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A novel Approach to improve biometric authentication using Steerable-Locality Sensitive Discriminant Analysis

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Abstract. With the increasing needs in security systems, palm vein authentication is one of the important and reliable solutions for identity security for biometrics based authentication systems. Palm vein, as a biological characteristic of an individual, has been increasingly utilized for personal authentication in advanced security applications. Palm vein patterns are a unique attribute of everyone and can therefore be used as a biometric characteristic. The human palm vein pattern is extremely complex and it shows a huge number of vessels. The biometric information is located inside the human body, and therefore it is protected against forgery and manipulation. In the proposed method, the Multilevel Gaussian-Second-Derivative (MGSD) is proposed for enhancement the palm vein images. Secondly, a new feature extraction method based on Steerable filter and Locality Sensitive Discriminant Analysis is proposed called Steerable - Locality Sensitive Discriminant Analysis (SLSDA). Finally, the Correlation Distance method is proposed for verify the tested palm vein. The EER to the proposed authentication system is 0.1087%.

1. Introduction

The human recognition to the vein patterns has been prefer by its value of application in the security system. Wherever security is required, whether to register access to constructing or to computer systems, it is necessary to used an access control system. Traditional personal verification methods rely heavily on the use of passwords, personal identification numbers (PINs), magnetic swipe cards, keys, smart cards, etc. Each of these offers only limited security. Many biometric recognition systems have been proposed, based on various human physiological features or behaviours including facial images, hand geometry, fingerprints, palm prints, retinal images, handwritten signature and gait to improve the security of personal verification [1]. Recently, the palm vein pattern is a new biometric technology has attracted the notice of biometrics based identification research community. Palm vein exhibits some excellent advantages in application. For instance, apart from uniqueness, universality, permanence and measurability [2].

There are many different features in palm vein images, such as the geometry, the principal line and the delta point. Furthermore, hand veins show significant textural differences and many minutiae, similar to the ridges and branches of fingerprints. Many verification technologies using biometric features of hand veins have been developed over the past decade. Wang et al. compared shape and texture-based methods for vein recognition, based on Hausdorff distance for shape similarity and Line Edge Map (LEM) and texture similarity measured via Euclidean distance of Gabor magnitude features. For the experimental used 100 persons, Hausdorff-, LEM- and Gabor-based methods achieved accuracies of 58, 66, 80 %, respectively [3]. Wang and Leedham, present another approach based on hand vein thermal imaging for personal authentication. They proposed the Hausdorff distance to calculate matching scores between the extracted line patterns and illustrated promising results [4]. Wang et al. proposed a multimodal personal identification system where palmprint and palm vein modalities were combined in a single image. Locality Preserving Projection (LPP) was used to extract features of the fused images, which they called “Laplacianpalm.” [5]. Kumar et al. presented a new approach to authenticate individuals using triangulation of hand vein images and simultaneous extraction of knuckle shape information [6]. Chen et.al. This paper proposed an efficient refinement method for palm vein matching by adopting the iterative closest point (ICP) algorithm, which can accurately align the rotation and shift variations introduced in data acquisition [7]. Zhou et. al. two palmvein representations method are proposed, based on Hessian phase information from the enhanced vascular patterns in the normalized images and secondly from the orientation encoding of palmvein line-like patterns using localized Radon transform. The proposed approach is rigorously evaluated on the CASIA database (100 subjects) and achieves the best equal error rate of 0.28% [8]. Wang et al. proposed a thermal palm vein pattern identification system. The Contrast Limited Adaptive Histogram Equalization is proposed for image enhancement. Gabor wavelet decomposition proposed in to extract feature eigenvectors of palm vein patterns. Finally, the correlation coefficient is proposed to make the classification decision [9]. Wei-Qi et. al. a recognition method for palm vein based on affine geometric properties is proposed. Firstly, the palm area of the palm vein image is obtained through image preprocessing. Secondly, a series of centroids of palm and segments are extracted. Feature vectors are constructed with the area radio of the triangles which are formed with centroids. Finally, Euclidean distance is used as the matching criteria [10]. Junwen Sun and Waleed Abdulla, they proposed a multiscale curvelet transform as a feature extraction and used a subset from the features for matching using Hamming distance. When used (40%) from the features set, the lowest EER is 0.66% [11].

