Artificial Neural Networks Based Fingerprint Authentication With Clusters Algorithm

Mohamed Mostafa Abd Allah
Minia University, Faculty of Engineering, Department of Electrical,
Communications and Electronics section, Egypt
E-mail: mohamdmostafa@hotmail.com

A novel and fast fingerprint identification technique is presented in this paper by using ANN. The proposed method use a novel clustering algorithm to detect similar feature groups from multiple template images generated from the same finger and create the cluster core set. The proposed feature extraction scheme is based on the reduction of information contents to the require minimum and define which part of the image is crucial and which is omitted. In the new method, a quick response was achieved by manipulating the search order inside the experimental databases. The novelty of our proposed method is to find the configuration of ANN system that could provide good generalization ability and sufficient discrimination capability at the same time. To achieve that goal, we have introduced new supervised recurrent neural-network. The experiments results demonstrate that this similarity search approach with ANN proves suitable one-to many matching of fingerprints on large databases.

Povzetek: Hitro prepoznavanje prstnih odtisov je realizirano z ANN in grupiranjem.

1 Introduction

Fingerprints Personal identification using biometric, such as person's fingerprint, face, iris, retina, hand shape, has received a great deal of attention during the past few years. The demand for remote authentication system now drastically increasing in many commercial domains on account of the convenience they provide. Biometric identification is now being studied as a way to confirm the identities of individuals. The fingerprint is known to be the most representative biometric for authentication of individual persons. The main reason of its population is, it is unique and remains invariant with age during a lifetime. In most of the present fingerprint authentication systems, personal confirmation is performed by two way verification (one to one match) and identification (one to many matches). In the verification procedure, a quick response can be expected because the matching is executed only once. Conventional automatic fingerprint identification methods consist of two steps: feature extraction and feature matching. A critical step in automatic fingerprint identification is to match features automatically and reliably from input fingerprint images. The classical approaches are tends to be extremely tedious and time consuming. However, the performance of a features matching algorithm relies heavily on the quality of input fingerprint images. Since the inherent features of fingerprint data are its great complexity and high spatial-frequency details. Moreover, the difference among diverse classes of patterns are small that requires high discrimination capability. Identification problems, a

particular case of point pattern matching, necessitate a large database search of individuals to determine whether a person is already in the database. Classical matching approaches proposed in [1] [2] [3] [4] usually include a liner search that composed from series of one to one matching and is executed step by step from the top of the database. When an amount of N data are enrolled in the database, one to one matching of N/2 times on average needs to be done until the identity data is finally found. Accordingly when N data is very large, the time needed for the one to one matching operation grows in proportion to N. The challenge of fingerprint identification application is how to achieve one to many searches over limited period of time. Many fingerprint identification methods have appeared in the literature over the years. The simplest way is to regard one to many matching problem as N time one to one matching. In this paper, we propose a new method of ANN that achieve Fingerprints Personal authentication in a short period of time. Neural networks can be classified into recurrent and feed-forward categories. Feed-forward networks do not have feedback elements; the output is calculated directly from the input through feed-forward connections. In recurrent networks, the output depends not only on the current input to the network, but also on the current or previous outputs or states of the network. For this reason, recurrent networks are more powerful than feed-forward networks and are extensively used in control, optimization, and signal processing applications. The rest of the paper is organized as follows. In section 2, we introduced the flow of the enrollment and identification phase of proposed identification algorithm.

Then, we present line pattern feature algorithm and how the system databases store the template record of all individuals that have access to the system. In section 3, a new supervised recurrent neural-network and authentication approaches was described. A quantitative experimental results used to evaluate the performance of the algorithm are presented in section 5. Our conclusions are described in section 6.
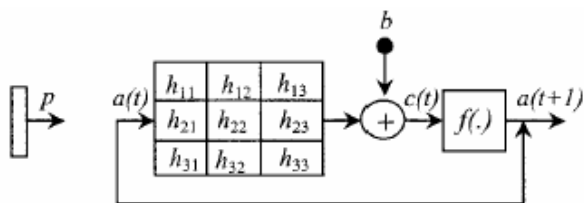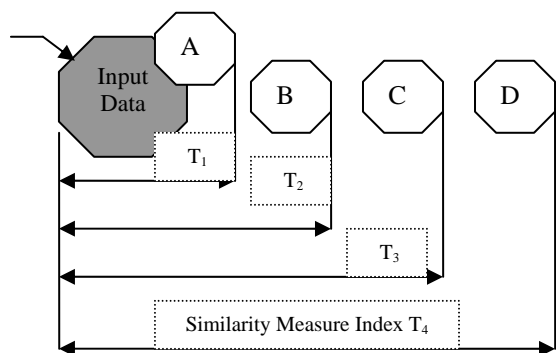

Figure. 1. Supervised ANN Architecture.

