Biometric Identification Through Hand Vein Patterns

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Abstract

Vein pattern is the vast network of blood vessels underneath a person's skin. These patterns in the hands are assumed to be unique to each individual and they do not change over time except in size. The properties of uniqueness, stability and strong immunity to forgery of the vein patterns make it a potentially good biometric trait. In this study, we present a novel biometric technique based on the statistical processing of the hand vein patterns. We considered the performance of four alternative feature sets and explored their fusion. The performance of the proposed algorithms was tested on a database of hand veins captured in the near infrared band and collected from 100 people. Our data collection is more realistic in that subjects had to undergo the procedures of holding a bag, pressing an elastic ball and cooling with ice, all exercises that force changes in the vein patterns. Our hand vein biometric tool outperforms the nearest competitor; furthermore tests of simulating real life conditions reveal the fusion scheme to be adequately robust.

1. Introduction

Developments in biometric technologies based on 2D and 3D faces, fingerprints, palmprints and iris have achieved sufficiently high recognition rates under controlled conditions, but the need for reliability, robustness and convenience is still a major requirement that remains unfulfilled. Vein patterns appear as a good candidate for a user friendly interface, potentially reliable against elapsed time and changes in physical conditions. Anatomically, the shape of vascular patterns in the back of the hand is claimed to be unique to an individual; even for identical twins [7] and it appears to remain stable over long periods. The structure of the vein patterns can be detected and captured with the help of infrared sensors. The visibility of the vein structure depends on various factors such as age, thickness of the skin, ambient temperature, physical activity, and the imaged part of the hand. In addition, surface features such as moles, warts, scars and hair can also affect the imaging quality of the veins. Typically, there are two kinds of imaging technologies, namely Far-infrared (FIR) and Near-infrared (NIR) imaging. FIR technology that works within the range 8-14 μm is more suitable for capturing the large veins in the back of the hand, but it is sensitive to ambient conditions and does not provide a stable image quality. On the other hand, NIR imaging that works within the range 700-1000 nm produces good quality images when capturing vein patterns in the back of the hand, palm, and wrist. This band is more tolerant to changes in environmental and body conditions, but it also faces the problem of disruption due to skin features such as hairs and line patterns [16].

L. Wang et al. [16], proposed a person verification system using the thermal-imaged vein pattern in the back of the hand based on the Line Segment Hausdorff Distance (LHD). They reported correct recognition of all subjects in a database of 30 persons. In another paper, Z. Wang et al. [17] gave comparisons of shape and texture based methods for vein recognition. While shape similarity is measured via Hausdorff and Line Edge Map (LEM), texture similarity was measured via Euclidean distance of Gabor magnitude features. In a dataset of 100 persons, Hausdorff, LEM and Gabor based methods achieved an accuracy of 58%, 66%, 80%, respectively. C.-L. Lin et al. [11] present person verification results using palm dorsal images acquired from infrared (IR) images in the 3.4 - 5 μm band. Their

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Table 1. Comparative Survey of Methods

Reference	Data	Methods and Results
		Verification
C.-L. Lin et al. [11],	32 users, 30 samples/subjects, total 960 images	Multi-resolution analysis. 5× enrollment. EER: 3.75
K. A. Toh et al. [14],	50 users, left and right hands, 10 samples/subjects, total 1000 images	Palm vein and palmprint scores are fused with SUM rule. SVM with RBF kernel is optimized for the vein features consisting of sub-sampled vein lines and for the directional wavelet energy features for palmprint. 5× enrollment.
L. Wang et al. [16],	30 users, 9 samples/subjects, total 270 images	Vein images are skeletonized as in [13] and LEM. Triple enrollment. EER is claimed to be 0.
		Identification
Y. Ding et al. [1],	48 users, 5 samples/subjects, total 240 images	The number of the end points and crossing points and the distances between them are used for feature extraction. Single enrollment. Identification rate: 99.1%
Z. Wang et al. [17]	100 users, 5 samples/subjects, total 500 images	Single enrollment. Hausdorff, LEM and Gabor methods yield respectively 58%, 66% and 80%
This paper	100 users, 3 samples/user, 4 conditions, total 1200 images	ICA1, ICA2, LEM and NMF methods as well as their fusion are considered. Identification rates are 80.25% for single enrollment and 88.97% for double enrollment