The rest of this paper is organized as follows. Section 2 describes the image enhancement. In section 3, describe the feature extraction methods based on Steerable- Locality Sensitive Discriminant Analysis. In Section 4, for the verification we propose the Correlation distance Matching Classifier and for the identification we propose the nearest neighbor method. Finally, the experimental result and conclusions are drawn in Section 5. Fig. 1 shown the flowchart of the propose work.

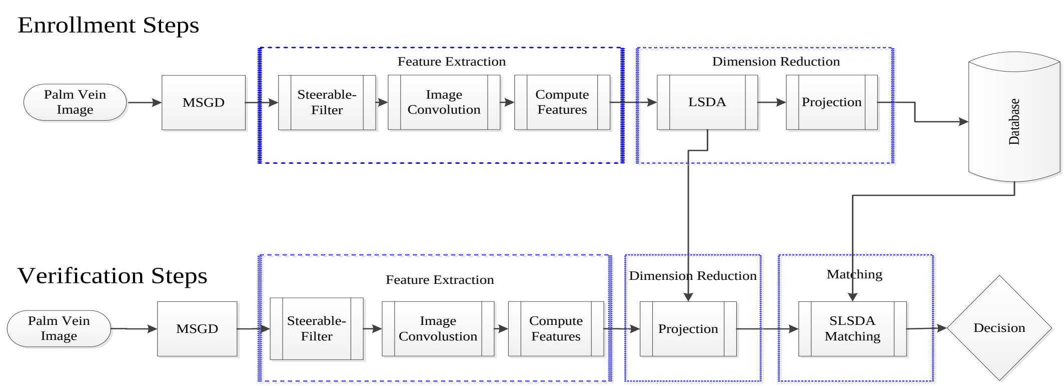


Fig. 1 System Flowchart

2. Image Enhancement

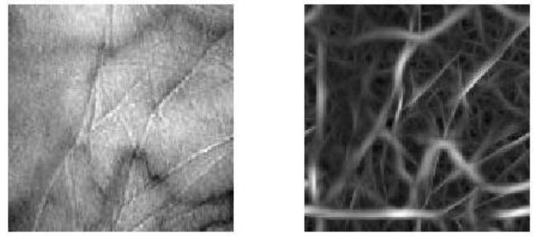
The image should be separated from other unnecessary data in the captured image such as the irregular shades and noises that result from the different thickness between the hand bones and muscles and the contrast of the image oscillation due to light intensity fluctuations. It is for this reason that needed to enhance the quality of the palm vein images before the extraction of features. Multilevel Gaussian-Second-Derivative (MGSD) method is proposed for image enhancement. The multilevel second derivative of the Gaussian filter is defined as [2, 12, 13]:

$$MGSD(x',y',\delta,\theta)=((x'^2-\delta^2)(y'^2-\delta^2)/(2\pi\delta^{10}))\exp(-(x'^2+y'^2)/\delta^2) \quad (1)$$

Where $x'=(x-x_\circ)\cos\theta+(y-y_\circ)\sin\theta$, $y'=-(x-x_\circ)\sin\theta+(y-y_\circ)\cos\theta$, $(x_\circ,y_\circ)$ is the center of the function and σ is the scales. The values of δ and θ is set empirically. In the proposed work the value of δ is $(\sqrt{2},2,2\sqrt{2})$ and for one δ, 12 different angle filters $\theta_j=\pi j/12$), where j = {1, 2, 3... 12}) are applied for each pixel, and the maximal response among these twelve directions is kept as the final response for the given scales

$$Enhancement(x,y)=\max(MGSD(x',y',\delta_{ij},\theta_{ij})*I(x,y)) \quad i=\{1,2,3\},\ j=\{1,2..12\} \quad (2)$$

Where $I(x,y)$ is the original image and * denotes the convolution operation. Fig. 2 has shown the result of proposed enhancement method.



