGNITION

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## ABSTRACT

Although some developments have been achieved in finger vein recognition recently, the image deformation problem has received relatively less attention and still intractable. In this paper, the reason and the harmfulness of this problem are analyzed firstly. And then, a deformable finger vein recognition framework is proposed to deal with this problem, consisting of the improved vein PCA-SIFT feature and bidirectional deformable spatial pyramid matching (BDSPM). Furthermore, we build a finger vein deformation database to imitate image deformation in real application. The experimental results, on the self-built deformation database and one public database, prove the effectiveness of the proposed framework for dealing with the image deformation problem.

***Index Terms*—** Finger vein recognition, image deformation, vein PCA-SIFT, bidirectional DSPM.

## 1. INTRODUCTION

Finger vein recognition is a tough task if the used images have deformation problem. Image deformation in this paper mainly means all kinds of variations between vein patterns in multiple genuine images, such as, relative translations on horizontal direction. And, this kind of vein pattern deformation is generally caused by the random finger placement in contactless and unrestrained image capturing. Large vein pattern variations can decrease the similarity of genuine images, and further make false rejection in recognition.

Some methods have been proposed to overcome this problem, and these methods can be divided into three main groups according to the recognition steps they exist:

**1) Methods in image preprocessing**. Most finger vein image preprocessing methods [1, 2] had one substep named finger alignment, which was used to overcome in-plane finger rotation. And a minutia based image alignment [3] was performed ahead of feature extraction.

**2) Methods in feature extraction**. Orthogonal neighborhood preserving projections (ONPP) [4] and scale invariant feature transform (SIFT) [5] were employed as finger vein feature to deal with image deformation. Different from these deformation-robust features, the ellipse projective coefficient [6] was used to normalize the extracted vein pattern for suppressing image deformation.

**3) Methods in matching**. In this kind, one typical method was maximal matched pixel ratio based matching [2, 7], in which multiple matches were performed to the enrolled image by translating the input image in horizontal and vertical directions, and the maximal score of multiple matches was used in recognition. Another one was non-rigid registration based matching [8]. In this method, non-rigid image registration was performed before the similarity measurement.

However, there are some limitations in the current methods. First, there is a lack of comprehensive analysis of finger vein image deformation problem. Second, current methods deal with this problem only in feature extraction or in matching. Third, the robustness of methods to image deformation cannot be exactly evaluated on the existing databases, as they are captured in laboratory and do not contain all potential image deformations in real application.

In this paper, we firstly make a deep analysis about finger vein image deformation, including its reason and harmfulness. And to overcome this problem, a deformable finger vein recognition (DFVR) framework is proposed. In the framework, we develop vein PCA-SIFT feature and bidirectional deformable spatial pyramid matching (BDSPM), which are separately extended from PCA-SIFT [9] and DSPM [10] to match the characteristics of finger vein image. Furthermore, to imitate all kinds of image deformations in real application, a finger vein deformation database is built. The experimental results, on this database and one public database, show that the proposed method outperforms the state-of-the-arts.

The rest of the paper is organized as follows. Section 2 presents the analysis of finger vein image deformation problem, and Section 3 introduces the proposed DFVR framework. The experimental results and analysis are given in Section 4. Finally, the paper is concluded in Section 5.

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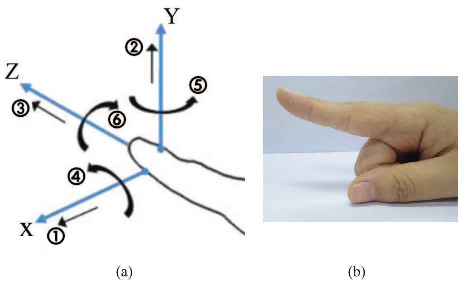


**Fig. 1**. (a) Rigid finger movements [3]; (b) Finger placement with combination of case 4 and case 6.

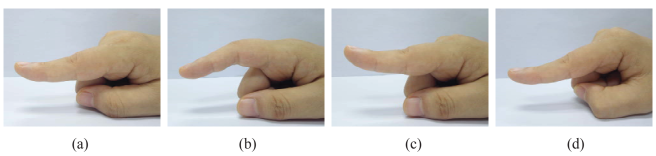


**Fig. 2**. (a) Natural finger placement; Finger placements with (b) Finger bending; (c) Fingertip cocking up; (d) Finger root cocking up.

## 2. IMAGE DEFORMATION PROBLEM ANALYSIS

**Deformation Reason**. Finger vein image is generally captured in a contactless and unrestrained way, which means finger is randomly placed and unfixed in imaging. And in imaging device, there is a big space between the light and the camera to place the finger. In a word, the contactless and unrestrained imaging and the big free space make finger placement varied largely, and further cause image deformation.