approach is based on the combination of multiresolution images obtained from the pre-processed thermal vein images. G. Wang et al. [15] proposed a multimodal person 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 and they called this "Laplacianpalm". A summary of literature has been presented in Table 1. We remark that none of these results are reproducible since the databases are not open.

2. Vein Biometry and Image Acquisition

A typical vein pattern biometric system consists of five processing stages: I) image capture II) hand image normalization III) extraction of the line segments IV) feature extraction V) matching and identity detection. In order to match hand veins correctly, pose and posture normalizations are necessary. Hand images captured in arbitrary postures are brought to standard finger orientations and pose, using the normalization algorithm proposed by Yoruk et al. [9, 18]. This algorithm involves several consecutive processing steps, namely, segmentation of the hand image from the background, hand rotation and translation, finding the finger axes and tips, removal of ring artifacts, completion of the wrist, estimation of finger pivots, rotation and translation of fingers to standard orientations.

A monochrome NIR CCD camera WAT-902H2 ULTIMATE (CCIR) [5] is used to capture the vein patterns in the back of the hand. The hand is irradiated by two IR light sources. In order to eliminate the effects of visible light, the setup is installed in a dark room. The camera in the overhead position is adjusted approximately 80 cm above the hand stand. Users were asked to place their hands on a black sheet with the back of the hand facing the camera. The images were digitized into 640×480 pixels with a gray-scale resolution of 8-bit per pixel and after deinterlacing, the image sizes were reduced to 300×240 pixels.

The data was collected from 100 people, 41 female and 59 male subjects. Three images were captured for each of the following conditions, hence overall twelve images per subject: I) Under normal conditions, II) After having carried a bag weighting 3 kg for one minute, III) After having squeezed an elastic ball repetitively (closing and opening the fist) for one minute, IV) After having cooled the hand by holding an ice pack on the surface of the back of the hand. In total we obtain 1200 left hand images. In addition, one image of the right hand is also taken to determine the degree of interchangeability of the left and right hands.

3. Feature Extraction

We have developed three hand recognition schemes that are quite different in nature. The first two recognition schemes consider the whole image and apply two different subspace methods, namely ICA and NMF. The third method, LEM is based on distances between the

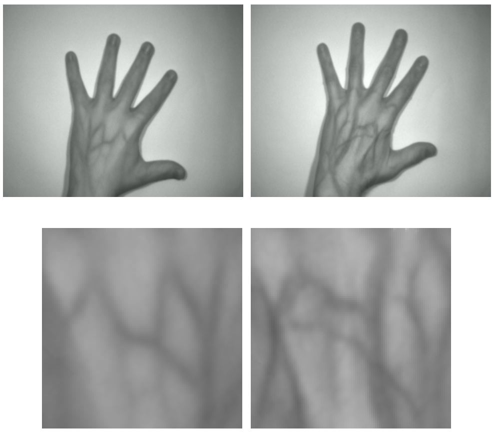

Figure 1. Hand vein images and their region of interest

contours representing the hands, and hence it is shape-based.

3.1. ICA

Independent Component Analysis (ICA) is a technique for extracting statistically independent variables from a mixture of them. There exist two possible formulations of ICA. In the first architecture each of N individual hand-data vectors is assumed to be a linear mixture of an unknown set of N statistically independent source hands. In the second architecture, the superposition coefficients are assumed to be independent, but not the basis images. Thus, this model assumes that, each of K pixels of the hand images result from independent mixtures of random variables.

