Parallel sub-neural network system for hand vein pattern recognition

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A hand vein authentication system in which the identity of an individual can be readily confirmed upon gripping a handle is proposed. This recognition method incorporates infrared light-emitting diode (LED) onto a door handle and sets a charge-coupled device (CCD) camera on the other side of the hand. It builds on fuzzy c-means clustering and parallel neural networks (NNs); moreover, it is expected to solve the pattern recognition problem in large-scale databases using NNs due to its self-learning and parallel processing capabilities and by effectively incorporating training patterns. The experimental results validate the efficiency of the proposed algorithm.

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Vein authentication technology is a new biometric tool that has recently attracted considerable attention[1−9]. The pattern of veins is generally known to be hardwired into the body at birth and remains relatively unaffected by aging, except for predictable growth, similar to that of fingerprints.

Vein geometry is based on the fact that an individual's vein pattern is distinct. The deoxidized hemoglobin in veins absorbs light at a wavelength of approximately 7.6×10^{-4} mm within the near-infrared (NIR) area. When the infrared ray image is captured, only the blood vessel pattern containing the deoxidized hemoglobin is visible as a series of dark lines. Based on this feature, a vein authentication device translates the black lines of the infrared ray image as the blood vessel pattern of the hand and then matches it with the previously registered blood vessel pattern of the individual.

Kumar *et al.*[1] thoroughly discussed the use of hand vein triangulation and knuckle shape for vein recognition. Wang *et al.*[2] presented a multi-resolution wavelet algorithm for hand vein pattern recognition. Zeng *et al.*[3] developed a method using curvelet transform to extract features from vein patterns as well as principal component analysis (PCA) and nearest-neighbor classifier method for vein recognition. In our previous work[4], we established a two-step minutia-based method for vein recognition. All these proposed methods demonstrated good experimental performance. However, problems in the vein recognition field remain. Such problems are as follows: (1) The current methods are not user-friendly as users must place their hands on the identification device and wait for authentication. (2) Most existing systems are unable to recognize a pattern from a very large database using neural networks (NNs) effectively, especially when there are numerous patterns registered in the database, indicating the significance of large-scale NNs. (3) Systems have yet to develop the capacity to incorporate and adjust training patterns in large databases and in a timely manner.

A new grip-type hand vein authentication system that is more convenient to use than previously developed systems is herein proposed. The incorporation of this authentication system onto a door handle allows the identity of an individual to be readily confirmed upon gripping the handle, without any additional maneuvers, such as placing the hand on the identification device. The proposed system differs from other hand vein recognition systems in that an infrared light is transmitted from the back of the hand. The hand is placed between the infrared light source and a camera. As hemoglobin in the blood absorbs the infrared light, the pattern of veins at the back of the hand is captured as a pattern of shadows. This new recognition method is based on fuzzy c-means (FCM) and parallel NNs, which are established as follows: (1) Based on the locations of extracted minutiae points, the system can classify the registers into several clusters using the FCM method. (2) A small-scale three-layer back-propagation NN (BPNN), called a sub-NN, is then created in each cluster, and the process of learning and recognition in each sub-NN is conducted independently and synchronously. The system can effectively recognize a pattern from very large databases because of the algorithm's self-learning properties and parallel processing capability. Furthermore, the system can incorporate training patterns, thus avoiding the expensive computational cost of retraining the whole system.

An example of the original images in the database is shown in Fig. 1. The system consists of one infrared light-emitting diode (LED) array and a charge-coupled device (CCD) camera. A band-pass filter was set between the infrared LED and the CCD camera to avoid the effects of varied illumination conditions.

This study focused on recognizing the hand vein pattern at the back of the hand because palm veins are compressed and deformed in the gripping action, rendering

Fig. 1. Hand vein images.

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standard image acquisition difficult. Conversely, as the veins on the back of the hand are stretched during gripping, a bright and clear vein pattern could be seen and smoothly scanned by placing the light source on top of the described handle, near the hand. The image device is illustrated in Fig. 2.

The region of interest (ROI) is extracted as previously described[2], an example of which is illustrated in Fig. 3.

