On Effective Palmprint Retrieval for Personal Identification

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Abstract

This paper presents a novel retrieval method for effective search of palmprints based on Principal Component Analysis (PCA) and Self-Organizing Feature Map (SOM). To reduce search space and speed up the query processing, an integration of PCA and SOM is proposed, where the coefficients obtained by PCA for global feature representation is considered as input features of SOM. The trained SOM can be used as a retrieval engine to identify similar palmprint images with respect to the query palmprint image for personal identification..

1. Introduction

Biometrics based personal identification plays an important role for automatic identification with high confidence [7]-[8]; Palmprint is one of the emerging physiological characteristics for personal identification that has drawn substantial attentions because it is user-friendly, inexpensive and of comparable recognition ability[1]. Recently, several palmprint identification systems are proposed, both on-line [1], [10] and off-line [9].

You *et al*. [9] have proposed an off-line palmprint identification system, which uses palmprints printed on paper by washable ink colored palms, based on hierarchical features: texture feature, Global Texture Energy (GTE), for coarse level classification and interesting points for fine level matching. Palmprints that are similar to the query one are retrieved with reference to GTE and thus the potential matching space for interesting point matching, which is more computationally intensive, is reduced.

Han *et al*. [10] have reported an on-line palmprint personal authentication system based on Sobel and Morphological features using multiple template matching and conjugate-gradient trained backpropagation neural network for verification. Palmprint is captured using on-the-self scanner at low resolution and preprocessed to locate the area of interests. However, such a neural network based approach requires significant computation power. Zhang *et al*. [1] have proposed an effective real-time on-line palmprint identification system based on low-resolution palmprint images using 2D Gabor features. Palmprint is captured by a specially designed device at low resolution and preprocessed to a sub-image of interests. Features are extracted by applying 2D Gabor filter and normalized Hamming Distance is used to measure the similarity between the query and registered samples. The increase in size of candidate palmprint images to match against, however, reduces the accuracy of the identification algorithm. Sequential search, moreover, is adopted in the identification algorithm to search for a match. For practical use of the system, the size of candidate palmprint images to match against is expected to be larger than that in the experiments; therefore, a method that can effectively reduce the size of the space for matching as well as guide the search to locate the match earlier is essential.

Self-Organizing Feature Map (SOM) [3]-[4], [11] is a well-known unsupervised learning neural network model and algorithm that have been used in industrial monitoring and analysis, statistical pattern recognition including texture analysis and classification and other areas such as image compression and encoding, robotics and telecommunication. It is capable of clustering the training data without any pre-classification of the training data. Nevertheless, primary data is seldom used directly in the application of neural network (e.g. SOM) because of some practical reasons; thus, feature extraction is usually performed before applying neural network for, e.g. clustering [11]. Principal Components' coefficients, which is resulted from projection of data space onto the feature space determined by Principal

Component Analysis (PCA), can be used as a compressed description (feature set) to approximate the data space at some statistical accuracy [11]. Such an approach has been reported to be successful in dealing with fingerprints using block directional image [5].

In this paper, we propose a novel retrieval method for on-line palmprint identification based on SOM using PCA coefficients as global feature of palmprints. Principal Components, which represent the lines and textures, are determined from the training set of the Palmprint Database. Principal Components' coefficients of each of the training sample in the Palmprint Database are used as inputs to train the SOM, which is used as the engine for both reducing the searching space and guiding the search.

This paper is organized in the following sections: Section 2 and 3 outline the two major techniques, Principal Component Analysis and Self-Organizing Feature Map. Our proposed method is described in Section 4 and the experimental results are reported in Section 5. Finally, the conclusion and future works are presented in Section 6.

2. Principal Component Analysis

Principal Component Analysis (PCA) [2]-[3],[5], which is also known as (discrete) Karhunen-Loève Transform or Hotelling Transform, is a statistical method that linearly maps the data space (original distribution) to feature space (usually a subspace of the original) with minimum mean square (approximation) error. It is famous for its capability in feature extraction/selection in pattern recognition, noise reduction in signal processing and de-correlation.

