A multi-resolution wavelet algorithm for hand vein pattern recognition

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A novel hand vein recognition algorithm is developed based on multi-resolution wavelet analysis. The texture feature of hand vein can be extracted by three-level wavelet decomposition. Furthermore, K-nearest neighbor (KNN) with support vector machines (SVM) and minimum distance classifier (MDC) are employed for feature matching. Finally, the experiments are respectively performed in identification and verification modes using Tianjin University (TJU) hand vein image database constructed by our group. The results show the feasibility and effectiveness of the proposed method.

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Biometrics uses the physiological or behavior characteristics to recognize the individual identity, which has higher reliability and security than the traditional authentication methods like password and certificate, because biometric feature is difficult to be forged and lost[1−4]. Among biometric identification technologies, hand vein recognition has attracted remarkable attention for its uniqueness, non-contact measurement, friendliness, and cost-effectiveness[5−7]. In hand vein recognition, the vein network of the back of a hand is utilized to verify the human identity. The existing recognition algorithms are mainly based on structure and phase information of hand vein. The structure feature is generally depicted by a binary image. Constrained sequential correlation was adopted to match the test dilated binary image with the registered vein skeleton image by Cross *et al.*[8]; Lin *et al.* used the location relation of ending and bifurcation points in the skeleton image as hand vein feature[9]. Besides, template matching directly based on binary images was proposed by Shahin *et al.*[7]. However, the diameter of the blood vessel is quite different, thus the weak and strong veins are difficult to be well extracted simultaneously from the image with a single resolution. In addition, image binarization and skeleton extraction are sensitive to various noises, so the structural information is easy to be lost or mistaken and it will reduce the recognition accuracy. Tanaka *et al.* employed phase only correlation and template matching[10], whereas the phase features are extracted by Fourier transforms of the test and registered samples. Therefore, the time and memory costs are very large for its complex computation, which limits the practicability of this algorithm.

Aiming at the above issues, we present a multi-resolution wavelet algorithm to extract texture feature of the hand vein. Furthermore, the classifier K-nearest neighbor (KNN) with support vector machines (SVM) is designed to achieve the effective identification. The algorithm is tested using Tianjin University (TJU) hand vein image database developed by our group and the results show that the proposed method is feasible and effective for hand vein pattern recognition.

To the best of our knowledge, there is currently no public hand vein image database available for the algorithm research and test. Therefore, we designed our own near infrared (NIR) hand vein image acquisition system and constructed TJU hand vein image database, which contains 820 hand vein images from 82 different hands with the resolution of 640×480 pixels. The ages of participants range from 18 to 60 years old. Several images from this database are shown in Fig. 1, where (a) and (c) are from females; (b) and (d) are from males. The brightness of blood vessels is lower than that of the surrounding tissues, so the network of hand vein can be clearly visualized.

There are much noises and useless information in the acquired image, so it should be preprocessed before feature extraction and matching. Firstly, the region of interest, that is, the back of a hand can be segmented from the background using threshold method, and then Gaussian and 5×5 median filters are successively adopted to reduce image noises. Besides, the grey-level distribution varies largely among the images because of the different illumination intensity and time, even though the images are from the same hand. Therefore, the images should be normalized to have the pre-specified mean and variance by

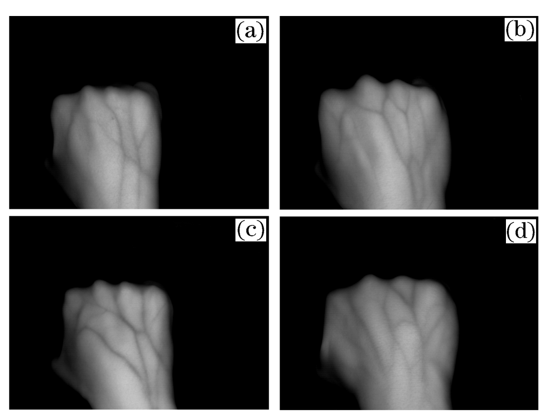

Fig. 1. Hand vein images of four different hands acquired in office environment.

$$I_1(i,j) = \begin{cases} M_1 + \sqrt{V_1(I_0(i,j) - M_0)^2/V_0} \\ \qquad\qquad I_0(i,j) \geq M_0 \\ M_1 - \sqrt{V_1(I_0(i,j) - M_0)^2/V_0} \\ \qquad\qquad I_0(i,j) < M_0 \end{cases}, \quad (1)$$

where $I_0(i,j)$, M_0, and V_0 are the grey value, mean, and variance of the image before normalization respectively; $I_1(i,j)$, M_1, and V_1 are the corresponding values after normalization.

Feature should be extracted based on the deep analysis of the test object, and the corresponding extraction method needs to be employed according to the specific characteristics. As shown in Fig. 1, we can see that hand vein possesses naturally the multi-resolution feature because the diameter diversity of the blood vessels is very prominent. Furthermore, hand vein also has steady directionality. Wavelet transform can decompose the image with different directions and levels, so it is competent to represent the vein texture feature. Wavelet transform has obvious advantages in time-frequency localization compared with other methods, and it can be used to distinguish non-stationary signals[11−13]. The wavelet basic functions $\psi_{a,b}(t)$ can be expressed as

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi(\frac{t-b}{a}), \quad (2)$$

where $a(a \in \Re_+)$ and $b(b \in \Re)$ are the scaling and translation parameters, respectively.