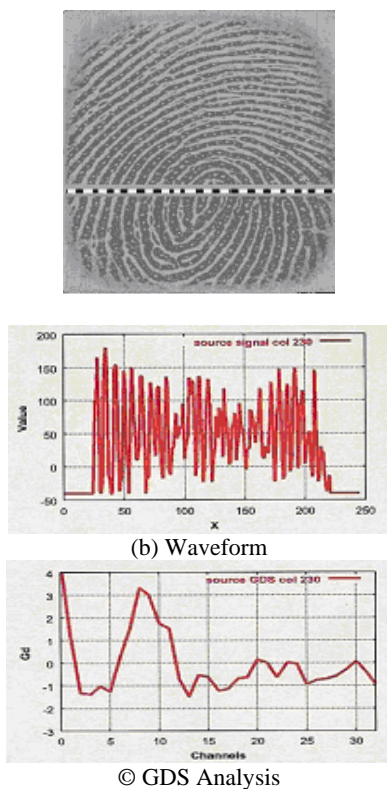Figure. 2. Similarity Measure Index of Clusters that represent the pattern of Template data

(b) Waveform

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Figure. 3. Template Line-Pattern Extraction Scheme in a One-Dimensional Representation.

2 The Proposed Cluster Algorithm

In this method data is classified to 4 clustering of patterns as shown in Fig.2. Cluster A is represented the closer pattern of template data. Cluster B, C, and D are represent how far the two units of template data are closed to each other. In the enrollment phase, each finger is classified due to the similarity measure of its features and stored in a cluster that the input data belongs to. In the identification phase, a cluster of input data is first chosen. In most cases, liner search is executed in each cluster. A problem identical to that in linear search method occurs because the cluster size gets larger when the number of enrolled data is increases. Other problems are, the rule of data classification should be defined for each cluster and any mis-classification in the identification phase can cause a slow response.

2.1   Identification Algorithm

We propose a method to identify a person in the database in an instant. In the new method, a quick response can be achieved by manipulating the search order inside the experimental databases. The proposed method does not require classification or data pre-ordering. It is based on the concept that, if unknown input data is equivalent to enrolled data, its ID wave form vector should become similar to that vector of enrolled data. Therefore, we have proposed ANN module that could determine how the input data units are closed to enroll one. The flow of the enrollment phase and identification phase of proposed identification algorithm is presented in following sections.

2.2   Proposed Enrollment Phase

The proposed enrollment phase is used to get the feature sets and store template information data into the database. The proposed scheme is partitioned into the following major stages: pre-processing, binarization, ridge direction detection and direction filter [5]. Accurately detecting ridge direction of each pixel is a critical stage for fingerprint enhancement. After direction filter, an enhanced binary image will be obtained. The proposed binary line-pattern feature extraction scheme is immediately extracted from this binary image [6].

2.2.1   Binary Line Pattern Extraction Scheme

Imagine for a moment a line running somewhere across the contour (ridge and valleys) of a 2-dimentional representation. The intersections of the contour lines with our erected line actually represent the crossing of the ridges and valleys from one side of the erected line to the other. The locations and spacing of these intersections are treated as points along the erected line that reflect the partial uniqueness of individual fingerprint in a one-dimensional, representation. As shown in Figure.2, each binary line-pattern is a one-dimension matrix. It has a fixed length (e.g. 64 pixels in our case), that only consists of 0 and 1 (illustrated by black and white pixels). The template file of the fingerprint input data is consists of three primary types of data: N (the number of the valid

line-pattern pairs in one fingerprint image), BWRatio (the unbalance ratio of the number of white and black pixels in a line-pattern, which is defined as follows:

$$(\frac{whitePixelCount}{LinePatternLength} - 0.5)*100\%$$

And, the position of singular points (Core and Delta) that associated to the position of line pattern. The feature vector of the line pattern is defined as

$$L_i=(N, BWRatio, X_k, Y_k, t)$$

Where, X_k, Y_k are the position of singular points, and t is the type of pattern line pair (parallel lines or cross lines). Compared to the classical schemes, a novel scheme achieves less memory and complexity as it achieves less computation time in both feature extraction and matching stages [6].