A method based on mathematical morphology was adopted in this research to enhance the contrast between backgrounds and vein patterns. This operation is based on morphologically opening images with a linear structuring element at different orientations. Six rotated structuring elements with a radial resolution of 30° were used. The length of a structuring element was selected such that it was larger than the smallest vessel. A length of eight pixels was empirically determined to give the best balance of the vein patterns. In each of the six opened images, only those parts of the vasculature in which the linear structuring element can fit were retained. A map of only the vasculature was obtained by taking the maximum pixel value at each pixel location in all six images. An image of emphasized veins is shown in Fig. 4.

The vein pattern is composed of vessels with various orientations. The proposed image emphasis method can obtain the most linear information on the vasculature and simultaneously remove undesired background information, which can be regarded as noise. In particular, granular image noise can be eliminated.

The obtained images are converted to binary images. The morphological skeleton method[10] is used to derive the thinning image. Consider the problem of representing a binary-valued image, $X \in Z^n$. Let B be a morphological structuring element, $B \in Z^n$, which is bounded, convex, as well as symmetric and contains the origin. The representation of X using the morphological skeleton is given as

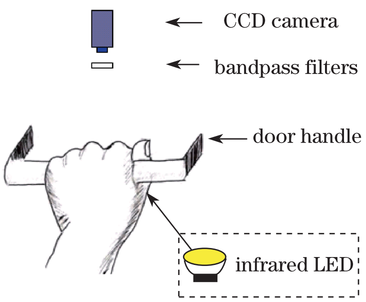

Fig. 2. Imaging device.

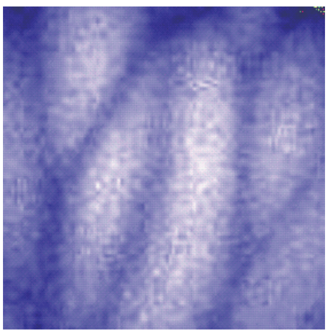

Fig. 3. Extracted ROI.

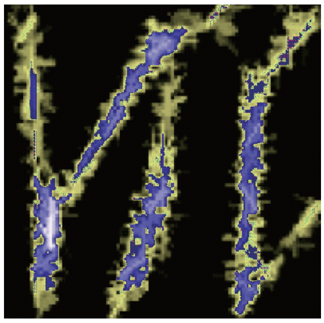

Fig. 4. Emphasized vein pattern.

$$X = \bigcup_{k=0}^{N} S(k) \oplus kB, \tag{1}$$

where

$$S(k) = (X \ominus kB) \backslash (X \ominus kB)_{B'}, \tag{2}$$

where $\ominus$ and $\oplus$ are the morphological erosion and dilation, respectively. The equation $X_B = X \ominus B \oplus B$ is the morphological opening of X by B, X/Y is that part of X that is not in Y, kB is the kth-order homothetic of B, and N is the largest integer, such that $X \ominus NB \neq \phi$. The $S(k)$ set, known as the skeletal subset, determines how the homothetic functions of B are combined to form components.

Two features extracted from the vein patterns are used in the recognition system: the location of the minutia (which represent general information on the vein patterns) and the ROI images (which provide the dark-line information and represent detailed information on the vein patterns). These features are combined in the present research. The FCM algorithm sorts the registers into several clusters using the locations of the minutiae, and binary images are entered into the input layer of the NNs.

Previous research has investigated face recognition systems[11−15], which serve as the foundation of the proposed vein pattern recognition system. A classifier technology similar to that used in the former systems is structured in the proposed system, and the method is shown to be effective. Furthermore, the incorporation of training data in a large-scale recognition system is proposed. The experimental results validate the efficiency of the proposed algorithm.

Minutia detection is a trivial task when an ideal thinned ridge map is available. If a pixel is on a thinned ridge (eight-connected), then it is assumed to have values of 1 and 0. Let (x, y) denote a pixel on a dark line, and let $N_0, N_1, \cdots, N_7$ denote eight neighbors. A pixel (x, y) is a ridge ending if $\sum_{i=0}^{7} N_i = 1$, and it is a dark-line bifurcation if $\sum_{i=0}^{7} N_i > 2$.