In laboratorial image capture, the subject is asked to put his/her finger naturally and horizontally over the camera. Nonetheless, small scale deformation exists in images of same finger but captured in different sessions, owing to unavoidable slight variations of finger placement. In fact, there may be no guideline for finger placement in real application. The variation of finger placement will be more complex, and the scale of caused image deformation will be larger.

**Finger placements**. Different finger placements are caused by finger movements, which can be divided into two groups, *i*.e., rigid finger movement and non-rigid finger movement. In the first group, finger is seen as a rigid object, and all rigid movements in three-dimensional space are shown in Fig. 1 (a). Finger placement can be with one rigid movement, or the combination of two or more ones. Fig. 1 (b) gives a placement with the combination of cases 4 and 6, *i*.e., finger rotation round both x-axis and z-axis.

What's worse, as there are three joints in finger, finger movement can be non-rigid. The non-rigid finger movement mainly includes finger bending, fingertip cocking up and finger root cocking up. The comparison between natural finger placement and finger placements with non-rigid movements is given in Fig. 2. In subfigure (b), finger bends, and fingertip and finger root cock up separately in subfigures (c) and (d).

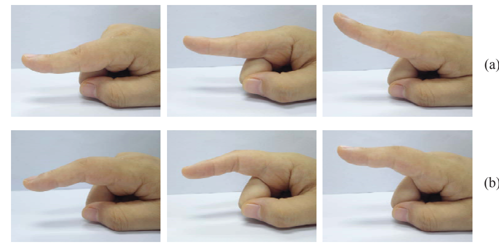


**Fig. 3**. Finger placements with (a) Rigid movement, (b) Rigid and non-rigid movements.

Worst of all, the rigid finger movement may be accompanied by non-rigid movement in finger placement, resulting in the more complicated and larger scale image deformation. Fig. 3 shows a comparison of finger placements only with rigid finger movement and these with both rigid and non-rigid movements. Compared with rigid movements in finger placements of the first row, non-rigid finger bending is mixed with rigid movements in the second row.

**Deformation harmfulness**. Different finger placements cause the variations of vein patterns in the captured images. We take two examples to explain how the vein pattern varies. If two images are captured with finger movement along z-axis in Fig. 1(a), there will be relative translation on horizontal direction between two vein patterns. And if finger bends in image capturing, relative convergent-divergent of the finger and its vein pattern can be found in two images. Further, these relative vein pattern variations can lead to the serious degeneration of recognition performance. More specifically, lots of images will be falsely rejected owing to big variation between them and their genuine enrolled images. For example, two genuine images with relative translation may be mistakenly recognized as imposter, as the number of overlapped vein points in their vein pattern is very limited. Therefore, it is essential to deal with image deformation problem.

## 3. PROPOSED DFVR FRAMEWORK

In this section, we present the proposed deformable finger vein recognition (DFVR) framework (shown in Fig. 4). The framework mainly includes vein PCA-SIFT feature and bidirectional deformable spatial pyramid matching (BDSPM), which separately are the improved versions of PCA-SIFT [9] and DSPM [10]. The improvement to PCA-SIFT is mainly based on the characteristic of finger vein image that the discriminative feature of one image mainly exists in vein pattern region. Correspondingly, the DSPM method is performed in a bidirectional way because of the asymmetry of vein patterns in two images, especially in two imposter images. In detail,

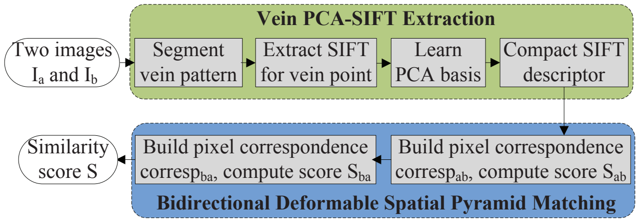


**Fig. 4**. Flowchart of DFVR framework.

the number of vein points varies from one image to another one, and the pixel correspondences, built by DSPM, from the first image to the second one and these from the second image to the first one may be different.