2.2.2 Line Pattern Template Data Stored

In order to introduce our fingerprint enrollment method, a list of notation and basic mathematical background are given below.

$$T_i = \left\{ T_{i,j}, J = 1, ..., n \right\}, i=1.......,m \quad (0.1)$$

Let T_i, represent the template image set of ith collected fingerprint of users who intend to access your system. Where m is the number of fingers in the image database, and n is numbers of template samples of finger.

$$L^I = \left\{ L_i^I, i = 1, ..., F^I \right\} \quad (0.2)$$

Let L^I be the line pattern set of the template image set, where F^I is the number of features of each template image.

$$C = \left\{ C_1, C_2, ..., C_n \right\} \quad (0.3)$$

Let C represent our clustering solution, where each subset C_n is called a cluster and represent the features that the input data belongs to.

1-Suppose that (N-1) fingerprint data has already been enrolled in the database of your system.

2- The input Fingerprint data for new enrollment (T_i) is compared with all fingerprint databases that has already been enrolled in the same database (T_j) by using our ANN module one by one.

3-The similarity measure function of the new supervised recurrent neural-network is supposed to show how far the enrolled data (T_i) are close to the input fingerprint data (T_j), if it satisfied the following equation:

$$\left| L_i - L_t \right| \leq T_n \quad (0.4)$$

Where L_i represent the line pattern set of the input image, and L_t Represent the line pattern set of the template image.

4- The similarity measure function is designed to have 4 types of judgment threshold matching score, T_1, T_2, T_3, and T_4 respectively. This judgment score could classify and sort each enrollment fingerprint data based on its similar features that is belongs to. This solution could define a new relation among each input fingerprint data and the rest of all enrollment fingerprint database,

where, it is expected to produce 4 clusters of matching response, cluster A (very close fingers), cluster B (close fingers), cluster C (far fingers), and cluster D (very far fingers) as shown at figure 2.

6-After N comparison process was calculated by the new supervised recurrent neural-network, an N*N matching response matrix is constructed to draw the new clustering relation among all enrollment fingerprint database.

In this new enrollment method, we can manipulating the search order inside the experimental databases, and sort the enrolled data based on how this feature are closed to each other.
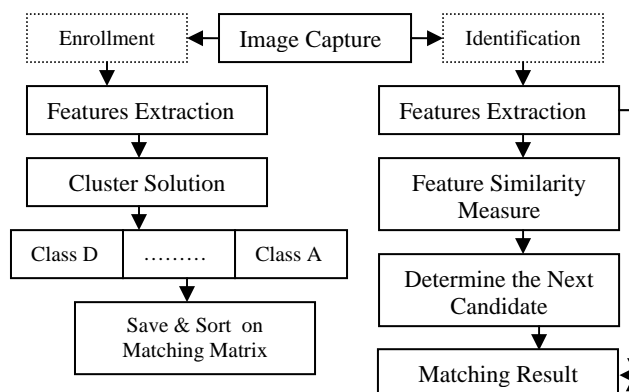

Figure. 4. The Flow Chart of the Proposed Fingerprint Identification Algorithm

2.3 The Proposed ANN Identification Phase

Figure 4 shows the flow chart of the identification phase, which consists of clustering computing and forming the candidate list. The proposed identification algorithm is described as below:

• An unknown user inputs his/her finger via system sensor device.

• Using the fine matcher (one to one matched) to match the line feature set of input finger with the feature set of the first candidate finger data in the database.

1- ANN matching response is calculated, if it is exceeds the judgment threshold T5, the answer is obtained that current unknown user cross ponds to the first candidate in the database, and the identification process finished. Otherwise, the next candidate is determine based on the N*N matching response matrix that are constructed by the enrollment procedures and shown in Figure.4.

2- The correlation values against the first un-matching response are calculated for all members of the first column of the matching response matrix. The max value is selected and its finger is chosen to be the next candidate data. The new candidate data is matched with the unknown input data and procedures is repeated till the result shows the equivalent to enrolled data that has ANN matching response is exceeds the judgment threshold T5. Otherwise, the answer is obtained that current unknown user does not belong to that database.

