Hand-Geometry Biometrics Identification Systems

A novel, simple method to recognize individuals based on their hand-palm geometry is now possible using a compact set of parameters.

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Two classification methods have been implemented: neural networks based on commonly used multilayer perceptrons and nearest-neighbor classifiers. Results indicate that complex algorithms are not required in the classification phase to obtain high recognition values. In simulations, rates beyond 99 percent have been achieved.

Biometrics-identification systems have seen an explosive growth in devices concerned with security applications. Such systems have a privileged position in methods used to identify or verify identities of users. Of these, hand-geometry systems are most often employed due to their reliability, efficiency and ease of use.

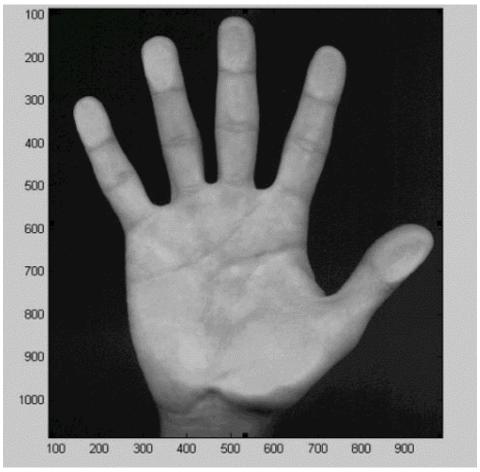
The goal was to develop a simple and effective recognition system to identify individuals using hand palms using simple and acquaintance classifiers such as neural networks and nearest-neighbor classifiers.

The first step is to set up a database containing a set of user characteristics. The database was built offline, and contains 500 samples taken from 50 different users. Two main parameters are extracted from user hand-palms: geometrical and contour information.

The database is then pre-processed to prepare images for the parameter-extraction phase. This process is composed of the following four stages: binarization, contour and main points extraction (finger tips and valleys between fingers), area and perimeter calculation, and finally hand-contour normalization.

Contour information generated in the previous step is too large to be efficiently used and classified with the proposed methods so it was reduced. Several techniques for reduction were used and compared. The objective was to reduce length of features keeping as much information as possible. Among these techniques, the simplest obtained was sub-samples of feature space, image descriptors using wavelet decomposition or more advanced techniques such as principal-component analysis based on transform-domain techniques.

Table.1 Image Specification



Both sets of features (geometric and contour-based) are classified using neural networks and nearest-neighbor. Most suitable classification techniques for parameter sets are determined from the results.

Database Elaboration and Image Processing

The database is composed of 10 scanned hand samples taken from 50 different individuals. The database has been built offline and users have to be enrolled before using it. For image acquisition, desktop scanners with a resolution of 150 dpi were used and hand size has been reduced to 20 percent to facilitate subsequent calculations and image processing. The main image specifications used in building the image database can be observed in Table 1.

Once the database was created, images are transformed into a suitable format to facilitate further parameter extraction. The gray-scale images provided new images containing contours or hand outlines. Two fundamental steps were followed to achieve these objectives:

Fig. 1 Show a Sample Image Taken from the Databse

Properties of the Images Contained in the Database	
Size	80% original size
Resolution	150 dpi
Color	256 gray levels
File Size	1405 Kbytes
Datamatrix Dimension	1403 x 1021

Fig.3 Contour Extracted from the Binariizted Image

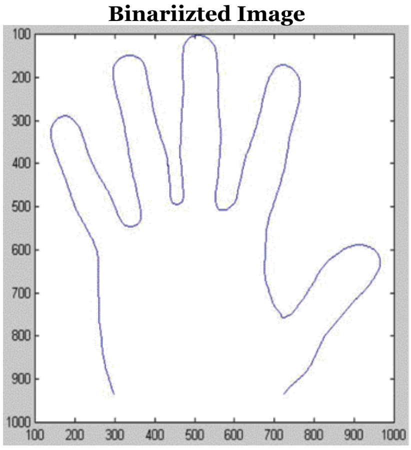
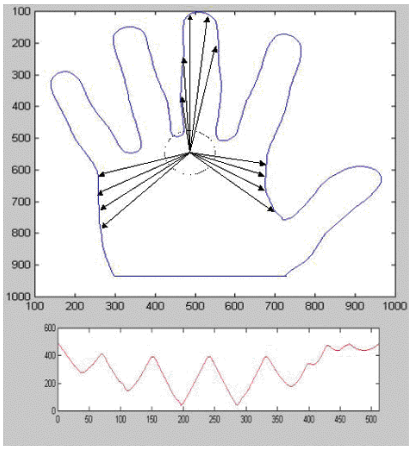


Fig.4 Contour and Measure Merits Extracted



• Image binarization: During search for the optimum threshold, different methods, such as those suggested by Lloyd, Ridler-Calvar and Outsu were used. The first two algorithms offered a threshold very similar (value of intensity 100); and the third a threshold of 185. The last value was totally ruled out since the processed image-with the threshold of 185-was worse than the high threshold shown in Fig. 2. For value 100, few differences existed since small variations in threshold do not affect final results in an important way. Therefore, search for a threshold is a heuristic process, resulting in a threshold in the range of 65-100.

