Artificial Bee Colony Based Multifeature Recognition

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Abstract

This paper presents a new approach to improve the recognition performance of existing authentication systems based on palmprint. The technique presented extracts multiple features namely, minutiae, texture and ridge from the palmprint image using novel algorithms. The images are then classified using Artificial Bee Colony Classifier. The proposed palmprint approach proves to be superior to existing methods in all scenarios. CASIA palmprint database is utilized to obtain the experimental results, thereby, conforming the effectiveness of the proposed approach.

Keywords *- Bee colony, Biometrics, Morphological, Palm-print recognition, RLTP.*

1. Introduction

Biometrics refers to the use of unique characteristics to identify an individual. Biometrics is widely used in security systems and login control. It also finds application in healthcare and financial services. Unlike cards and passwords, biometrics provide enhanced security, accuracy and can’t be shared, copied or lost[1],[2].Biometric identifiers are often classified as physiological and behavioral characteristics.

Palmprint Technology is a relatively novel and efficient biometric technology. It plays a significant role in forensic applications. It has considerable potential as a personal identification technique. Although there are numerous distinguishing traits used for personal identification, palmprint technology has the capability to correctly and efficiently identify different personnel through classification at a low cost. Palmprint is distinctive, easily captured by low-resolution devices, as well as contains additional features such as principal lines, wrinkles, delta points, minutiae and several more [3].

With the help of palm geometry, a highly accurate biometric system can be designed. Iris input devices are expensive, the method is intrusive and for people affected with diabetes the eyes get affected resulting in differences. Fingerprint identification requires high resolution capturing devices and may not be suitable for all as some may be finger deficient. In case of voice biometric, when the person has flu or throat infection the voice changes. Palmprint is therefore suitable for everyone and it is also non-intrusive. Palmprint images are captured by acquisition module and are fed into recognition module for authentication. Recognition module has many numbers of stages which are preprocessing, feature extraction, template extraction as well as matching with the database.

1.1 Related Work

Previous work on palmprint recognition mainly focuses on single feature extraction. Iterative Closest Point Method to refine the alignment of palmprint images was suggested [4]. ICP method is applied to the extracted principal lines. Another method is to convert palmprint images to the frequency domain using 2D DFT [5] and thereafter bandpass filtering is performed using a log-Gabor filter to extract the phase symmetry information. Palmprint recognition system based on extraction of feature points, which is the intersection of creases and lines was proposed [6-8]. SVD factorization was implemented to carry out the matching of palmprint images [9]. Classification of sub-blocks obtained from the palmprint image using Principal Component Analysis was suggested [10]. The phase difference is binarised to obtain features from good blocks. [11-12] Division of matching step into several stages such that many false palmprint are rejected at each stage was suggested, thereby, consuming very less time for identification. Techniques, namely, orientation pattern hashing and principal orientation pattern (POP) hashing for fast palmprint identification was proposed[13].POP hashing has the capability to find the most appropriate template at a very fast rate, thus, speeding up the identification process [14]. Fragile bits of coding based approaches have been investigated. E-BOCV (Extended Binary Orientation Co-occurrence Vector) improves the verification accuracy by incorporating fragile bits information in suitable ways.

2. Proposed Work

A review of previous work on palm-print authentication presented in the previous section outlines the need to extract multiple features using promising algorithms and thus greatly improve the accuracy of existing palm-print authentication systems. In this paper, a novel approach is presented to extract multiple features and classify them.

