Efficient Features Extraction for Fingerprint Classification with Multi Layer Perceptron Neural Network


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Abstract—In this paper, we present a complete fingerprint recognition system using an Artificial Neural Network (ANN). The ANN is trained by back-propagation algorithm on a set of fingerprint images. Pseudo Zernike Moments (PZM) will be used as a features vector for all images. To detect the region of interest on the fingerprint image, we have used shape information which is characterized by elliptical shape PZM of the elliptical shape constitute the input of the ANN. The data set is divided into two sets, training set and test set. The ANN is trained using the training set and tested on the test set which was hidden during training stage. The recognition rate is measured by the number of correctly classified fingerprints. The structure of the ANN is decided experimentally. The proposed algorithm was tested on a database of more than 400 fingerprints with 10 samples of each person fingerprints. Experimental results have shown that the proposed feature extraction method with an ANN classifier gave a faster training phase and yields a 98% recognition rate.

I. Introduction

The importance of fingerprints comes from their uniqueness and portability. It is believed that every person has unique fingerprints which remain invariant over time. Unlike identification cards, fingerprints cannot be lost or stolen. Due to these mentioned properties, automatic fingerprint recognition systems are becoming increasingly important and finding applications in variety of fields. These fields include access control systems, criminal identification and authentication and access to security systems such as computers or bank teller machines [1][2]. Despite the advances in fingerprint classification, efficient fingerprint verification is stills a challenging problem especially when matching a fingerprint to all registered fingerprint images of large database. A fingerprint is the pattern of ridges and valleys on the surface of finger. The uniqueness of a fingerprint can be determined by the overall pattern of ridges and valleys as well as local ridge anomalies: a ridge bifurcation or a ridge ending, called minutia points[1].

A complete fingerprints recognition system should include three stages. The first stage is detecting the location of the most important features of the fingerprints image, which is difficult and complicated because of the orientation and scaling of the image. The second stage is the extraction of the pertinent features from the localized image and third stage involves classification of the image based on the extracted features vector obtained in the last step. This classification can be performed using artificial Neural Networks (ANN)[3-4].

In order to design a high recognition rate system, the choice of feature vector is very crucial and extraction of pertinent features from two-dimensional images of human fingerprint plays an important role in any fingerprint recognition system.

In this paper, an efficient feature extraction technique is developed. The technique is based on the combination of local and global information of fingerprint images. First, fingerprint localization based on shape information with a new definition for distance measure threshold called fingerprint candidate threshold (FPCT) for distinguishing between non fingerprint image and fingerprint image candidate is introduced. We present the effect of varying the FPCT on the recognition rate of the proposed technique. A new parameter, called the axis correction ratio (ACR), is defined to eliminate irrelevant data from the fingerprint images and to create a subimage for further feature extraction. Once the fingerprint localization process is completed, pseudo-Zernike moment invariant (PZMI)[5] with a new method to select moment orders are utilized to obtain the feature vector of the fingerprint under examination. In this thesis, PZMI was selected over other types of moments because of its utility in fingerprint recognition approaches. The last step in fingerprint recognition requires classification of the fingerprint image into one of the known classes based on the derived feature vector obtained multilayer perceptron in the previous stage. The multilayer perceptron (MLP) neural network is used as the classifier. The training of the MLP neural network is done, based on the Backpropagation algorithm [6]. It’s shown that the proposed feature extraction method with an MLP neural network classifier gives a faster training phase and yields a better recognition rate.
II. FINGERPRINTS LOCALIZATION

To ensure a robust and accurate feature extraction, the exact location of the fingerprint in an image is needed. The ultimate goal of the fingerprint localization is finding an object in an image as a fingerprint candidate whose shape resembles the shape that contains the most important information of a fingerprint and, therefore, one of the key problems in building automated systems that perform fingerprint recognition task is fingerprint localization. Many algorithms have been proposed for fingerprint localization and detection, which are based on using shape color information, minutiae-based matching and so forth. A critical survey on fingerprint localization and detection can be found [7]. In this paper, we have used a modified version of the shape information technique for the fingerprint localization presented in that an ellipse can generally approximate the fingerprint of a human. The localization algorithm utilizes the information about the edges of the fingerprint image or the region over which the fingerprint is located. The advantage of the region-based method is its robustness in the presence of noise and changes in illumination. In the region-based method, the connected components are determined by applying a region growing algorithm then, for each connected component with a given minimum size, the best-fit ellipse is computed using the properties of the geometric moments. To find a fingerprint region, an ellipse model with five parameters is used: \( X_0, Y_0 \) are the centers of the ellipse, \( \theta \) is the orientation, and \( \alpha \) and \( \beta \) are the minor and the major axes of the ellipse, respectively, to calculate these parameters, first we review the geometric moments. The geometric moments of order \( p + q \) of a digital image are defined as

\[
M_{pq} = \sum_{x} \sum_{y} f(x, y) x^p y^q,
\]