In this paper, we apply both ICA architectures as a feature extraction tool on grayscale images. ICA assumes that each one of the observed signals $\{x_i(k), k = 1, .., K\}, i = 1, .., N$ is a mixture of a set of N unknown independent source signals s_i which are linearly combined through an unknown mixing matrix A. In ICA x_i and s_i are combined to form the X and S matrices. In ICA1, x_i and s_i are rows of $N \times K$ matrices and in ICA2, they are columns of $K \times N$ matrices. We have the following model:

$$X = AS \quad (1)$$

The data vectors for the ICA analysis are the lexicographically ordered hand image pixels. The dimension of these vectors is K = 10000, if we assume a 100×100 vein image. Briefly, ICA aims to find a linear transformation W for the inputs that minimizes the statistical dependence between the output components y_i, the latter being estimates of the hypothesized independent sources s_i:

$$S \cong WX \quad (2)$$

In order to find such a transformation W, which is also called separating or de-mixing matrix, we implemented the fastICA algorithm [6].

Table 2. Comparison of binarization methods

	Accuracy	ME	Hausdorff	MHD
Niblack	0.69	0.30	15.85	1.16
Bernsen	0.86	0.13	15.03	0.41
Yasuda	0.94	0.05	12.31	0.27
Wang [16]	0.74	0.25	14.86	0.81
Otsu	0.78	0.21	29.65	2.04

3.2. NMF

Non-negative Matrix Factorization (NMF) is another matrix factorization technique with the added constraint that each factor matrix has only non-negative coefficients [10]. Given a non-negative data matrix X of size $K \times N$, we obtain two nonnegative matrices W and H such that:

$$X \cong WH \quad (3)$$

where W is of size $K \times L$ and H of size $L \times N$. Since we force the two matrices to be non-negative, we can only reconstruct X approximately from their product. The columns of W can be regarded as basis vectors and the columns of H are utilized as feature vectors of the corresponding vein images. We use Hoyer's code [4] for NMF representation.

3.3. LEM

Line Edge Map (LEM) is an approach that extracts lines from an image edge map as features. The algorithm can be considered as a combination of template matching and geometrical feature matching. It was proposed by Gao and Leung [2] and originally applied for face recognition. The steps of binarization, skeletonization and line extraction as adapted to vein images are detailed below. The basic unit of LEM is the line segment grouped from pixels of the edge map and matching of line segments is based on the Line Segment Hausdorff Distance (LHD). Two image patterns are considered to be similar if their LHD distance is small.

3.3.1. Image Binarization Global thresholding of NIR images does not always prove to be successful; hence, we resort to local binarization methods such as Yasuda [12], Bernsen [12], Niblack [12], Wang [16]. For comparison we also include one global method, Otsu [12]. Based on several ground truth-images the scores of various similarity criteria [12], such as accuracy, misclassification error (ME), Hausdorff distance and Modified Hausdorff Distance (MHD) between ground-truth images and test images are shown in Table 2. The best results have been obtained with the Yasuda method.

In the Yasuda method [12] one first applies a normalization process, followed by a nonlinear smoothing, which preserves the sharp edges and culminating in an adaptive thresholding and segmentation stage. Noise filtering and skeletonization yields the vein line segments.

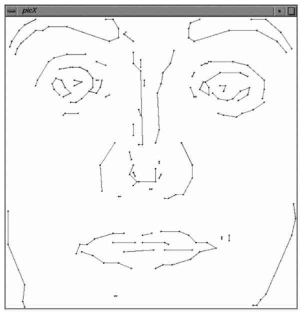

Figure 2. An illustration of a face LEM [2]

Figure 3. LEM extraction steps: A vein image, Yasuda binarization and noise removal, skeletonization and line segments generation

3.3.2. LHD While Hausdorff distance is a natural measure for comparing similarity of sets and shapes, its extension called Line Segment Hausdorff Distance (LHD) is a measure to compare line patterns. LHD incorporates structural information of line segment orientations and line-point associations, and hence is effective in comparing two shapes made up of a number of curve segments.