The locations of the minutiae are used in the algorithm, and the system sorts the learning patterns into several clusters using FCM. The FCM is a data clustering algorithm in which each data point is associated with a cluster via a membership degree. Firstly, based on the FCM algorithm, if the difference between two cluster centers is less than the minimum difference value, the two clusters will be integrated and one cluster will be deleted. For instance, N persons divided into r clusters may be described by an $r \times n$ matrix U, where i, in the kth entry μ_{ik}, is the membership between zero and one and the sum of the entries in each line is one. The following parameters are then set to de-fuzzify the memberships: one register is allowed in five small-scale subnets simultaneously, and up to six registers are permitted to belong to one subnet. In brief, for the de-fuzzification of a membership function, the number of clusters that a pattern may belong to is set as five. In addition, the maximum cluster redundancy that determines the maximum number of elements in a cluster is set as six. Finally, as the maximum number of elements in one subnet is set as six, small subnets with members fewer than six are integrated with another subnet. For example, in this work, 50 registers were divided into 13 subnets using the proposed algorithms. This FCM-based distributing algorithm has been previously reported in detail[11−13].

The images must be normalized due to the various sizes of the extracted images. The illustrated binary images are standardized into 32×32, and these patterns are entered into the input layer of the NNs.

The parallel NNs are constructed according to the results of FCM. Each subnet constructs one small-scale NN, thus giving 13 small-scale NNs that are constructed and connected in parallel. The training process is independently carried out in each small-scale NN.

In this work, the parallel NNs are composed of three-layer BPNNs. A connected NN with 32×32 input neurons and six output neurons was simulated (six individuals are permitted to belong to each subnet); the structure of the proposed parallel NNs is illustrated in Fig. 5. As no concrete rule states how to determine the number of the hidden layer nodes, the optimal number must be obtained considering the circumstances.

A standard pattern (average pattern) is obtained from five patterns per registrant. Based on the FCM algorithm, 50 standard patterns are divided into 13 clusters. Similar patterns in one cluster are entered into one subnet, yielding 13 structured subnets (Fig. 5).

The BP algorithm is then performed in each subnet, and it is repeated until the sum of squared errors becomes equal to or smaller than a certain value:

$$E = \sum_{p=1}^{P} (t_p - y_p)^2, \tag{3}$$

where t_p and y_p are the target and actual output for the output layer p, respectively, and P is the total number of output layer neurons in the training set. The training rule is used to adjust the weights and move the network

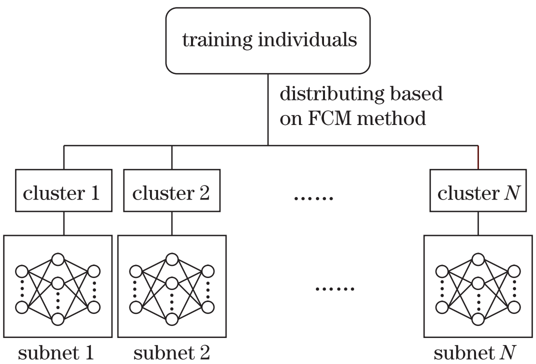

Fig. 5. Training process for proposed parallel NNs.

outputs closer to the targets (0.99 is the target value of the correct pattern, whereas 0.01 is the target value of any other pattern).

When a test pattern is added to the parallel NNs based on the outputs in each subnet and the similarity values, the result can be obtained as follows.

Firstly, exclusion by the negation ability of NNs. All registrants are initially regarded as candidates, but only the candidate with the maximum output is retained in each subnet. Corresponding candidates are deleted if the maximum output values are less than the threshold value, which is set as 0.5 based on the maximum output value of the patterns of the non-registrants. Based on this step, candidates similar to the desired individual are excluded, because similar individuals are distributed into one subnet. Secondly, exclusion by the negation ability of parallel NNs. Among the candidates remaining after the first step, the candidate that has been excluded in one subnet will be deleted from the other subnets. If all candidates are excluded in this step, the test pattern is judged as a non-registrant. When a candidate similar to the desired individual is simultaneously assigned to several clusters, the candidate may become the maximum output of the subnets to which the desired individual does not belong to and may be mistakenly selected as the final answer. Performing the second step avoids such possibility. Thirdly, judgment by the similarity method. Similarity measures between candidates that are retained after the second step are used for judgment. Particularly, the similarity value between the patterns of each remaining candidate and the test pattern is calculated. The candidate with the greatest similarity value is regarded as the final answer using cosine similarity. Let

$$\text{similarity}_{\text{c}} = \frac{1}{k^{(l)}} \sum_{k=1}^{k^{(l)}} \frac{(x, x_k^l)}{\parallel x \parallel \times \parallel x_k^{(l)} \parallel}, \tag{4}$$

where l is the number of individuals, $k^{(l)}$ is the number of trained patterns for each individual, x is the test face pattern, and $x_k^{(l)}$ is the lth candidate pattern belonging to individual k.