Considering discrete wavelet transform, the scale and translation parameters are generally given by

$$a = a_0^j, \quad (3a)$$

$$b = kb_0a_0^j. \quad (3b)$$

Submitting Eqs. (3a) and (3b) into Eq. (2), we have

$$\psi_{j,k}(t) = a_0^{-j/2}\psi(a_0^{-j}t - kb_0). \quad (4)$$

The one-dimensional (1D) discrete wavelet transform of the signal $f_w(t) \in L^2(\Re)$ is defined as

$$f_w(t) = \sum_j \sum_k \langle f_w(t), \psi_{j,k}(t)\rangle \psi_{j,k}(t). \quad (5)$$

The two-dimensional (2D) wavelet transform can be achieved by applying 1D wavelet transform to the rows and columns of 2D data. In this contribution, the hand vein image is analyzed by three-level wavelet decomposition. In each level, we can obtain three detail images in horizontal, vertical, and diagonal directions. These detail images are closely related to the edge intensity and can reflect the texture feature of hand vein. To describe the local feature, every detail image is divided into $s \times s$ non-overlapping sub-images, and then the mean deviation of the sub-image is calculated as hand vein feature by

$$V_m^n = \frac{1}{N}\left(\sum_N |I_m^n(i,j) - M|\right),$$
$$m = 1,2,\cdots,9, \quad n = 1,2,\cdots,s^2, \quad (6)$$

where $I_m^n(i,j)$ is the nth sub-image in the mth detail image; M is the mean value of $I_m^n(i,j)$, N is the pixel number of $I_m^n(i,j)$.

Consequently, the feature vector of hand vein can be described as the following equation, which is a 1D vector consisting of $9 \times s^2$ values.

$$\mathbf{V} = [V_1^1, V_1^2, \cdots, V_1^{s^2}, \cdots, V_9^1, V_9^2, \cdots, V_9^{s^2}]. \quad (7)$$

Depending on the application context, a biometric system operates typically in two cases: identification or verification[14]. In identification mode, the algorithm performs a one-to-many search in the whole database to determine which class the test sample belongs to. In verification mode, for a test sample from a claimed class, a one-to-one comparison is made to verify whether the test sample is from the claimed class. Two different feature matching methods are used in identification and verification modes, which are KNN-SVM and minimum distance classifier (MDC).

KNN is a kind of distance-based learning method. To classify the test sample x, it ranks the distances between the test and registered samples. Let $K_1, K_2, \cdots, K_c$ be the numbers of samples that belong to the class $\varpi_1, \varpi_2, \cdots, \varpi_c$ in the K-nearest samples, and the KNN decision function is defined as

$$\text{If } K_j(x) = \max_i K_i(x), \quad i = 1,2,\cdots,c,$$
$$\text{then } x \in \varpi_j. \quad (8)$$

Besides KNN, SVM is another efficient classification algorithm, which is based on the principle of structure risk minimization[15−17]. Considering the problem of classifying the given samples into two classes, the samples can be denoted by

$$\mathbf{S} = \{(x_1,y_1),(x_2,y_2),\cdots,(x_l,y_l)\},$$
$$x_i \in \Re^n, y_i \in \{-1,1\}, \quad (9)$$

where x_i and y_i are respectively the feature vector and class label of the ith sample, l is the number of the given samples.

The optimal hyperplane is constructed to separate the samples by maximizing the margin between the feature vectors of the two classes. For the linear classification problem, the hyperplane is defined as

$$f(x) = \omega \cdot x + b. \quad (10)$$

The optimal values for ω and b can be obtained through solving a constrained minimization problem, and then the SVM decision function can be expressed by

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{l} \alpha_i^* y_i(x_i \cdot x) + b^*\right), \quad (11)$$

where α_i^* is the Lagrange multiplier denoting the contribution of the ith support vector; the bias b^* can be calculated by any support vector. $f(x)$ is the distance between the testing data x and the optimal hyperplane.

If $f(x) \geq 0$, we will classify x as the class labeled by 1. Otherwise, x is classified as the other class denoted by -1.

KNN and SVM have their respective advantages and shortcomings, and they can remedy each other. KNN is suitable to solve the classification of large samples because the increase of the training samples will accelerate its convergence speed. Unfortunately, the performance of KNN will be debased when the features of training samples have poor clustering ability. In comparison with other algorithms, SVM not only is excellent to be applied to multidimensional pattern recognition of small samples, but also has higher classification accuracy. For the multi-class problem, multi-classifiers are obtained by constructing the hyperplane to separate each class from the remaining classes. However, most of the remaining classes have no effect on the hyperplane construction which may be misled by some of classes, and it will reduce the classification accuracy of SVM. If the number of the remaining classes is restricted within a small one K by KNN algorithm, and then the aforementioned problem can be well settled. Based on this idea, KNN and SVM are combined to improve hand vein recognition accuracy. The flow of KNN-SVM is as follows: for a test sample x, firstly compute the distances between x and all registered database, and then search the K-nearest samples. To reduce the error recognition rate, a threshold T_k is specified. If $K_j(x) > T_k$, then x belongs to the class ϖ_j. Otherwise, x is classified by SVM using the K-nearest classes as training samples. K and T_k are set to 5 and 3 respectively in this letter.