Original Image Enhancement Image

Figure 2. Image enhancement

3. Feature Extraction Based on Steerable-Locality Sensitive Discriminant Analysis (SLSDA)

The feature extraction step goal to extract the existing features of the palm vein pattern, from an image, that then are going to be used for matching. In the propose work, we proposed the steerable filter for create a bank filters and then extract statistical features from the convolving images then based on Locality Sensitive Discriminant Analysis to remove unnecessary and duplicate features.

3.1 Steerable Filter Bank

The steerable filter enables us to obtain the response at a distinct orientation as a linear combination of the responses to a bank of basis filters, which has following form [14, 15]:

$$h(x,y)=\sum_{k=1}^{M}\sum_{i=0}^{k}\alpha_{k,i}\underbrace{\frac{\partial^{k-i}}{\partial x^{k-i}}\frac{\partial^{i}}{\partial y^{i}}g(x,y)}_{g_{k,i}(x,y)} \quad (3)$$

Where $g(x,y)$ is an arbitrary isotropic window function, $g_{k,i}(x,y)$ is a basic filter, $\alpha_{k,i}$ is the interpolation coefficient, and M is the order of steerable filter. The convolution of a 2D signal $f(x, y)$ with any rotated version of $h(x, y)$ can be expressed as

$$f(x) * h(R_\theta x) = \sum_{k=1}^{M} \sum_{i=0}^{k} b_{k,i}(\theta) f_{k,i}(x) \quad (4)$$

Where $x = (x, y)$, R_θ is the rotation matrix, and $f_{k,i}(x, y) = f(x, y) * g_{k,i}(x, y)$ are filtered versions of the signal $f(x, y)$ the weights $b_{k,i}(\theta)$ are given by

$$b_{k,i}(\theta) = \sum_{j=0}^{k} \alpha_{k,i} \sum_{l,m \in S(k,j,i)} \binom{k-j}{l} \binom{j}{m} (-1)^m \cos(\theta)^{j+(l-m)} \sin(\theta)^{(k-j)-(l-m)} \quad (5)$$

Where

$$S(k, j, i) = \{l, m | 0 \le l \le k - j; 0 \le m \le j; k - (l + m) = i\}$$

.

Once the $f_{k,i}(x, y)$ are available, $f(x) * h(R_\theta x)$ can be evaluated very efficiently via a weighted sum with its coefficients that are trigonometric polynomials of θ. The steerable filter's response at an arbitrary orientation can be expressed as

$$f * h_\theta = q_0 \cos(\theta)^M + q_1 \cos(\theta)^{M-1} \sin(\theta) + ... + q_M \sin(\theta)^M \quad (6)$$

Where h_θ the rotate version of is filter $h(x, y)$, and $q_0, q_1, ..., q_M$ can be determined by the basic filters' response $f_{k,i}(x, y)$.

3.2 Create Feature Vector

The palm vein image is convolving based on the steerable filter bank. The features that compute from each 4×4 sliding block in each convolving image are the Mean for each column in the block and Standard Deviation for each column in the block and the Norm for the siding block. For each block four mean values, four standard deviation values and one norm value.

3.3 Locality Sensitive Discriminant Analysis

Computational intelligence similar to pattern recognition is frequently confronted with high-dimensional data. Therefore, the reduction of the dimensionality is critical to make the manifold features amenable. Procedures that are analytically or computationally manageable in smaller amounts of data and low dimensional space can become important to produce a better classification performance [16]. An important question in the fields of machine learning, knowledge discovery, computer vision and pattern recognition is how to extract a small number of good features. A common way to attempt to resolve this problem is to use dimensionality reduction techniques [17].

Locality Sensitive Discriminant Analysis, that exploits the geometry of the data manifold. Firstly, construct a nearest neighbor graph to model the local geometrical structure of the underlying manifold. This graph is then split into within-class graph and between-class graph by using the class labels. In this way, the geometrical and discriminant structure of the data manifold can be accurately characterized by these two graphs. Using the notion of graph Laplacian, then can find a linear transformation matrix which maps the data points to a subspace. This linear transformation optimally preserves the local neighbourhood information, as well as discriminant information. Specifically, at each local neighbourhood, the margin between data points from different classes is maximized. LSDA is supervised feature-selection problem described by [16], which respects both discriminant and geometrical structure in the data manifold by building a nearest neighbor graph. For example, LSDA is widely used in image processing recognition. To improve the discriminative ability of the low-dimensional features, the class label information is incorporated into the feature extraction process. The following algorithm is describe in [16-18]:

Input: Given m data points $x\{x_1,x_2,...,x_m\}\subset \mathbb{R}^n$ sampled from the underlying submainfold M , Let $l(x_i)$ be the class label of x_i

Step 1: Built a nearest neighbor graph G to model the local geometrical structure of M.