The following algorithm is proposed to incorporate the training patterns in a large-scale database efficiently and to avoid the expensive computational cost of retraining the whole system.

If $\text{Number}_{\text{add}} = 1$, the $\text{similarity}_{\text{c}}$ between the added training pattern and the test pattern should be computed using Eq. (4) and compared with the outputs of the other subnets.

If $1 < \text{Number}_{\text{add}} \leq 6$, a new subnet should be constructed and added to the parallel NNs.

If $\text{Number}_{\text{add}} > 6$, FCM should be used to classify the added training patterns into two or three clusters and the subnets should be added to the parallel NNs.

$\text{Number}_{\text{add}}$ is the number of individuals added to the training database.

To the best of our knowledge, no public hand vein image database is currently available for research into and testing the algorithm. Therefore, an NIR hand vein image acquisition system was designed and a hand vein image database was constructed. Experiments were carried out using the vein images of 60 individuals (age

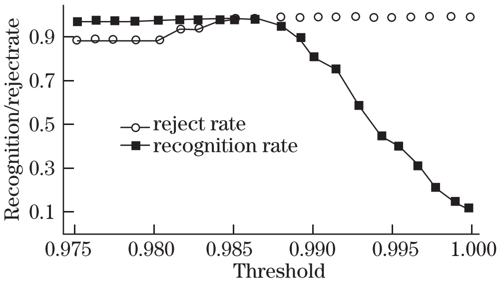

Fig. 6. Recognition results.

Table 1. Equal Error Rates of Different Approaches

Approach	Error Rate (%)
Minutiae and Dark-Line Matching	1.6
PCA	2.4
Proposed Approach	0.4

range, 21–42 years old; 50 individual patterns were selected as registrants and 10 individual patterns served as non-registrants). Each person provided 15 images of one hand. In the system, five images were randomly selected as the training set by a computer for each individual. The remaining images were used for the recognition tests. Hand patterns with different rotations were applied in the database. The camera used supports a 512×512 resolution, and the system uses Pentium IV 2.8 GHz PC and virtual C++ 2008 software.

Five individual patterns (each individual provided five images of each hand) were treated as the new training patterns. These had to be added to the trained parallel NN as N+1. The system constructed a new subset using the five patterns to improve the efficiency of the training process, and only the patterns in this subnet were trained. This trained subnet was then connected with the overall trained NN system in parallel.

Five hundred patterns for 50 registrants were used for recognition. One hundred additional patterns were prepared for 10 non-registrants to determine whether the system can judge that these patterns were not registered. The overall recognition rates for different threshold values are illustrated in Fig. 6. When the threshold was set as 0.985, the recognition rates were 99.6% (two errors among 500 patterns) for registrants and 0% (none among 100 patterns) for non-registrants. The total processing time for vein pattern recognition in a 512×512 image was 70 ms on average.

The recognition rate, rejection rate, and equal error rate are defined as follows:

(recognition rate) = 100 × (number of correct images for registrants)/(number of all registrants)

(rejection rate) = 100 × (number of rejected Images for non-registrants)/(number of all non-registrants)

(error rate) = 100 × (number of error images for registrants)/(number of all registrants)

A series of experiments was conducted for vein pattern recognition to evaluate and compare the performance of the proposed system with the performances of two popular approaches: the minutia and dark-line matching system[4] and PCA[6]. The same database and experimental parameters were used. The results are listed in Table 1. The proposed method performed better compared with the existing methods in that its recognition error rate was much lower.

In conclusion, a new grip-type hand vein authentication system is proposed: an ROI extracting algorithm that can extract the same part of the same hand every time and in which a new modifiable parallel NN algorithm is incorporated. This method achieved a recognition accuracy rate of 99.6% for 500 patterns of 50 registrants and a rejection rate of 100% for 100 patterns of 10 non-registrants. The results indicate that this algorithm has prospective applications. A large-scale database will be constituted to test the capability of this method in such a system.

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