Based on the covariance matrix of (training) samples, eigenvectors of the covariance matrix, which are orthogonal, are found and sorted in descending order according to their importance, i.e. the magnitude of corresponding eigenvalues. Transforming from original space (Analysis), data can be effectively represented by a subspace of fewer dimensions, i.e. Principal Components, with the essential information retained such that mean-squared error is optimized and is equal to the sum of variances of truncated elements. The method is as follows [2]-[3].

Suppose there are M real valued vectors $\{X_i \in \boldsymbol{R}^n | X_i = [x_1, x_2, \ldots, x_n]\}$, where $i = 1 \ldots M$.

The covariance matrix C_X is calculated as

$$C_X = \frac{1}{M}\sum_{i=1}^{M}(X_i - \overline{X})(X_i - \overline{X})^T \quad (1)$$

$$\text{where} \quad \overline{X} = \frac{1}{M}\sum_{i=1}^{M} X_i \quad (2)$$

Eigenvectors, which are orthonormal bases, are then computed from the symmetric matrix C_X by solving the eigenvalue problem, i.e. the following equation

$$C_X Q = Q \lambda \quad (3)$$

where Q is a $n \times n$ matrix containing eigenvectors such that $Q^T Q = \boldsymbol{I}$, i.e. each vector is orthogonal to others and is normalized, and λ is a $n \times n$ diagonal matrix containing eigenvalues as diagonal elements $\{\lambda = \mathrm{diag}\,[\lambda_1, \ldots, \lambda_n] | \lambda_1 = \lambda_{max} > \lambda_2 > \ldots > \lambda_n\}$

2.1 Feature Selection/Dimensionality Reduction

Since the columns of Q is ordered in descending order of the magnitude of their eigenvalues, by truncating $(n - m)$ columns of Q, the columns of the resulting matrix P (of m dimension) is known as the Principal Components and the space spanned by P is known as the Principal Subspace, i.e. the feature space. Through the use of Principal Components, the Principal Subspace can effectively represent the data space. Thus the important features are selected or the dimension of data space is reduced.

3. Self-Organizing Feature Map

Self-Organizing Feature Map or Self Organizing Map (SOM) [3]-[4], [6], which is proposed by T. Kohonen, is one of the well-known unsupervised learning algorithms in the field of neural networks for modeling the neurobiological behaviour of human brain. It is basically a kind of competitive learning that only one neuron will fire after mutual competition of neurons, i.e. winner-takes-all. Its aim is to locate adaptively the input patterns (of arbitrary dimension) into a lower dimension, usually one- or two-dimension, topologically ordered discrete map. Although, in general, it can be extended to higher dimension, one or two dimension SOM is commonly adopted because of its simplicity and expressiveness.

There are two stages of operation in SOM: Formation of SOM and then Calibration of SOM. Formation of SOM has four phases: first is initialization (of synaptic weights), second is competition, third is cooperation and the final one is synaptic adaptation. [3]

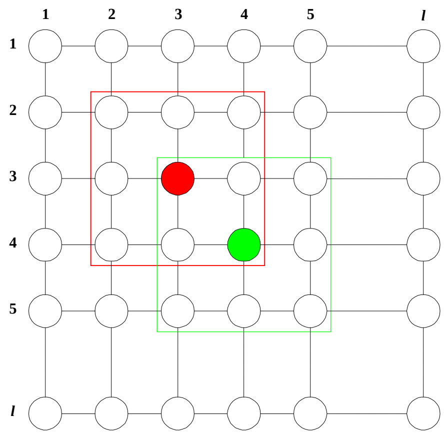

Figure 1 Rectangle-grid topologically ordered SOM

Consider the SOM given in Figure 1 consist of, in total, l^2 neurons. Let the input space is of m dimension.

$$\boldsymbol{x} = [x_1, x_2, \ldots, x_m]^T \qquad (4)$$

3.1 Initialization (of synaptic weights)

The synaptic weight vector (wi) of each neuron is of the same dimension as the input space. Each synaptic weight (wij) can be initialized randomly within the range of the domain or by picking small values from a random number generator.

$$\boldsymbol{w_i} = [w_{i1}, w_{i2}, \ldots, w_{im}]^T \text{ for } i = 1, 2, \ldots, l^2 \qquad (5)$$

3.2 Competition

A discriminant function, d(x, wi), set the basis for neurons' competition and each neuron computes its resulting value using the discriminant function. The neuron with the most distinct value is chosen to be the winner; since only one winning neuron is selected for each input pattern, if more than one neuron have same distinct value, one of them will be selected randomly to be the winner.