Step 2: For each data point x_i , find k nearest neighbors

Step 3: Put an edge between x_i and its neighbors.

Step 4: The weight matrix of G can be define as the following:

$$W_{ij}=\begin{cases}1, & if\ x_i\in N(x_j)\,or\,x_j\in N(x_i)\\ o, & otherwise\end{cases} \quad (7)$$

Step 5: Construct two graphs (within class graph G_w and between class graph G_b).

Step 6: For each data point x_i , the set $N(x_i)$ can be naturally split into two subset, $N_b(x_i)$ and $N_w(x_j)$. $N_w(x_i)$ contains the neighbors sharing the same label with x_i , while $N_b(x_i)$ contains the neighbors having different labels. Specifically,

$$N_w(x_i)=\{x_i^j\,|\,l(x_i^j)=l(x_i),1\le j\le k\} \quad (8)$$

$$N_b(x_i)=\{x_i^j\,|\,l(x_i^j)\ne l(x_i),1\le j\le k\} \quad (9)$$

Clearly, $N_b(x_i)\cap N_w(x_i)=\varnothing$ and $N_b(x_i)\cup N_w(x_i)=N(x_i)$.

Step7: Let W_w and W_b be the weight matrices of G_w and G_b , respectively. We define:

$$W_{b,ij}=\begin{cases}1, & if\ x_i\in N_b(x_j)\,or\,x_j\in N_b(x_i)\\ 0, & otherwise\end{cases} \quad (10)$$

Step8: $W=W_b+W_w$ and the nearest neighbor graph G can be thought of as a combination of within-class graph G_w and between-class graph G_b. Step9: Let $y=(y_1,y_2,...,y_m)^T$ be such a map. A reasonable criterion for choosing a “good” map is to optimize the following two objective function:

$$\min\sum_{ij}(y_i-y_j)^2W_{w,ij} \quad (11)$$

$$\max\sum_{ij}(y_i-y_j)^2W_{b,ij}$$

(12)

In the proposed work, the features vector that created from the convolving images and based on Locality Sensitive Discriminant Analysis to project that features vector from high dimension space to low dimension space. That features vector is called Steerable Locality Sensitive Discriminant Analysis (SLSDA).

4. Matching

As any biometric system, the palm vein recognition is also based on pattern classification. Hence, the discriminability of the proposed SLSDA determines its reliability in personal authentication. To test the discriminability of the extracted SLSDA, The correlation metric method is used to compute the matching between the train set and test set. As any biometric system, the palm vein recognition is also based on pattern classification. Hence, the discriminability of the proposed features vector SLSDA method, this determine its reliability in personal authentication. To test the discriminability of the extracted features vector, the correlation metric measure classifier here is adopted for classification. The classifier is defined as [19]:

$$\tau = \arg\min_{y_t^K \in C_K} d(x_s, y_t^K) \tag{13}$$

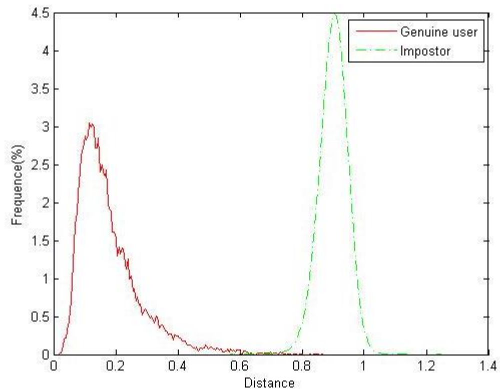
$$d(x_s, y_t^K) = 1 - \frac{(x_s - \overline{x}_s)(y_t - \overline{y_t^K})'}{\sqrt{(x_s - \overline{x}_s)(x_s - \overline{x}_s)'}\sqrt{(y_t - \overline{y_t^K})(y_t - \overline{y_t^K})'}} \tag{14}$$

Where x_s is the feature vector of an unknown sample and y_t^k represent the train features vector the *k*th class, C_k is the total number of templates in the *k*th class, and $d(x_s, y_t^k)$ is the correlation metric measure. Using similarity measure $d(x_s, y_t^k)$, the feature vector x_s is classified into the τ th class.