This paper investigates new approaches which extract palm-print features, namely, minutiae, texture, and ridge and hence achieves the highest performance. The morphological based feature extraction investigated in this paper detects minutiae efficiently using hit or miss transform. It saves a lot of effort in the post-processing stage and also completely eliminates false minutiae, unlike the crossing number technique [11].Relaxed Local Ternary Pattern (RLTP) presented in this paper as a technique for texture feature extraction encodes the small pixel difference into an uncertain state. This state X is encoded into 0 and 1 with equal probability. It is insensitive to noise and the dimensionality of the histogram is small. This approach thus overcomes the disadvantages of local binary pattern [12] and local ternary pattern [13] proposed in the literature for texture feature extraction. To extract ridge, a new algorithm has been employed which detects and eliminates false ridges. This method uses the greatness relation of curvatures. It employs Gaussian filter for better efficiency and the presented approach is robust to noise. For classification of extracted features, Artificial Bee Colony algorithm is employed. ABC algorithm gives the best classification accuracy and average error rate. Based on the calculated probability for different solutions, the best solution is chosen and the classification is done. ABC has an advantage of employing fewer control parameters. This algorithm proves to be relatively efficient.

The organisation of the rest of the paper is as given below: Section 2 presents details of the preprocessing steps done to normalise and enhance the segmented image. Section 3 describes our proposed feature extraction and classification approach for the automated palm-print authentication. The experimental results are presented in section 5 and section 6 provides discussion on the experimental results obtained, which includes the simulation results for the palm-print authentication. Finally, the key conclusions from this paper are summarized.

2.1 Preprocessing

When capturing a palmprint, the position, direction and stretching degree may vary from time to time. As a result, even the palmprint from the same palm could have a little rotation and translation. Also, the sizes of palms are different from one another, so the preprocessing algorithm is used to align different palmprint and extract the corresponding central part for feature extraction.

To allow for effective and efficient authentication results, the preprocessing algorithm should locate the coordination system of the palmprint, which is invariant to rotational and translational changes. Using a threshold we convert the original gray scale image into a binary image. The boundary of the gaps between fingers is traced and the common tangent of the boundaries is computed. We then align the tangent points to determine the Y-axis of the palmprint coordination system .A line is made to pass through the midpoint of the two tangent points, which is perpendicular to this Y-axis to determine the origin of the system. The central part of the image is extracted at a desired distance from the tangential line symmetrically positioned about the perpendicular line.

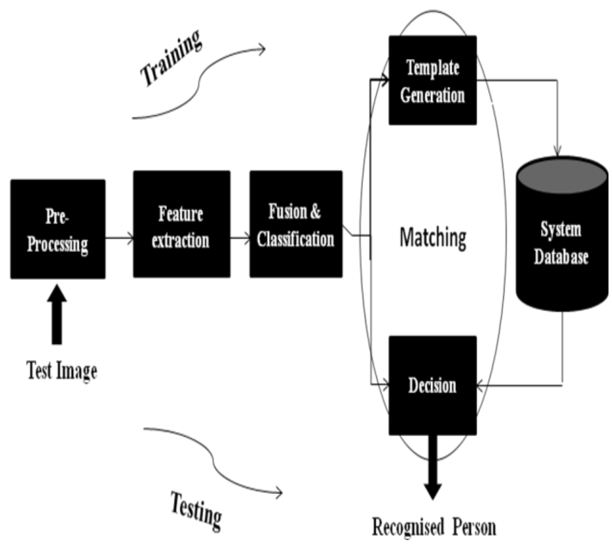
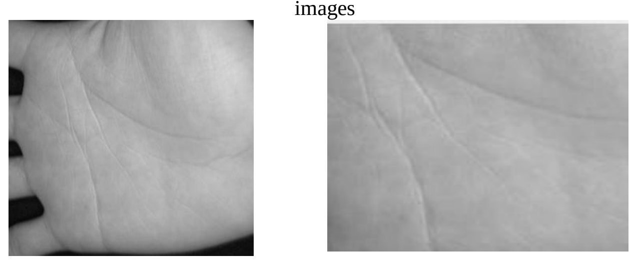


Fig. 1. Block diagram for personal authentication using palm-print images



(i) (ii)

Fig. 2.Illustration of segmentation of palm-print ROI from an (i) acquired sample image (ii) ROI image

The acquired palmprint images might appear dark with low contrast. Hence, the acquired images must be enhanced to display the details and also improve the contrast. The image is divided into slightly overlapping blocks of smaller size to estimate the background intensity profiles. The average gray-level pixels in each block are then computed.