The winning neuron nw is defined as

$$n_w = arg\ min_i\ d(\boldsymbol{x}, \boldsymbol{w}_i) \text{ for } i = 1, 2, \ldots, l^2 \qquad (6)$$

3.3 Cooperation

The winning neuron n_w becomes the center for determining the spatial position of topological neighboring neurons through a neighborhood function $N(n_w, n_i, t)$ that defines neighborhood members with respect to the central element, based on the distance between the center (i.e. winning) and surrounding elements and, training time. For 2D topology, rectangular, 2D Guassian or Mexican hat is commonly chosen to defines neighborhood [5]. Both the winning neuron and its neighboring neurons, unlike general competitive learning, learn from the input pattern to recognize neighboring section; nearer neurons are adjusted more. The size of neighborhood, however, decreases with training time (t). The following neighborhood function is a 2D Guassian function

$$N(n_w, n_i, t) = \exp\left(\frac{h(n_w, n_i)}{2s^2(t)}\right) \qquad (7)$$

For a two dimensional case,

$$h(n_w, n_i) = \| c(n_i) - c(n_w) \| \text{ for } i = 1, 2, \ldots, l^2 \qquad (8)$$

where $\|\cdot\|$ denotes the Euclidean norm and $c(n_i)$ determine the spatial location, i.e. coordinate, of neuron n_i in the topographic map.

In Figure 1, the dark and gray filled circles are center elements while the dark and gray squares correspondingly surrounded the neighboring elements of neighborhood size (rectangle grid) equaling one.

3.4 Synaptic Adaptation

The synaptic weight of neuron j is adjusted in relation to the input vector x at time t can be expressed as follows. This adjustment is applied to the winning neuron n_w and its neighboring neurons determined by $N(n_w, n_i, t)$. There are two phases of Synaptic Adaptation, namely, Ordering and then Convergence/Tuning. The size of neighborhood $N(n_w, n_i, t)$ and learning rate $?(t)$ of SOM at two phases are different. At the early ordering phase, we would like the whole SOM to learn quickly about the input patterns, so the neighborhood may include all neurons and the learning rate is relatively larger, e.g. 0.1. The two parameters are expected to decrease gradually with the time of ordering phase. At the convergence/tuning phase, we would like to fine tune the feature map so as to provide an accurate statistical quantification of the input space, so the eighborhood may only include the nearest ones and the learning rate is small, e.g. 0.01, but not zero to avoid the occurrence of metastable state.

$$\boldsymbol{w_i}(t+1) = \boldsymbol{w_i}(t) + ?(t)\, N(n_w, n_i, t)\, (\boldsymbol{x} - \boldsymbol{w_i}(t)) \text{ for } i = 1, 2, \ldots, l^2 \qquad (9)$$

where $?(t)$ is the learning rate

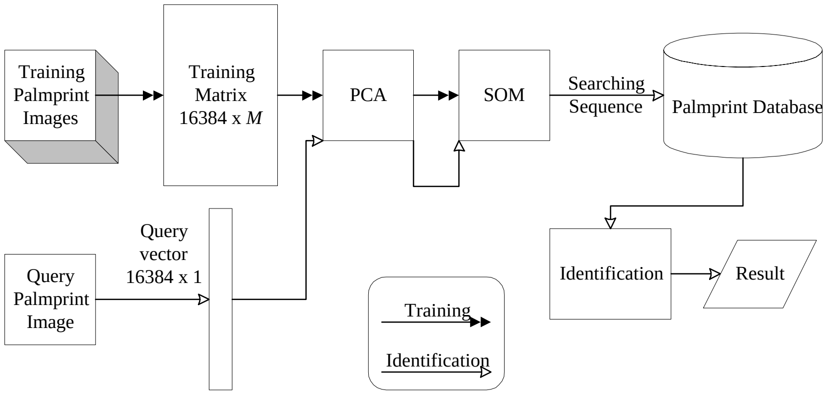

Figure 2 Our proposed palmprint retrieval method for on-line palmprint identification

The SOM formation can be summarized as follows [3], [5].