LHD measures the degree of dissimilarity between two LEMs. LEM is a representation which records only the end points of line segments on curves. An example LEM for the face matching problem is given in Figure 2. Given two LEMs, $M^l = \{m_1^l, m_2^l, .., m_p^l\}$ representing a model in the database and $T^l = \{t_1^l, t_2^l, .., t_q^l\}$ representing a test input LEM where the superscript l stands for line, LHD computes vectors such as $\vec{d}(m_i^l, t_j^l)$ that represents the dissimilarity between two line segments m_i^l and t_j^l. It is defined as:

$$\vec{d}(m_i^l, t_j^l) = \begin{bmatrix} d_\theta(m_i^l, t_j^l) \\ d_{\|}(m_i^l, t_j^l) \\ d_\perp(m_i^l, t_j^l) \end{bmatrix} \tag{4}$$

where $d_\theta(m_i^l, t_j^l)$, $d_{\|}(m_i^l, t_j^l)$ and $d_\perp(m_i^l, t_j^l)$ are the angular distance, parallel distance and perpendicular distance, respectively. Using these distances, LHD has been calculated using the equations defined in [2]. We have calculated angular distance by taking the tangent of the angle between lines and W_a, the weight for angle distance, has been taken as 20 empirically.

4. Feature Matching and Classifier Fusion

In identification mode, the user does not provide any identity claim, but the system must find out the user's identity from a database of enrolled users. For the person identification task, we measure the distance between the test feature vector and all the feature vectors in the database belonging to N different subjects. Notice that, there could be more than one vein image stored per person. Consequently, the number of comparisons amounts to the number of subjects times the number of images per subject. Cosine Similarity Measure (CSM) that tries to maximize the cosine angle between a template and test data is used to classify the new test sample.

For a person verification task, one must differentiate the genuine hand from the impostor hands as the user provides her hand image in support of her claimed identity. For this purpose, the distances between the hand of the applicant and all the hands in the database are calculated and the scores compared against a threshold. Feature organization and classification methods are identical for the the LEM method and the subspace (ICA, NMF) method, except that subspace methods use CSM distance while LEM uses LHD distance.

We have considered four fusion techniques to improve the performance of the individual schemes used for the identification and authentication tasks. We have used two score level fusion schemes and two decision level fusion schemes [3].

Table 3. Results for single training set: Identification rates and equal error rates (EER) for verification

Training		ICA1	ICA2	NMF	LEM
N1N2N3	Iden.Rate:	88.66	94.16	81.33	68.5
	EER:	4.02	2.47	8.14	13.52
B1B2B3	Iden.Rate:	78.33	72.33	71.44	73.77
	EER:	8.01	13.04	12.77	12.13
A1A2A3	Iden.Rate:	75.55	68.88	68.88	71.77
	EER:	9.20	13.23	14.11	12.76
I1I2I3	Iden.Rate:	68.77	64.88	66.55	65.77
	EER:	11.52	14.88	15.08	14.07
Average	Iden.Rate:	77.82	75.06	72.06	69.95
	EER:	8.18	10.90	12.53	13.12

Table 4. Results for double training set: Identification rates and equal error rates (EER) for verification

Training		ICA1	ICA2	NMF	LEM
N1N2N3	Iden.Rate:	94.33	97.33	89.67	78.00
	EER:	2.43	1.53	4.00	8.95
B1B2B3	Iden.Rate:	88.55	82.88	83.33	82.66
	EER:	4.75	8.69	7.33	9.54
A1A2A3	Iden.Rate:	86.44	79.44	81.89	82.22
	EER:	6.22	8.00	8.33	7.98
I1I2I3	Iden.Rate:	77.66	74.77	77.22	77.00
	EER:	8.22	10.76	10.89	10.24
Average	Iden.Rate:	86.74	83.60	83.03	79.97
	EER:	5.40	7.24	7.64	9.17

4.1. Borda Count

Each method assigns its own rank to all the vein patterns in the database based on their distances to the input vein pattern. The ranks from individual schemes are summed up to obtain a final rank for each person in the database. Then the identity of the vein pattern is declared to be the one with the highest rank.