3. Feature Extraction

3.1 Texture feature extraction using Relaxed Local Ternary Pattern

Local Binary Pattern (LBP)[12] encodes the pixel differences between the center pixel and neighbouring pixels. LBP is not robust to noise. In Local Ternary Pattern (LTP)[13],the small pixel difference is encoded into a separate state. This technique has the disadvantage of resulting in a very large histogram. Loss of information occurs when the ternary code is split into a positive LBP and a negative LBP code in order to overcome the problem of large histogram. RLTP is presented to overcome the disadvantage of LBP and LTP. Let g_n be the intensity level of the neighbouring pixels and g_c be the intensity level of the center pixel. Let m represent their difference. The thresholding function is defined as:

$$h(m,t)=\begin{cases}1, m \geq t \\ X, |m| < t \\ 0, m \leq t\end{cases} \tag{1}$$

where, t is a pre-defined threshold. The small pixel difference is encoded into an uncertain state X. Strong states 0 and 1 correspond to large pixel difference. The small pixel difference is easily distorted by noise. To overcome this, the uncertain state is deduced into two strong states. Since, the small pixel difference can be either positive or negative with equal probability; the uncertain state is encoded into both State 0 and 1. RLTP is thus more robust to noise. From the sub-images, we obtain a trinary code, which is in turn encoded into binary codes. The shortcoming of LTP is also overcome in the process.

3.2 Ridge Extraction Algorithm

This section deals with the extraction of ridges. A ridge is a sequence of connected pixels whose intensity differs from the neighbouring pixel sequence. It can also be defined as the curved feature present on the surface of an image. Before starting with the algorithm explanation, some notations are to be noted down. The 2-D image is represented by M(x,y). The image function in the scale space with scale value σ is given by H(x,y,σ). This is obtained using the following formula:

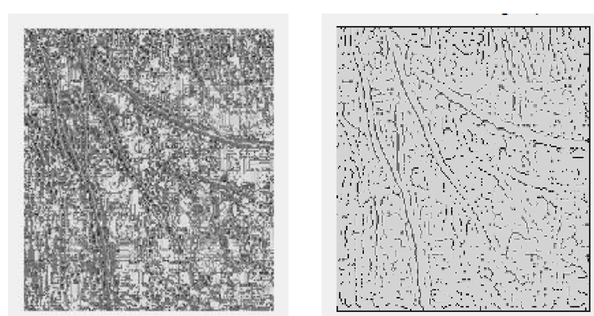
$$H(x,y,\sigma) = F(x,y,\sigma) * M(x,y) \tag{2}$$

where F(x,y,σ) is the filter which decides a ridge's presence.

The geometrical properties corresponding to the local surface of a ridge point are considered for ridge extraction. The surface has two main curvatures α_1, α_2 along with two main directions β_1, β_2. The curvatures correspond to the eigenvalues of the Hessian matrix and the direction corresponds to its eigenvectors. The local surface is approximated to a quadric by the Hessian matrix. The ridge point is detected by the relations of sign and the greatness of curvature. Same sign exists for both the curvatures, with one of the curvatures dominating the other. The local direction of the ridge at this point gives the main direction of the curvature. To overcome the discontinuous ridges, the criterion about the greatness relation of the curvature is implemented. The greatness relation of the curvature is given by

$$G=\begin{cases}'-ve', c < -x \\ 0, -x < c < x \\ '+ve', c > x\end{cases} \tag{3}$$

where C denotes the curvatures and x is a predefined threshold. Considering the geometrical properties of the surface alone will produce regions and not ridge points. Therefore, filters also play an important role in extracting the ridges. The Gaussian filter is used in convoluting the image. This filter results in smoothing of the image. It is designed in such a way that it characterises the structure of the object. A filter should produce a strongest response at a ridge point. Therefore, Laplacian of Gaussian filter is computed. This filter produces an extreme response in the direction normal to the ridge. It efficiently results in the extraction of ridge points eliminating false ridges.