1. Initialization

   Randomly choose values to initialize weight vectors $\boldsymbol{w_i}(0)$ for $i = 1, 2,\ldots, l^2$; or Randomly select from the available input vectors as weight vectors $\boldsymbol{w_i}(0)$
2. Sampling

   Randomly draw one from the available input vectors as $\boldsymbol{x}$
3. Similarity matching

   Apply $d(\boldsymbol{x}, \boldsymbol{w}_i)$ on all neurons and determine n_w
4. Updating

   Adjust $\boldsymbol{w_i}(t)$ to $\boldsymbol{w_i}(t+1)$ as described above
5. Continuation

   Continue with steps 2 to 5 until no observable changes in the feature map

Calibration of SOM [6] is actually labeling the training samples/input patterns with a corresponding (winning) class/node number that is computed using the same discriminant function, $d(x, w_i)$, in the *formation stage* of SOM. This can provide some qualitative information about the topological ordering between the input and output space.

4. PCA–SOM based Retrieval

Our proposed method is depicted in Figure 2 and it is assumed that we have the preprocessed palmprint sub-images of size 128×128 [1] as input. In the training phase, as the training set first undergoes PCA (analysis), which is a noise-sensitive process, we have set a threshold to filter out those noisy images (resulted from the image capturing process [1]) from the candidate training samples to form the training set. So the training set will form a matrix T of dimension 16384×M (M is the number of images in the training set), with each palmprint image in the training set is deformed column-wisely to be a column vector v of size 16384×1 of T. T will then undergo PCA (analysis), which serves in two ways in our proposed method. One is to generate feature values: coefficients of chosen Principal Components are used as global line and texture features to represent palmprint images (See Figure 3); another is to perform dimensionality reduction, or more commonly referred as feature selection. In our case, only the first ten Principal Components are chosen as they preserved more than 99.5% energy of the analyzed palmprint image training set while the dimension is the smallest (See Table 1).

Table 1 Energy Preservation of first *m* Principal Components

Feature Subspace Dimension (m)	Energy Preserved (%)
5	99.42%
10	99.55%
20	99.68%
30	99.75%
40	99.79%
50	99.82%

According to Table 1, Principal Components of 5 dimensions can already preserve 99.42% of the original energy. However, the increase of the number of Principal Components used does not help the increase of Energy Preservation much, only 0.13%, 0.26%, 0.33%, 0.37% and 0.4% for the increase of 5, 15, 25, 35 and 45 dimensions used. Thus, we choose to use 10 dimensions, which can preserve more than 99.5% of energy with a smaller number of dimensions.

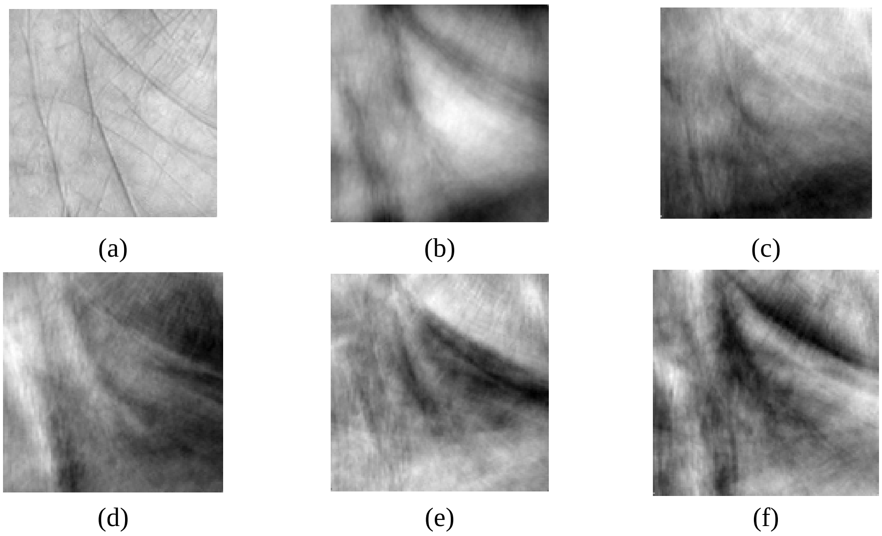

Figure 3 (a) a sample left hand sub-image in Palmprint Database(b)–(f) first 5 Principal Components acquired after PCA

A left hand palmprint sub image from the Palmprint Database is shown in Figure 3(a) and Figure 3(b)–(f) show respectively the first 5 Principal Components resulted from the PCA. It can be observed that the first Principal Component has captured the information of the three principal lines and the other Principal Components have captured texture information of various parts of the palm.