### 3.1. Vein PCA-SIFT Extraction

In vein PCA-SIFT extraction, vein point in an image is firstly labeled by a thresholding method. Assuming $p_{i,j}$ is a point at $i$th row and $j$th column of an image $I$ with size of $M\times N$. Its neighborhood can be denoted by $p^{nei}_{i,j} = \{p_{x,y} | i-r \leq x \leq i+r, j-r \leq y \leq j+r\}$, and its threshold $p^{thr}_{i,j}$, *i*.e., the mean gray value of the neighborhood, can be computed by:

$$p^{thr}_{i,j} = \frac{sum(p^{nei}_{i,j})}{(2*r+1)^2} = \frac{sum(p_{x,y})}{(2*r+1)^2}, \quad i-r \leq x \leq i+r, j-r \leq y \leq j+r. \tag{1}$$

in which $(2*r+1)^2$ is the number of points in the neighborhood. As vein point has lower gray value than its neighbors in finger vein image, the vein map $V$ can be roughly segmented from the image $I$ by the following equation:

$$V_{i,j} = \begin{cases} 1, & \text{if } p_{i,j} \leq p^{thr}_{i,j} \\ 0, & \text{if } p_{i,j} > p^{thr}_{i,j} \end{cases}, 1 \leq i \leq M; 1 \leq j \leq N. \tag{2}$$

In vein map $V$, the pixels with value 1 are vein points. By labeling of the vein map, we can only extract SIFT descriptor for vein point. The extracted SIFT descriptor of the point $p_{i,j}$ is denoted by $sift_{i,j}$.

Next, PCA basis is learned from SIFT descriptors of training vein points. The training points consist of $m$ vein points in each of $n$ images, both selected randomly. The learned P-CA basis can be represented by $w = [\lambda_1, \lambda_2, ..., \lambda_k]$. In the end, the SIFT descriptor of each vein point is compacted by the basis $w$ as following:

$$csift_{i,j} = \begin{cases} sift_{i,j} * w, & if\ V_{i,j} = 1 \\ \text{a zero vector}, & \text{otherwise} \end{cases}, \quad 1 \leq i \leq M, 1 \leq j \leq N. \tag{3}$$

The descriptor $sift_{i,j}$ can be seen as $1\times128$ matrix, and the size of PCA basis $w$ is $128\times k$, so the dimension of the compact $csift_{i,j}$ is $k$. In this paper, we set $k$=20.

The compact vein PCA-SIFT has two advantages. First, the feature matrix is sparse, and the descriptor of one vein point is low-dimensional, which reduces the computational cost largely. Second, the topology of vein pattern is implicitly exploited, which can increase the feature discrimination.

### 3.2. Bidirectional DSPM

In bidirectional matching of two images, the pixel correspondences from the first image to the second one, and these from the second image to the first one are both built by DSPM. Based on two kinds of correspondences, two matching scores are computed, and the minor one is used in recognition.

Formally, we denote two images by $I_a$ and $I_b$, and for one pixel located at $(i, j)$ in one image, it best-match pixel in another image is denoted by $corresp(i, j)$. Based on the pixel correspondences from image $I_a$ to image $I_b$, the matching score $S_{ab}$ is defined as

$$S_{ab} = \frac{sum(sum(s_{i,j}))}{vein_a}, 1 \leq i \leq M, 1 \leq j \leq N \tag{4}$$

$$s_{i,j} = \sum\nolimits_1^k ||sift^a_{i,j} - sift^b_{corresp(i,j)}||_1 \tag{5}$$

in which $vein_a$ is the number of vein point in image $I_a$. Similarly, based on the correspondences from $I_b$ to $I_a$, we can also compute the score $S_{ba}$. The minor matching score $S$ is finally obtained and employed in recognition.

$$S = \min(S_{ab}, S_{ba}) \tag{6}$$

By the proposed bidirectional DSPM, each pixel in one image can be aligned, and the difference between two images is sufficiently explored. So, the method has power to overcome all kinds of image deformations and to keep the similarity of genuine images avoiding false rejection.

## 4. EXPERIMENTS

### 4.1. Databases and Experimental Settings

The robustness of the proposed framework is assessed on two databases, *i*.e., one open database (named HKPU database [2]) and one self-built deformation database (named SDUD database). In SDUD database construction, the subjects put their fingers with large scale rigid and/or non-rigid movement. There are 23 subjects and six images are provided from each of the index and middle fingers of two hands for one subject. Big finger variation in image capturing makes the image quality varied largely. So, 342 relatively high quality samples (57 fingers×6 images) are used in the experiments.

In comparison with the state-of-the-arts, the ellipse projective coefficient based normalization is used for vein pattern in WLD [6], and for other methods (*i*.e., RLT [7], MaxiC [11] and so on), maximal matched pixel ratio based matching is used in similarity measurement. Besides, all experiments are performed by six-fold cross validation.

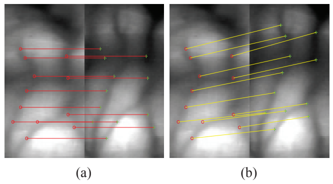

Fig. 5. Comparison of (a) coordinate based matching and (b) deformable matching.