3 Supervised ANN Module

By utilizing the aforementioned properties, we developed a new supervised recurrent neural-network and authentication approaches that could classify and sort each finger on database due to the similarity measure of its features and stored in a cluster that the input data belongs to. Instead of weight matrices and weighted summations, supervised ANN employs a fixed-sized weight mask and convolution operation, as shown in Fig. 1. The proposed network consists of 4 layers of clusters, input layer, output layer, and two hidden layers. The number of clusters in these layers are variant, which can be can be describe as 1-X-Y-4, that means there are one cluster in the input layer, X clusters in the first hidden layer, Y clusters in the second hidden layer, and 4 clusters in the output layers. Each cluster is composed of matrix of neural units. The units in the input layer have a liner activation function, whereas the units in all other layers are described by formation of a convolution between the input and the template mask and then summation of the bias scalar value in the nonlinear activation function. Mathematically, this can be expressed as

$$a_{m,n}(t+1) = f\left(\left(\sum_{i=-s}^{s}\sum_{j=s}^{s}h_{i,j}a_{m+i,n+j}(t)\right)+b\right) \quad (0.5)$$

where h_{ij} is the weight mask that is designed for a size of *SxS* pixels, b is the scalar bias value, f is the nonlinear activation function, t is the iteration step, and $a_{m,n}(t+1)$ and $a_{m,n}(t)$ are outputs and inputs of the system, respectively. In this study, a 3x3 weight mask is selected. Initially, the input image is defined as

$$a_{m,n}(0) = p \quad (0.6)$$

Where, p is the entire input image. The activation function can be formulated as a nonlinear piecewise function, expressed as

$$f(x) = \begin{cases} -1 & x \le -1 \\ X & -1 < x < 1 \\ 1 & x \ge 1 \end{cases} \quad (0.7)$$

The initial values of weight and biases are randomly distributed in the range of (-2.38/√n, 2.38/√n), where n is the fan-in of each neural unit. The smaller initial values of weight tend to make the learning process vulnerable to undesirable local minima [4]. In the training of the supervised ANN, the goal is to minimize a cost function E. The minimization is accomplished by adjustment of the weight coefficients in an appropriate manner. The cost (error) function can be defined by use of the actual output $a_{m,n}(t+1)$, and the desired output, $d_{m,n}$, as

$$E = \frac{1}{2}\sum_{m}\sum_{n}(a_{m,n}(t+1)-d_{m,n})^2 \quad (0.8)$$

The gradient-descent algorithm6 includes the derivation of the error function in order to minimize the cost function. For each iteration, the weight coefficients and the bias value are updated as follows:

$$h(t+1) = h(t) - \eta\frac{\partial E(t)}{\partial h(t)} \quad (0.9)$$

$$b(t+1) = b(t) - \eta\frac{\partial E(t)}{\partial b(t)} \quad (0.10)$$

where η represents the learning rate. The partial derivatives of Equ. (1.9) and (1.10) can be conveniently computed with the chain rule of calculus, given by

$$\frac{\partial E}{\partial h} = \frac{\partial E}{\partial c(t)}\frac{\partial c(t)}{\partial h} \quad (0.11)$$

$$\frac{\partial E}{\partial b} = \frac{\partial E}{\partial c(t)}\frac{\partial c(t)}{\partial b} \quad (0.12)$$

The second term in Eqs. (1.11) and (1.12) can easily be computed, because the net input c is an explicit function Of the coefficients and bias value in that iteration:

$$C_{m,n}(t) = \left(\left(\sum_{i=-s}^{s}\sum_{j=s}^{s}h_{i,j}a_{m+i,n+j}(t)\right)+b\right) \quad (0.13)$$

Therefore

$$\frac{\partial c(t)}{\partial h} = a(t)$$
$$\frac{\partial c(t)}{\partial b} = 1 \quad (0.14)$$

The first term in Eqs, (1.11) and (1.12) is called the sensitivity of E, which is calculated by use of the following equation:

$$\frac{\partial E}{\partial c(t)} = -2f'(c(t))(d-a(t+1)) \quad (0.15)$$

Where f' represents the derivation of the activation function, d is the desired output, and $a(t+1)$ is the actual output of the network at iteration $(t+1)$

