Inner Knuckle Print Identification Using Artificial Neural Network

[1]Hema Rajini N and [2]Chandra Prabha K

[1,2] Department of Computer Science and Engineering,

[1,2] Alagappa Chettiar Government College of Engineering and Technology, Karaikudi – 630003, Tamil Nadu, India

[1]auhemasmith@yahoo.co.in, [2] kcprabha@gmail.com

Abstract – A inner knuckle print identification system has been designed and developed. This work presents a new approach to authenticate people according to their finger textures. This proposed method consists of three stages. They are preprocessing, feature extraction and matching. In the first stage, noise is suppressed using an image filtering. In the second stage, features are extracted by local line binary pattern. Artificial neural network and support vector machine are used to provide an efficient matching algorithm for inner knuckle print authentication. After matching, the algorithm returns the best match for the given fingerprint parameters. The use of inner knuckle print in biometric identification has been the most widely used authentication system. A classification with an accuracy of 89% and 97% has been obtained by support vector machine and artificial neural network classifier.

Keywords — Local line binary pattern; Feature extraction; Artificial neural network.

1. Introduction

The personal authentication based on hand biometric traits has been widely used in most of the modern security applications due to its low cost in acquiring data, its reliability in verifying the individuals and its degree of acceptance by the user. Palmprint, fingerprint, hand geometry, vein and finger knuckle print are samples of biometric systems based on hand [1,2]. One of the new approaches that is drawn attention of research is Inner Knuckle Print (IKP). IKP refers to the flexion shrinks in the inner skin of knuckles. IKP features like palmprint are divided in three categories of principal line, wrinkles and edges. Similar to palmprint features, IKP features are extracted from low resolution images. Although edge features cannot be extracted from low resolution images, wrinkles and lines can be extracted. Since principal lines can be similar in some person, both principal lines and wrinkles are useful for identification. In general, each finger has three knuckles but second knuckle contains more lines and more complex pattern which is better for feature extraction. Uniqueness, universality and permanence are the three important aspects in biometrics system and research conducted in biometric systems based on IKP are shown that having these characteristics has brought good results.

In this research work verification is based on finger descriptor features. In the first step a database that contains whole of the hand, in order to extract the Region of Interest (ROI). In the step 2 denoising, binarization, extraction datum points in root and tip of fingers, normalization and ROI cropping is made. Here finger descriptor features are extracted by Local Line Binary Pattern (LLBP). The last step and in IKP verification systems is matching. For this purpose, Artificial Neural Network (ANN) and Support Vector Machine (SVM) classifiers are used.

The rest of this paper is organized as follows. The introduction part is given in Section 1 and the studies of several research papers are portrayed in the Section 2. Section 3 describes the proposed methodology following Section 4 signifies the experimental results and the work are concluded in Section 5.

2. Literature Survey

There are many automated systems for finger print recognition in the literature, most of them are used for personal authentication. Baldi et al. developed a neural network algorithm for fingerprint recognition [3]. The algorithm outputs an estimate of the probability that the two images originate from the same finger. In one experiment, the neural network is trained using a few hundred pairs of images and its performance is subsequently tested using several thousand pairs of images originated from a subset of the database corresponding to 20 individuals. The error rate currently achieved is less than 0.5%.

Srinivasan et al. proposed a technique for the detection of singular points in a fingerprint image [4]. The singular points, namely the core and the delta points, are used as points of registration in fingerprint matching. This method makes use of structural information culled from the directional histograms of the directional image of a fingerprint. The usage of the histogram allows for a fairly high degree of noise tolerance. Redhu et al. developed fingerprint recognition system using minutia score matching method [5]. Chatterjee et al. developed a fingerprint identification and verification system by minutiae extraction using artificial neural network [6].

3. Methodology

Recognition or fingerprint authentication refers to the

automated methods of verifying a match between two human fingerprints. Fingerprints are widely used in daily life for more than 100 years due to its feasibility, distinctiveness, permanence, accuracy, reliability and acceptability.