**Table 1**. Comparison of all kinds of SIFT and their matching methods on SDUD database.

| Method | EER(%) | Rank-one recognition rate(%) | Lowest rank of perfect recognition |
|---|---|---|---|
| SIFT+ number of matched pairs [5] | 12.37 | 66.08 | 39 |
| PCA-SIFT+BDSPM | 3.45 | 96.49 | 4 |
| Vein PCA-SIFT+L1 norm | 22.87 | 54.09 | 50 |
| Vein PCA-SIFT+L1 norm with translation | 13.14 | 83.92 | 36 |
| Vein PCA-SIFT+DSPM | 4.64 | 94.74 | 11 |
| Vein PCA-SIFT+BDSPM | 3.18 | 96.49 | 9 |

### 4.2. Evaluation of Improved Feature and Matching

Firstly, the visual comparison between deformable matching and coordinate based matching is illustrated in Fig. 5. Relative translation and convergent-divergent exist in two genuine images. With these relative variations, pixel correspondences between two images, built by same coordinate, are obviously wrong in subfigure (a). Fortunately, by the deformable matching, the best-matched point can be found in second image for each point in the first image of subfigure (b).

Secondly, the recognition performance of the improved feature and matching is evaluated on SDUD database. The involved features vary from SIFT, to PCA-SIFT, further to proposed vein PCA-SIFT, and the compared matching methods include the number of matched keypoint pair, L1 norm, DSPM, and the proposed BDSPM. The EER values in verification mode, rank-one recognition rate and lowest rank of perfect recognition in identification mode are all reported in Table 1. The experimental results show that, no one combination of feature and matching is comparable to the proposed one (*i*.e., Vein PCA-SIFT+BDSPM), even the methods with PCA-SIFT and DSPM. It indicates that, our improvements to PCA-SIFT and DSPM are helpful for performance enhancement in finger vein recognition.

### 4.3. Comparison with State-of-the-art

Here, the comparison between the proposed DFVR framework and the state-of-the-arts is conducted on both HKPU database and SDUD database. Three benchmarks of all involved methods are given in Table 2. The table shows, all methods have better performance on HKPU database than on SDUD database. The reason is that, the scale of image deformation on the public database is smaller than it on the self-built deformation database. It also can be seen from the table that, the significant improvement is achieved by the proposed framework, especially on SDUD database. It is mainly attributed to the robustness of the framework to image deformation. The scale and rotation-invariant feature and the bidirectional deformable matching powerfully prevent the false rejection of the genuine images, and further achieve the best recognition performance. Especially, the pixel correspondences built by the deformable matching can overcome large image deformation, and therefore avoid the big difference between deformable genuine images.

**Table 2**. Verification and identification performance of different methods on two databases.

| Database | Method | EER(%) | Rank-one recognition rate(%) | Lowest rank of perfect recognition |
|---|---|---|---|---|
| HKPU database | LBP [12] | 1.34 | 99.20 | 21 |
| | LLBP [13] | 1.56 | 99.15 | 28 |
| | RLT [7] | 1.71 | 97.22 | 189 |
| | MaxiC [11] | 1.60 | 97.81 | 100 |
| | WLD [6] | 1.96 | 98.24 | 178 |
| | EGM [2] | 1.39 | 98.29 | 123 |
| | DFVR | 0.70 | 99.41 | 44 |
| SDUD database | LBP [12] | 11.75 | 80.12 | 20 |
| | LLBP [13] | 11.40 | 80.70 | 39 |
| | RLT [7] | 16.64 | 69.01 | 50 |
| | MaxiC [11] | 15.94 | 71.64 | 43 |
| | WLD [6] | 15.53 | 72.22 | 42 |
| | EGM [2] | 17.94 | 69.59 | 46 |
| | DFVR | 3.18 | 96.49 | 9 |

## 5. CONCLUSION

In this paper, we do a deep analysis of finger vein image deformation problem. And the proposed deformable recognition framework tries to overcome the problem by both scale and rotation-invariant vein PCA-SIFT feature and the bidirectional DSPM matching. The compact vein PCA-SIFT implicitly exploits the topology of vein pattern, which increases the feature discrimination. And the bidirectional pixel correspondences based matching can overcome image deformations powerfully and measure the similarity of vein based features more precisely. In addition, the self-built deformation database contains all kinds of deformation images, is more suitable for studying image deformation problem than other ones. The experimental results, on the deformation database and one open database, show that, the proposed framework is effective for dealing with the image deformation problem.

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