(i) (ii)

Fig. 3. Illustration of feature extraction (i) Extracted texture using RLTP (ii) Ridge extraction

3.3 Minutiae Extraction using morphological operators

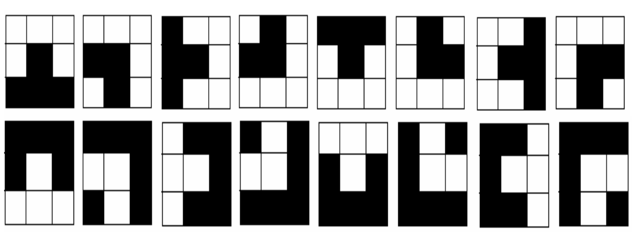
Crossing Number technique [11] proposed in the literature for minutiae extraction results in false minutiae. To overcome the limitations of this technique, an efficient algorithm is presented in this paper. With the help of morphological operators and the Hit or Miss Transform, a very effective minutiae extraction is made possible. The algorithm proposed in this paper proceeds by starting with the enhancement of the image where Gabor filters are used to fix the problems regarding noise and broken minutiae. Following the enhancement, binarization is done to reduce the number of levels present in a gray scale image. Now, the binarized image has only two levels-Black and White. A binarized image may have broken ridges which leads to false minutiae detections. This is where a morphological operator comes to play its role. These operators are designed in such a way that it removes spurious holes, islands, spurs, and bridges effectively. Following the pre-processing stage, thinning is done, in which the ridges are made one pixel wide. The image Q is thinned using a structuring element given b y P = (P_1,P_2). The formula used to thin an image is as follows

$$T(Q,P) = Q - (Q \otimes P) \tag{4}$$

Here, the subtraction done in this method is logical and is given by

$$R - S = R \cap \overline{S} \tag{5}$$

This process is iterated till the convergence of the image is obtained. The structuring element P can be represented as follows



The first eight elements belong to P_1^r and the next eight belongs to P_2^r, where r=1,2...8. Running this structuring element over the image results in thinning.

Now, the minutiae extraction using Hit or Miss Transform can be performed on the image. Various types of Minutiae exist, namely ridge ending, ridge bifurcation, lakes, island, spur, bridge, etc. Our features of interest include ridge endings and ridge bifurcations.

The extraction of a ridge ending is explained below. Pixels with only one neighbour in a 3×3 neighbourhood correspond to ridge endings.

To obtain an image R1 containing a ridge ending, Hit or Miss Transform is applied on the image Q using the structuring element P. This can be defined using the following formula:

$$R_1 = Q \otimes P \tag{6}$$

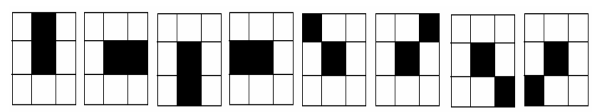
where

$$Q \otimes P = (Q \Theta P_1) \cap (Q^C \Theta P_2) \tag{7}$$

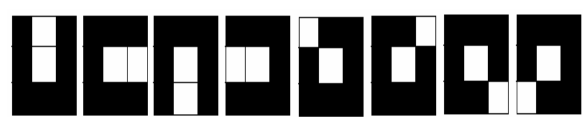
The symbol 'Θ' used above defines the erosion of the image Q by the structuring element P.

The structuring elements are designed such that the output contains only the ridge endings leaving out the remaining points from the thinned image.

The structuring element P_1^r (r=1,2…8) is represented by



The structuring element P_2^r(r=1,2…8) is represented by



The next step in this algorithm is the extraction of ridge bifurcation. Pixels with only three neighbours (but not in adjacent positions) in a 3×3 neighbourhood correspond to ridge bifurcations.