The proposed method has three stages, namely pre-processing, feature extraction and classification. The proposed technique for automatic fingerprint authentication is illustrated in Fig. 1. The proposed system is developed using Matlab (The Math Works, Inc., Natick, MA, USA). In the first stage, noise is suppressed using an image filtering. In the second stage, features are extracted by LLBP. Artificial neural network and support vector machine are used to provide an efficient matching algorithm for inner knuckle print authentication. This proposed system produced very promising recognition rates for this application with same set of features and classifiers.
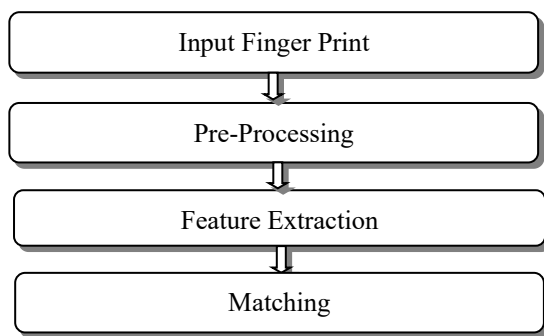
Input Finger Print

Pre-Processing

Feature Extraction

Matching

Fig. 1. Methodology of the proposed technique

3.1 Preprocessing
Here the input image is a hand image. The size of the image is 188x240. The aim of preprocessing is used to remove the noise and to enhance some image features relevant for further processing and analysis task. Median filter is used to remove noise in the image.

In this work two series datum points are extracted. The first series are points that exist in the gaps of fingers and second series are points that exist in the tip of fingers. For detection first series of datum point is used. Border Pixel Vector (BPV) coordinates is known, and the Euclidean distance $D_E(i)$ between Wm and BPV is calculated.

$$D_E(i) = \sqrt{(X_{wm} - X_b(i))^2 + (Y_{wm} - Y_b(i))^2} \qquad (1)$$

Where (X_{wm}, Y_{wm}) is the coordinate of the wrist middle point W_m, $(X_b(i), Y_b(i))$ is the coordinate of the ith border pixel, and $D_E(i)$ is the Euclidean distance between the ith border pixel and the wrist middle point Wm. If the distance distribution of D_E be drawn, it will see that three of local minimums refer to the first points series. Distance distribution of D_E is depicted. For detection second series of points to consider local maximums that are exits in distance distribution of D_E. Now by using this point, a rectangle is created that almost is included whole of the index finger. The images are normalized before feature extraction, so that the location of the features would be consistent among different images in the data set.
3.2 Feature Extraction
Local Binary Pattern (LBP) has been utilized in many

applications in image processing field such as face recognition, pattern recognition and feature extraction. Local Derivative Pattern (LDP) and LBP are used to extract the binary codes from the enhanced images. Although the performance of LDP is better than the LBP, the computation time for LDP is about 2.5 times slower than the LBP. Moreover, the code length for LDP is four times longer than the LBP. The computation time and template size are two important factors that need to be considered in designing a biometric system. To overcome the above-mentioned problems, the binary codes in this work are extracted from the enhanced images using the LLBP [7,8].

Its mathematic definitions are given in equations (2) – (4). $LLBP_h$, $LLBP_v$ and $LLBP_m$ are LLBP on horizontal direction, vertical direction, and its magnitude, respectively. N is the length of the line in pixel, hn is the pixel along with the horizontal line and vn is the pixel along with the vertical line, c = N/2 is the position of the center pixel hc on the horizontal line and vc on the vertical line, and s(x) function defines a thresholding function as in LBP.

$$LLBP_h(N,c) = \sum_{n=1}^{c-1} s(h_n - h_c). 2^{(c-n-1)} + \sum_{n=c+1}^{N} s(h_n - h_c). 2^{(c-n-1)} \qquad (2)$$

$$LLBP_v(N,c) = \sum_{n=1}^{c-1} s(v_n - v_c). 2^{(c-n-1)} + \sum_{n=c+1}^{N} s(v_n - v_c). 2^{(c-n-1)} \qquad (3)$$

$$LLBP_m = \sqrt{LLBP_h^2 + LLBP_v^2} \qquad (4)$$

Employing equations (2) the horizontal component of LLBP ($LLBP_h$) extracts a binary code of N-1 bits for each pixel. The same numbers of bits are extracted by the vertical component of LLBP ($LLBP_v$) using equations (3). Consequently, by concatenating the binary codes from $LLBP_h$ and $LLBP_v$, the total binary code of LLBP for each pixel is 2(N-1) bits.