Where \( p, q = 0, 1, 2 \), and \( f(x, y) \) is the gray-scale value of the digital image at \( x \) and \( y \) location. The translation invariant central moments are obtained by placing origin at the center of the image

\[
\mu_{pq} = \sum_{x} \sum_{y} f(x, y) (x - X_0)^p (y - Y_0)^q,
\]

\[
\theta = \frac{1}{2} \arctan \left( \frac{2 \mu_{11}}{\mu_{20} - \mu_{02}} \right),
\]

Where \( \mu_{pq} \) denotes the central moment of the connected components as described. The length of the major and the minor axes of the best-fit ellipse can also be computed by evaluating the moment of inertia. With the least and the greatest moments of inertia of an ellipse defined as

\[
I_{\text{min}} = \sum_{x} \sum_{y} [(x - x_0) \cos \theta - (y - y_0) \sin \theta] ^2
\]

\[
I_{\text{max}} = \sum_{x} \sum_{y} [(x - x_0) \sin \theta - (y - y_0) \cos \theta] ^2
\]

The length of the major and the minor axes are calculated from as

\[
\alpha = \frac{1}{\pi I_{\text{max}}/I_{\text{min}}} \frac{1}{1/8},
\]

\[
\beta = \frac{1}{\pi I_{\text{min}}/I_{\text{max}}} \frac{1}{1/8},
\]

To assess how well the best-fit ellipse approximates the connected components, we define a distance measure between the connected components and the best-fit ellipse as follows

\[
\phi_i = \frac{P_{\text{inside}}}{\mu_0}, \quad \phi_o = \frac{P_{\text{outside}}}{\mu_0},
\]

Where the \( P_{\text{inside}} \) is the number of background points inside the ellipse, \( P_{\text{outside}} \) is the number of points of the connected components that are outside the ellipse, and \( \mu_0 \) is the size of the connected components. The connected components are closely approximated by their best-fit ellipses when \( \phi_i \) and \( \phi_o \) are as small as possible. We have named the threshold values for \( \phi_i \) and \( \phi_o \) as FPCT. Our experimental study indicates that when FPCT is less than 0.1, the connected component is very similar to ellipse; therefore it is a good candidate as a fingerprint region. If \( \phi_i \) and \( \phi_o \) are greater than 0.1, there is no fingerprint region in the input image, therefore, we reject it as a non fingerprint image.

III. FEATURE EXTRACTION TECHNIQUES

The aim of the feature extractor is to produce a feature vector containing all pertinent information about the fingerprint while having a low dimensionality. In order to design a good fingerprint recognition system, the choice of feature vector is very crucial. To design a system with low to moderate complexity, the feature vectors created from feature extraction stage should contain the most pertinent information about the fingerprint to be recognized. In the statistics-based feature extraction approaches, global information is used to create a set of feature vector elements to perform recognition. A mixture of irrelevant data, which are usually part of a fingerprint image, may result in an incorrect set of feature vector elements. Therefore, data that are irrelevant to fingerprint portion such background should be disregarded in the feature extraction phase. Fingerprint recognition systems should be capable of recognizing fingerprint appearances in a changing environment. Therefore we use PZMI to generate the feature vector elements. Also the feature extractor should create a feature vector with low dimensionality. The low-dimensional feature vector reduces the computational burden of the recognition system; however, if the choice of the feature elements is not properly made, this in turn may affect the classification performance. Also, as the number of feature elements in the feature extraction step decreases, the neural network classifier becomes small with a simple structure. The proposed feature extractor in this paper yields a feature vector.
with low dimensionality, and, by disregarding irrelevant data from fingerprint portion of the image, it improves the recognition rate. The proposed feature extraction is done in two steps. In the first step, after fingerprint localization, we create a subimage which contains information needed for the recognition algorithm. In the second step, the feature vector is obtained by calculating the PZMI of the derived subimage.

To create a subimage for feature extraction phase, all pertinent information around the fingerprint region is enclosed in an ellipse while pixel values outside the ellipse are set to zero. Unfortunately, through creation of the subimage with the best-fit ellipse, as described before, many unwanted regions of the fingerprint image may still appear in this subimage. These include part of the background as an example. To overcome this problem, instead of using the best-fit ellipse for creating a subimage, we have defined another ellipse. The proposed ellipse has the same orientation and center as the best-fit ellipse but the lengths of its major and minor axes are calculated from the lengths of the major and minor axes of the best-fit ellipse as follows:

\[
A = \rho \cdot \alpha, \quad B = \rho \cdot \beta,
\]

Where A and B are the lengths of the major and minor axes of the proposed ellipse, and \(\alpha\) and \(\beta\) are the lengths of the major and minor axes of the best-fit ellipse that have been defined. The coefficient \(\rho\) is called ACR and varies from 0 to 1. Our experimental results with 400 fingerprint images show that the best value for ACR is around 0.90 Fig. 1 shows the effect of ACR (\(p\)). By using the above procedure, data that are irrelevant to fingerprint portion are disregarded. The feature vector is then generated by computing the PZMI of the subimage obtained in the previous stage. It should be noted that the speed of computing the PZMI is considerably increased due to smaller pixel content of the sub images.