• Computation of hand contour: Binarized images follow image edges to outline hand silhouettes. Contour monitoring sweeps over hand outlines, distinguishing between objects (hand) and background. Implemented algorithm is a modification of the algorithm created by Sonka, Hlavac and Boyle. In the original algorithm, contours based on four values codify direction of each point located in hand contours. In this case, eight possible changes in direction are taken into account. The result of this process can be observed in the following figure:

The last step in the pre-processing phase is to center images with respect to centroids, which gives the desired translation invariance.

Parameter Extraction

Different techniques have been undertaken to determine which provide higher identification rates. Two completely different sets of parameters are extracted from images.

• Geometric measurements: Ten direct features are extracted from every image: length of fingers, three hand-ratio measurements, area and perimeter. Fig. 4 shows geometric measurements graphically.

• Contour information: Besides information obtained directly from hands, extra information is garnered from contours. In order to reduce parameter sets, a module representation of contours (distance from origin to every point in the contour) is used. This process provides a wave-shaped signal (Fig. 5) particular to every user.

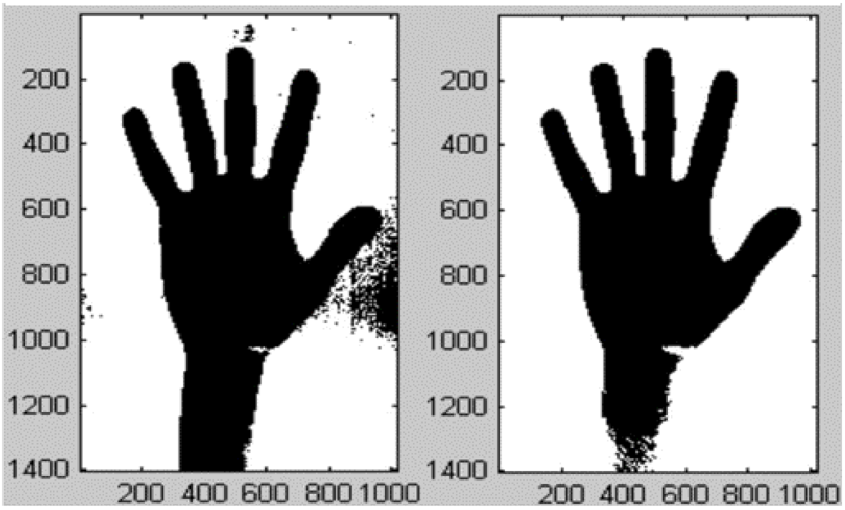
Other parameters come from hand counters. These are obtained by sweeping polar coordinates (modules and phases).

A typical problem with this technique is length of template vector. Generally, it is desirable to find or reduce characteristic sets to one new vector-the minimum but sufficient. This can be achieved by means of judicious elimination because elements that compose this vector are close enough. In order to reduce template-vector length, the following techniques are used:

• Principal Component Analysis: PCA, also known as Karhunen Loeve transformation, can reduce feature-vector dimension while retaining feature information by constructing a linear-transformation matrix. The transformation matrix is composed of eigenvectors, which are more significant than the covariance matrix, which is formed from characteristic vectors. Eigenvectors are orthonormals (orthogonal and normalized) and are used to transform original data in independent characteristics having maximum variance.