3.3 Classifiers: SVM and ANN
1) Support Vector Machine Classifier: Support vector machine (SVM) is a powerful supervised classifier and accurate learning technique. From the statistical theory it was derived and developed by Vapnick in 1982. It yields successful classification results in various application domains, e.g. medical diagnosis. SVM is based on the structural risk minimization principle from the statistical learning theory [9]. The kernel controls the empirical risk and classification capacity in order to maximize the margin between the classes and minimize the true costs. SVM searches an optimal separating hyper-plane between members and non-members of a given class in a higher dimensional feature space. The inputs to the SVM algorithm are the features extracted using the LLBP method.
2) Artificial Neural Network Classifier: An ANN is a mathematical model consisting of a number of highly interconnected processing elements organized into layers, geometry and functionality of which have been resembled to

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that of the human brain. The ANN may be regarded as a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use [10,11]. The cascade-forward back propagation network which was employed as the classifier required in this study had two layers (after several trails for different hidden layers with a different number of neurons). The neural network has been trained to adjust the connection weights and biases in order to produce the desired mapping. In this stage, the feature vectors are applied as an input to the network and the network adjusts its variable parameters, the weights and biases, to capture the relationship
between the input patterns and outputs.

4. Results and Discussion

The algorithm is implemented using MATLAB as the development tool. Two set of images are required, one for the training of the neural network and another set of images upon which testing is done. Each image is of size 188×240 pixels. In this research work, the testing contains 100 images taken from 100 different peoples
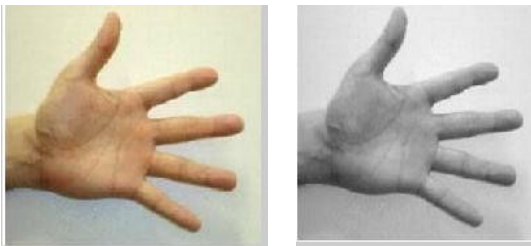

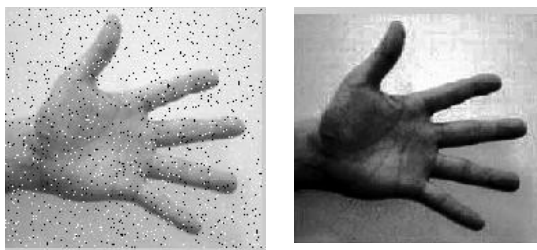**Fig. 2**. Input image and Gray scale image
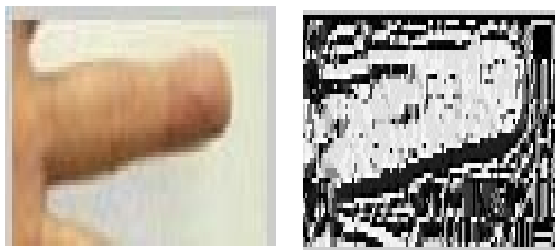