By projecting each sample palmprint images in the training set onto the space spanned by the first 10 Principal Components, we obtained the 10 coefficients of each sample. They are then used as the training data to train the SOM. After training, SOM is calibrated on the basis of an individual person; majority voting mechanism is employed to resolve conflicts.

In the identification phase, query image is projected onto the principal subspace. The principal subspace coefficients obtained are passed into the trained SOM to generate a search sequence that guides the search of the Palmprint Database during Identification. The trained SOM is used as the engine to guide the searching in identification phase by arranging, according to the query input for identification, the order of searching. Supposed the query input for identification is from Person 30 and the winning node of the SOM is the one containing Persons 5, 30, and 34; in Figure 4, the one on the left is the sequential searching sequence while the one on the right is generated by our proposed method that presents earlier to the identification engine the potential matching sub-images in correspondence to the input.

5. Experiments and Results

Palmprint images of 50 different people are used in our experiment. Each people have registered 10 palmprint images of left hand by putting the hand in the palmprint capturing device and then preprocessed to be of size 128×128; each people has registered twice on two different dates [1]; therefore, there are 1,000 images in the database. Three images of each set of images are selected as candidate training samples (300 images) while others is used as the testing set.

Since there are at most 50 categories (50 different people), we choose SOMs of sizes 3×3 and 5×5 for experiments. SOMs of all sizes are trained for 3,000, 5,000 and 10,000 epochs respectively and the training parameters and results are shown in Table 2.

Table 2 SOM Training Parameters

	Ordering Phase	Tuning Phase
Learning Rate	0.1	0.01
Size of Neighborhood	ALL	1

Total number of images in training set, i.e. discarding noisy ones, is 280. Therefore, the average number of images searched for Sequential Searching is equal to half of the size of training set, i.e. 140. Our proposed method, under all conditions, performs much better than the sequential search by reducing the search space to 25% – 30% of the original space. (See Table 3)

Person 1	sub-image 1
	sub-image 2
	⋮
Person 2	sub-image 1
	sub-image 2
	⋮
Person3	sub-image 1
	sub-image 2
	⋮
⋮	sub-image 1
	sub-image 2
	⋮
Person 50	sub-image 1
	sub-image 2
	⋮

Sequential Search

Person 5	sub-image 1
	sub-image 2
	⋮
Person 30	sub-image 1
	sub-image 2
	⋮
Person 34	sub-image 1
	sub-image 2
	⋮
⋮	sub-image 1
	sub-image 2
	⋮
Person 2	sub-image 1
	sub-image 2
	⋮

Proposed Method

Figure 4 Searching sequence generated by Sequential Search and Proposed Method

Table 3 Average number of images searched for 2 Sizes and 3 Training Times

SOM size	Training Time (epochs)		
	3,000	5,000	10,000
3×3	85.4440	85.520	84.3913
5×5	70.7733	70.7827	71.6047

Total number of images in Training Set (M) = 280
Average number of images searched for Sequential Search $= M/2 = 140$

6. Conclusion

Using palmprint for personal identification has recently drawn considerable attentions. Several on-line and off-line identification/authentication systems based on palmprint have been proposed; most of them sequentially scanned the database during identification/verification process. Hence, a novel retrieval method for on-line palmprint identification based on Self-Organizing Feature Map (SOM) using PCA coefficients as global feature of palmprints is proposed. PCA is a recognized feature extraction/selection technique while SOM is a well-known unsupervised learning neural network model and algorithm. Regarding to palmprints, Principal Components obtained from PCA on registered palmprints capture the information of lines and textures, which is considered as global feature; SOM is then trained to cluster automatically the palmprints for the generation of a searching sequence for identification. Each time a query palmprint is presented, a searching sequence is computed, i.e. dynamically determined, with respect to that query. Only 10 PCA coefficients are required in our proposed method; thus, it is computationally favored. Experiments conducted have shown its effectiveness in the reduction of the search space in the identification process.

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