![Figure 1. Subimages created using different values of \(p\)](image)

IV. PSEUDO ZERNIK MOMENT

Statistics-based approaches for feature extraction are very important in pattern recognition for their computational efficiency and their use of global information in an image for extracting features. The advantages of considering orthogonal moments are that they are shift, rotation, and scale invariants and are very robust in the presence of noise. The invariant properties of moments are utilized as pattern sensitive features in classification and recognition applications [8]. Pseudo-Zernike polynomials are well known and widely used in the analysis of optical systems. Pseudo-Zernike polynomials are orthogonal sets of complex-valued polynomials defined as [5][8].

The PZM is defined as follows:

\[
V_{nm}(x, y) = R_{nm}(x, y) \exp \left( j m \tan^{-1} \left( \frac{y}{x} \right) \right),
\]

Where \(x^2 + y^2 \leq 1, n \geq 0, |m| \leq n\), and the radial polynomials \(R_{n,m}\) are defined as

\[
R_{n,m}(x, y) = \sum_{s=0}^{n-|m|} \sum_{t=0}^{n} \sum_{l=0}^{n-|m|-s} D_{n,m,s} (x^2 + y^2)^{(n-s)/2},
\]

Where

\[
D_{n,m,s} = (-1)^s \frac{(2n+1-1+s)!}{s!(n-|m|-s)!|n-|m|-s+1|}
\]

The PZMI of order \(n\) and repetition \(m\) can be computed using the scale invariant central moments \(CM_{pq}\) and the radial geometric moments \(RM_{pq}\) as follows [5, 7]:

\[
CM_{pq} = \frac{\mu_{pq}}{M_{00}^{(p+q+2)/2}},
\]

\[
RM_{pq} = \frac{\sum_{x} \sum_{y} f(x, y) (x^2 + y^2)^{1/2} \Psi^p \Psi^q}{M_{00}^{(p+q+2)/2}}
\]

Where \(x = x - x_0, y = y - y_0\), and \(x_0, y_0, \mu_{pq},\) and \(M_{00}\) are defined before.

VI. MLP CLASSIFIER

Neural network is widely used as a classifier in many fingerprint recognition systems[2][3]. Neural networks have been employed and compared to conventional classifiers for a number of classification problems. The results have shown that the accuracy of the neural network approaches is equivalent to, or slightly better than, other methods. Also, due to the simplicity, generality, and good learning ability of the neural networks. MLP neural networks have been found to be very attractive for many engineering problems because (1) they are universal approximators, (2) they have a very compact topology, and (3) their learning speed is very fast.
because of their locally tuned neurons. In this paper, an MLP neural network is used as a classifier in a fingerprint recognition system where the inputs to the neural network are feature vectors derived from the proposed feature extraction technique described in the previous section. The construction of the MLP neural network involves three different layers with feed forward architecture. The input layer of the neural network is a set to the dimension of the PZM. The input units are fully connected to the hidden layer. Connections between the input and hidden layers have unit weights and, as a result, do not have to be trained. The goal of the hidden layer is to cluster the data and reduce its dimensionality. In this structure, the hidden units are referred to as the MLP units. The MLP units are also fully connected to the output layer. The output layer supplies the response of the neural network to the activation pattern applied to the input layer as shown in Fig. 2. The transformation from the input space to the MLP-unit space is nonlinear (nonlinear activation function), whereas the transformation from the MLP-unit space to the output space is linear (linear activation function).

\[ y_1, y_2, y_3 \]

Output layer

\[ \sigma \]

\[ x_1, x_2, x_3 \]

Input layer

\[ \sigma \]

Closed units

\[ w_{ij} \]

Sigmoid Function

\[ x_i \]

Input node

Fig. 2. MLP Structure

VII. EXPERIMENTAL RESULTS

A database of 400 fingerprints images was used. This database contains fingerprints of 40 person. For each person there are 10 samples in deferent position. From each image we create a subimage and calculate the PZM. The data set is randomly divided into two different set. One set is used for training and the second set is used for testing. The PZM feature vector constitute the input to the MLP. The number of input neurons in the MLP is same as the dimension of the PZM and the number of output neurons is 40 since we have 40 classes. The number of hidden neurons is determined experimentally. After training on the training set, the MLP is tested on the test set which has never been seen by the MLP before. If the input vector is classified correctly to it corresponding class, the recognition is considered correct and wrong otherwise. This was repeated several times and the average error which is a measure of the difference between the desired output and the obtained output is recorded. Table 1 shows the obtained results of the recognition, error and number of training cycles.

<table>
<thead>
<tr>
<th>Table 1. Experiment result using 10 hidden neurons</th>
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<tr>
<td>MLP input</td>
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VIII. CONCLUSIONS

This paper presented an efficient method for the recognition of human fingerprint in frontal view of fingerprint images. The proposed technique utilizes a modified feature extraction technique, which is based on a flexible fingerprint localization algorithm followed by PZM. An MLP neural network was used as a classifier. In this paper we have introduced several parameters for efficient and robust feature extraction technique These include PFCCT, ACR, We have shown that the proposed system was able to classify all fingerprints in the database with accuracy of 100%.

References