4.2. Majority Voting

In Majority Voting, each method assigns 1 if the classifier decides that the unknown pattern belongs to the class and assigns 0 otherwise. The class having the highest vote is declared to be the unknown pattern x's class.

Table 5. Fusion results of ICA1, LEM and NMF for single training set

Training	Majority Voting	Borda Count	Sum	Product
N1N2N3	86.33	86.00	86.67	85.67
B1B2B3	77.33	79.00	80.78	79.89
A1A2A3	75.00	76.22	78.67	78.78
I1I2I3	72.44	73.44	74.89	74.33
Average	77.78	78.67	80.25	79.67

Table 6. Fusion results of ICA1, LEM and NMF for double training set

Training	Majority Voting	Borda Count	Sum	Product
N1N2N3	92.33	93.00	93.67	92.33
B1B2B3	87.44	89.67	88.00	88.11
A1A2A3	86.33	87.89	88.89	88.56
I1I2I3	81.89	84.11	85.33	84.56
Average	87.00	88.67	88.97	88.39

4.3. Z-score Normalized Sum and Product

Each method produces a distance value from the test image to the classes. The distance values are first mapped to the range [0, 1] with z-score normalization and then summed up for Sum Method or a product is applied for Product rule to obtain the final distance.

5. Experimental Results

The hand vein database we used contains 1200 images of left hands of 100 different people, each person having three images of his left hand under four different conditions. There were no control pegs to orient the fingers. Thus, for each individual, three hand images were recorded, denoted by the sets 1, 2, 3 and four different session are N, B, A, I, denoting normal conditions, bag carrying exercise, ball pressing exercise and cooling with ice. In order to see the effect of training sample size, we ran the identification experiments with a single training set and then with the double training set. More explicitly, in the single set experiments, the ordering of the training sets were $\{$(N1), (N2), (N3)$\}$ and the test sets were $\{$(N2,N3), (N1,N3), (N1,N2), (B1,B2,B3), (A1,A2,A3), (I1,I2,I3)$\}$.

Finally the identification scores given in Table 3 and Table 4, were averaged from these training and test set combinations. For the verification experiments, we provide Equal Error Rate (EER) for the same test and training sets. The best results are obtained with ICA1 for both single and double training set. The experiments revealed that both appearance-based methods, ICA and NMF, outperform LEM, which is a geometry-based method. In the LEM method, as the veins become visible in the bag and activity, the identification rates slowly increase. Score fusion under the Sum Rule seems to perform slightly better than score fusion under the Majority Voting, Borda Count and Product Rules. Fusing the best three methods ICA1, NMF and LEM outperforms the individual techniques.

6. Conclusion

We have collected a near-infrared based hand vein database, acquired under adverse conditions mirroring real life situations and developed a new biometric algorithm based on hand vein patterns. The novelty of the algorithm is the joint consideration of appearance-based and geometry-based features. The appearance-based features are extracted using ICA and NMF algorithms, and they both have proved superior to the geometry-based LEM technique. Under normal conditions there is no advantage accruing to the verification rate from any classifier fusion. However their fusion turns out to be beneficial for hand vein biometry under stressed conditions. The major conclusions can be summarized as follows:

- For normal conditions, ICA architecture 2 is the best feature set, yielding 94% and 97% verification, respectively, for single and double training sample per subject.
- For stressed conditions, such as strenuous exercise with the hand, there are large performance drops. For example, there is 25 percentage point loss between normal conditions and the stressed conditions (average of the three A, I, B conditions) for single training and 21 percentage points for double training.
- Fusion of the four classifier scores under sum rule improves the performance by 10%.

We have shown that hand vein pattern biometry is a promising spoof-proof technique. Our future research will address methods to make this biometric technique more robust in adverse conditions. Our database will be soon made open for the sake of reproducable results.

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