In verification mode, the similarity of features is measured by MDC based on Euclidean distance. The smaller the distance is, the more similar the two hand vein will be. A threshold T_d is set to confirm whether the two hand vein belong to one class. Euclidean distance $D_{\mathrm{r,t}}$ is defined as

$$D_{\mathrm{r,t}} = [(V_{\mathrm{r}} - V_{\mathrm{t}})(V_{\mathrm{r}} - V_{\mathrm{t}})^{\mathrm{T}}]^{1/2}, \tag{12}$$

where V_{r} and V_{t} are the features of registered and test samples respectively.

The performance of the proposed algorithm was evaluated in TJU hand vein image database, and experiments were performed in both identification and verification modes. In all experiments, 4 images of each hand were used as the registered samples, and the other 6 images were the test samples to confirm personal identity. Though the data acquisition system has constrained the hand location by a grasping attachment, human hand may still have small shift (x-shift, y-shift) or rotation. Considering the process of wavelet feature extraction, the x-shift does not influence the feature extraction, but the y-shift and rotation will result in the feature deviation. The range of possible y-shift is from -25 to 25 pixels, and the rotational scope is from $-15°$ to $15°$. Therefore, the registered images after 2D transformation (y-translation and rotation) were utilized to match with the test samples, which helped to improve the matching results.

In identification mode, the correct recognition rate (CRR) was used to test the algorithm performance. Various wavelets were compared to determine the most efficient wavelet for feature extraction of hand vein, as shown in Table 1. We can see that Haar and bior1.3 wavelets have better performance, especially Haar wavelet, the CRR is up to 99.59%. Compared with other wavelets, Harr wavelet has the shortest supporting, which makes it have better capability to capture the detail feature of hand vein.

Table 1. CRR Comparison of Feature Extraction Using Different Wavelets

Wavelet	CRR (%)	Wavelet	CRR (%)
db2	93.50	sym1	98.37
db3	93.50	sym2	95.93
db4	94.51	sym3	93.50
db5	91.06	sym4	94.51
db6	94.51	sym5	92.07
db7	89.63	sym6	91.87
db8	93.09	sym7	89.43
bior1.1	98.37	Haar	99.59
bior1.3	98.98	Dmey	93.29
bior1.5	96.95	coif1	95.53
bior2.2	92.68	coif2	93.09
bior2.4	92.68	coif3	90.45
bior2.6	92.28	coif4	91.26
bior2.8	93.50	coif5	89.02

Table 2. CRR Comparison of Different Classifiers

Classifier	MDC	KNN ($K = 5$)	SVM	KNN-SVM
CRR (%)	94.31	96.14	98.17	99.59

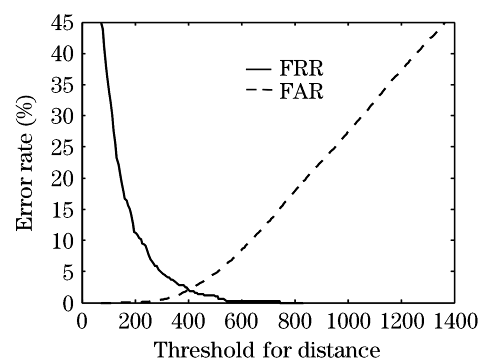

Fig. 2. Curves of FAR and FRR using Haar wavelet.

After feature extraction using Haar wavelet, the classification performence of KNN-SVM was compared with the traditional MDC, KNN, and SVM, and the result is listed in Table 2. The highest CRR is achieved by KNN-SVM, which proves that KNN-SVM has better classification performance and can improve the recognition accuracy for hand vein pattern.

In verification mode, the false acceptance rate (FAR), false rejection rate (FRR) and equal error rate (EER) were used to appraise the performance of proposed method. The FAR and FRR curves are shown in Fig. 2. When threshold T_d is set to 293.20, the FRR is 5.08%

for a small FAR 0.46%. EER corresponds to the error value when FAR is equal to FRR. As shown in Fig. 2, EER is only 1.96% at threshold 400.42, thus the result is quite encouraging and indicates good performance of our algorithm.

In conclusion, a multi-resolution wavelet algorithm is presented for hand vein recognition. Hand vein feature can be extracted by wavelet transform directly after simple filtering and grey normalization, which can avoid complicated image preprocessing like binarization and skeleton extraction. Moreover, KNN-SVM is incorporated in our method for the personal identification, which can improve CRR greatly. The experimental results show the excellent recognition performance of the proposed algorithm in both identification and verification modes.

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