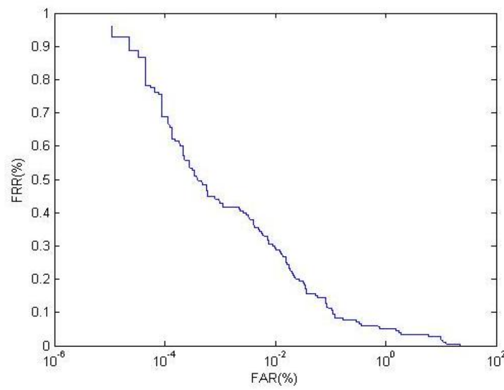
5. Experiential Result

Our experiments are performed to evaluate the effectiveness of proposed palm vein verification methods based on PolyU database. The biometric research centre at the Hong Kong Polytechnic University has developed a real time multispectral palm print capture device which can capture palm print images under blue, green, red and near-infrared (NIR) illuminations, and has used it to construct a large-scale multispectral palmprint database. The database contains 6,000 images from 500 different palms for each one illumination. The proposed method used the near-infrared (NIR) illuminations images of PolyU multi-spectral palm print database [20].

Each person has 12 palm vein images. We use 6 palm vein image for the enrollment and 6 images for the test of each individual in our experiments. We used the Equal error rate (EER) for performance measures. The EER is the point where FRR is equal to FAR, and the smaller EER indicates a better performance. Fig. 5 (a) showed the distribution between genuine user and impostor and Fig.5 (b) shown the ROC curve for the proposed system.



(a)



(b)

Fig. 5. (a) Distribution of the Genuine user and Impostor. (b) ROC Curve.

In this paper, we also make a comparison between the proposed method and the methods of the ICP [7] and Curvelet Transform [11], the researchers are worked on the PolyU database. TABLE 1 show that our method outperforms the other two methods in terms of EER.

TABLE I. THE EER COMPARATION WITH OTHET METHOD

	Our method	ICP	Curvelet Transform
EER%	0.1062	0.557	0.66

6. Conclusion

This paper has addressed the problems of palm vein segmentation and verification. The MGSD filters are exploited to extract palm vein pattern. The SLSDA features are extracted based on steerable filter bank and Locality Sensitive Discriminant Analysis to describe the palm vein pattern. Then the matching SLSDA feature associations between the registered and test images are computed using Correlation distance to verify the personal identification. At last, the experimental results illustrate that our matching method effective and competitive with other approaches in the literature. In the future, we intend to fuse another type of the palm vein features. By the proposed method we get a lower EER value equal to 0.1062%.

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علي محسن الجبوري
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المستخلص :

مع زيادة الحاجة لأمنية النظام، تمييز شرايين اليد هو واحد من أهم و أوثق الحلول لتعريف أمنية الهوية بالاعتماد على توثيق البايومترك. شرايين اليد هي من المواصفات البايلوجية للفرد. نموذج شرايين اليد هي تحمل خصائص فريدة ومميزة للشخص. نموذج شرايين يد الإنسان هي جدا معقدة و تظهر بشكل معقد و يمكن مشاهدتها بشكل عدد كبير من الأوردة. المعلومات البايومترية هي تقع داخل جسم الإنسان وبالتالي فهي محمية من التزوير والتلاعب. في العمل المقترح، متعددة مستويات كاوسين تم استخدامه لتحسين صورة اليد. ثانيا، طريقة جديدة مقترحة لاستخلاص المواصفات بالاعتماد Steerable filter و Locality Sensitive Discriminant Analysis تم استخدامه. في النهاية، تم استخدام مسافة الارتباط للتحقق من أوردة اليد. EER للطريقة المقترحة هو.0.1087%