Finally the updated coefficients and bias value are rewritten by use of Eqs. (1.14) and (1.15) as

$$h(t+1) = h(t) - 2\eta f'(c(t))a_{m,n}(t)(d-a(t+1)) \quad (0.16)$$

$$b(t+1) = b(t) - 2\eta f'(c(t))(d-a(t+1)) \quad (0.17)$$

In contrast to the feed-forward neural network, the proposed technique uses consecutive iteration values called recurrent flow, as shown in Eqs. (1.16) and (1.17), respectively. When the learning algorithm converges to the minimum error, the last updated weight and bias coefficients are saved for the test phase of supervised ANN.
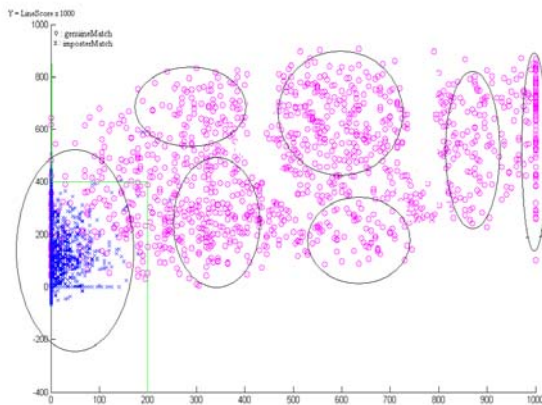

Figure.5 Sample Images of FVC2002 Database

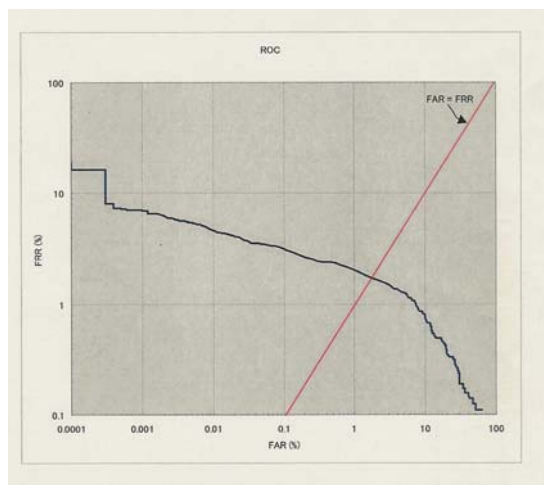Figure.6. Score Map clusters Matcher of the proposed ANN.

Figure. 7. ROC curve on FVC2002 database

4 Experimental Results

In order to test the performance of the proposed matching scheme with ANN, experiments are conducted on different database. Therefore, our experiments were selected on FVC2002. Regarding FVC2002 databases, three databases are collected with different sensors, including optical and capacitive sensor and one database is synthesized with SFinGE [7]. For each database, it is split into set a (100 x 8 images) and set B (10 x 8 images) for evaluating and training, respectively. The sample images in FVC2002 databases are shown at Figure. 5. The performance of the proposed enrollment scheme is remarkable with FVC2002 database. It is because average Score map distribution of the three databases are represented at Figure.6 where, enrollment input data are represented by X axis, and average Line Pattern score is represented by Y axis. Circle symbol "O" represented the same pair matching (very close fingers) and "x" symbol represented the different pair matching (very far fingers). In figure 6, score Map distribution of the proposed ANN explain how each finger is classified due to the similarity measure of it's features and stored in a cluster that the input data belongs to. FAR (False Accept Rate) and FRR (False Reject Rate) are two important error rates, which estimate the performance of a fingerprint identification system at various thresholds. As shown at figure 7, ROC (Receiver Operating Characteristic) curve plots the average FRR against the average FAR at different thresholds on DB1a, DB2a. DB3a and DB4a.

5 Conclusion

We have focused on application of clustering analysis to fingerprint identification. Because matched feature pair from two matched images must have similar expression patterns, while the un-matched feature pair should have distinct pattern. So, the proposed clustering algorithm can be used in fingerprint identification to detect similar features groups from multiple template images that generated from the same finger. The proposed feature extraction methodology reduced the traditional and complicated fingerprint image from 2-dimentioal to one-dimensional representation. Compared to the classical schemes, a novel scheme achieves less memory and complexity as it meets the response time requirement of on-line verification systems because of the achievement of less computation time in both feature extraction and matching stages. Furthermore, it improves both the true acceptance rate and false rejection rate. Therefore, it can be integrated to an automate fingerprint identification system (AFIS) easily in one chip.

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