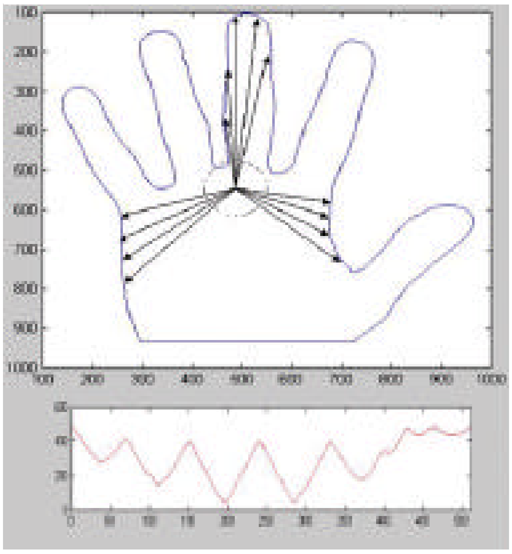
• Wavelet transformation: These transformations are mathematical functions that divide data into different components, studying each component and assigning it appropriate resolution to scale. The advantage of Wavelet transformation over traditional Fourier methods is that they can analyze situations where signals contain interruptions and abrupt peaks. Discrete Wavelet transformation is a lineal operation that generates a structure of data that contains log2(n) variable segments of length.

Fig.2 Process of Binarization



(a) High Threshold **(b) Selected Threshold**

Fig.5 Outline of Hand and Module Representitive



• Cosine transformation: Inspired by Fourier descriptors, examination is made to see if other transformations could be used to obtain better results. High information redundancy present in images turns out to be ineffective when images are used directly for tasks of recognition, identification and classification. To reduce quantity of information, discrete-cosine transformation is used to compact signal energy. Karhunen-Loeve transformation is best in transforming energy compaction. The problem is that KLT is the data clerk so obtaining KLT base images is a very high computational task. DCT has interesting advantages such as possession of an excellent property of energy compaction for highly correlated data. In addition, it transforms as rapidly as DFT.

Recognition rates were computed for the following features lengths: 128 and 512 values for sub-sampling, 50 and 128 values for PCA, and 128 and 512 values for wavelets. With this parameter extraction, success rates in user identification are shown in Table 1. These experiments were repeated ten times for averaging. Results of maximum recognition rate, in function of employed training percentage are shown in Table 1.

Classification

Two classifier methods were used. In both cases, learning was supervised, creating a two-phase process in classification, training and test phase.

The neuronal network used was feedforward and this was trained with the system of learning perceptron multilayer by means of algorithm-back propagation. A hidden layer containing 58 neurons was utilized to offer best results.

Another classifier method is nearest-neighbor classifier. This algorithm is one of the simplest methods of classification. Algorithm codes store data presented to develop predictions on new characteristic vectors, while KNN algorithms find nearest vector from training vectors to new vector, and predict new class. KNN is a method of learning based on nearest-neighbor. The algorithm calculates similarity in testing and training samples, considering nearest k vectors in training to find similar class. To find vector of similar training, majority vote was used.

The degree of similarity between two samples is distance between based on a metric distance. In the simulations, Euclidean distance was used.

Be t a sample with n characteristic represented by characteristic vector $<v_1(t), v_2(t), K, v_n(t)>$ where term is the value of the characteristic one i of the sample t. Therefore the distance among two samples ti and tj are d(ti,tj), where:

$$d(t_i,t_j)=\sqrt{\sum_{m=1}^{n}(v_m(t_i)-v_m(t_j))^2}$$

Fig.5 Comparison between Different Techniques of Identificantion

		Maximum Recognition Rate			
Number of hands		3	5	7	9
Sub-Sampling	KNN-128	82,2%	87,92%	90,24%	90,46%
	NN-128	92,21%	96,2%	98%	99%
	KNN-512	91,25%	94,36%	95,26%	96,6%
PCA	KNN-50	88,22%	92,96%	94,93%	96,4%
	NN-50	92,11%	96,92%	98,4%	98,8%
	KNN-128	89,94%	94,32%	96,26%	97,6%
	NN-128	80,9%	89,76%	94,2%	97%
Wavelets	KNN-128	90,71%	94,28%	95,8%	97,6%
	NN-128	84,02%	92,92%	94,66%	96,2%
	KNN-512	90,77%	93,76%	96,46%	97,6%
Geometry Measurements	KNN-10	99,28%	99,56%	99,73%	100%
	NN-10	99,02%	99,56%	99,73%	99,8%

Experiments and Results

The realized experiments have been carried out according to classifiers, applying each to the techniques cited previously (vector reduced and geometric parameters). These were carried out varying percentage of training to use a number of hands to create training, while trying to discover the minimum possible. The following table shows results, expressing rate of success in function of type of parameterization, classification method, length of parameters and number of hands for training (with 10 hands, each hand represents 10 percent of the training).

A simple and efficient biometrics-identification system has been proposed based on hand geometry since with 10 parameters, recognition rates of 100 percent were obtained with the database, using nearest neighbors as classifiers.

The other results were also suitable, although lower success rates were obtained. AS

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