Fig. 3 Noisy image and Normalized image

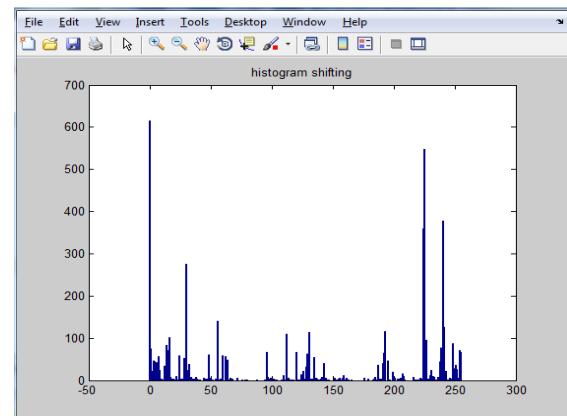**Fig 4** Middle finger and Feature extraction
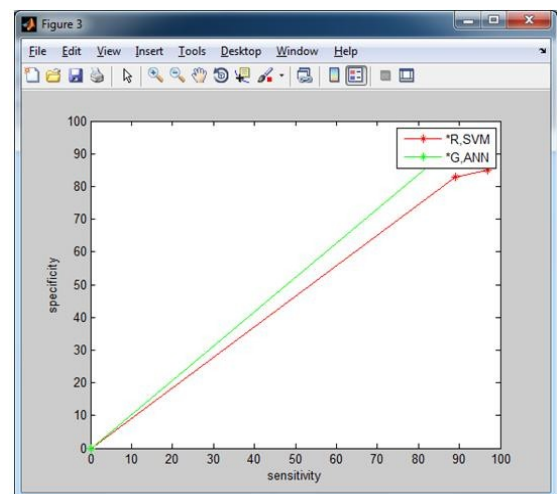

Fig 5 Histogram shifting

Fig. 6 Graphical representation of SVM and ANN

The 100 images are divided into 50 known images (previously trained one) and 50 images (newly untrained one). In this research work verification is based on finger descriptor features. Figure 2 shows the input image and gray scale image.

This proposed method consists of three stages. They are preprocessing, feature extraction and matching. In the first stage, noise is suppressed using an image filtering. Figure 3 shows noisy image and normalized image. In the second stage, features are extracted by local line binary pattern. Figure 4 shows the middle finger and feature extraction Finally, artificial neural network and support vector machine are used to provide an efficient matching algorithm for inner knuckle print authentication. After matching, the algorithm returns the best match for the given fingerprint parameters.

In the proposed technique neural network uses back propagation algorithm for error computation and new weights calculation for each neuron link. The network undergoes process of training, continuously in an iterative manner it calculates output from each layer, extracting the mean square error and propagating it backwards if it is not approaching targets. Due to this backward error propagation, error-signal for each neuron is calculated. This in fact is used for neuron weight updating. If its approaching targets then training is considered done. The process of training curve is

Corresponding author at: Hema Rajini N, Alagappa Chettiar Government College of Engineering and Technology, IN.   117

approaching its goal through readjustment of weights and biases.

The response of the Neural Network is dependent upon weights, biases and activation functions. The activation functions used in the feed-forward back propagation neural network are Tangent sigmoid (tansig) used in hidden layer and purelin used in output layer. These functions acts as summation junction and calculates the output from the inputs presented. After the training phase is completed, the identification process must be implemented in order to evaluate the proposed system. The evaluation process is accomplished by testing the system with known and newly fingerprints images. New images for testing are applied to the trained neural network along with already trained images for calculating the percentage of accuracy and error. Figure 5 shows histogram shifting. Figure 6 shows the graphical representation of SVM and ANN.
The use of inner knuckle print in biometric identification has been the most widely used authentication system. A matching with an accuracy of 89% and 97% has been obtained by support vector machine and artificial neural network classifier.

Table I. Classification Accuracy for The Used Classifiers.

Classifier	Sensitivity (%)	Specificity (%)	Accuracy (%)
SVM	83	85	89.0
ANN	93	94	97.5

5. Conclusion

A personal recognition system based on the inner knuckle print has been developed. The image recognition system contains three steps: image pre-processing, feature extraction, and feature matching. In the first step, noise is suppressed using an image filtering. Then, the features are extracted by local line binary pattern. Following this, we employ artificial neural network and support vector machine to provide an efficient matching algorithm for inner knuckle print authentication. After matching, the algorithm returns the best match for the given fingerprint parameters. A matching with an accuracy of 89% and 97% has been obtained by support vector machine and artificial neural network classifier. This recognition rate of fingerprints depends on the quality of inner-knuckle and effectiveness of preprocessing system.

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