To obtain an image R1 containing a ridge bifurcation, Hit or Miss Transform is applied on the image Q using the structuring element P. This can be defined using the following formula:

$$R_2 = Q \otimes P \tag{8}$$

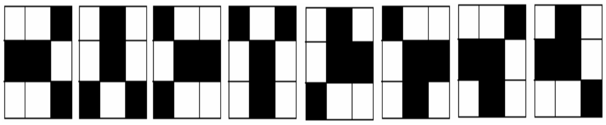
where

$$Q \otimes P = (Q \Theta P_1) \cap (Q^C \Theta P_2) \tag{9}$$

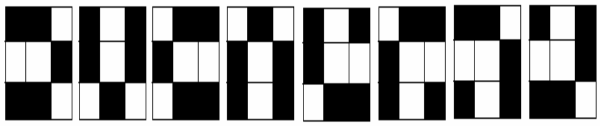
The symbol 'Θ' used above defines the erosion of the image Q by the structuring element P.

The structuring elements are designed such that the output contains only the ridge bifurcations leaving out the remaining points from the thinned image.

The structuring element P_1^r (r=1,2…8) is represented by



The structuring element P_2^r(r=1,2…8) is represented by



Performing the above steps on the thinned image Q results in effective and efficient extraction of minutiae points.

The final stage is the post processing stage where the false minutiae resulted from the previous step is eliminated. In order to remove the spurious minutiae, a threshold Z is set appropriately. The distance between (a) two terminations, (b)two bifurcations and (c)a termination and a bifurcation are calculated. If any of (a), (b) and (c) are found to be less than Z, then they are removed thereby eliminating false minutiae.

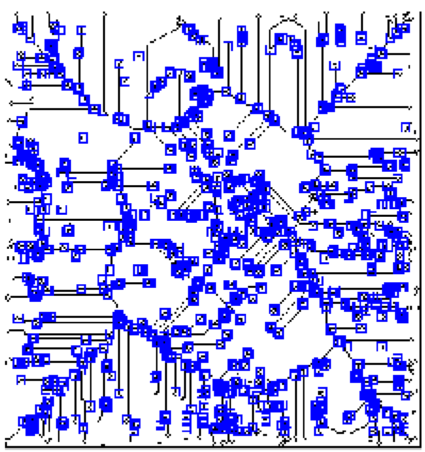


Fig.4. Extracted minutiae points

4. Classification

This section deals with the classification of fused features. The algorithm used in this paper is Artificial Bee Colony (ABC) optimisation. ABC makes use of a bee's way of finding a solution. The bees in nature are classified as employer bee, onlooker bee and scout bee. The employer bees leave the hive hunting for a food source. Each employer bee finds a nearby food source and then it returns to the hive convincing its nest mates about the food source by its way of dancing. The onlooker bee then decides the best food source by comparing the nectar amount of each food source. The employer bee erases the position of the previous food source from its memory and adapts to the location of the new food source if the fitness of the new solution is better. In the next step, the scout bees leave the hive and randomly find new food sources. These locations are then followed by the employer bees and the same procedure is followed as above. The onlooker bee then decides on the solution to be followed and also about abandoning the previous solution. This searching process is repeated till a termination criterion is satisfied. The number of employer bees is equal to the number of food sources and also equal to the number of scout bees.

Let the initial population of food source be NF solutions and the number of artificial bees is represented as NA. Each food source Z_n is a D-dimensional vector, where D is the number of optimisation parameters. An onlooker bee decides on the solution based on the probability value associated with each food source. The probability can be calculated by the following expression:

$$P_n = fit_n \div \sum_{n=1}^{NA} fit_n \qquad (10)$$

where fit_n is the fitness value of the solution n which is proportional to the nectar amount of the food source in the position n and NA is the number of food sources which is equal to the number of artificial bees.

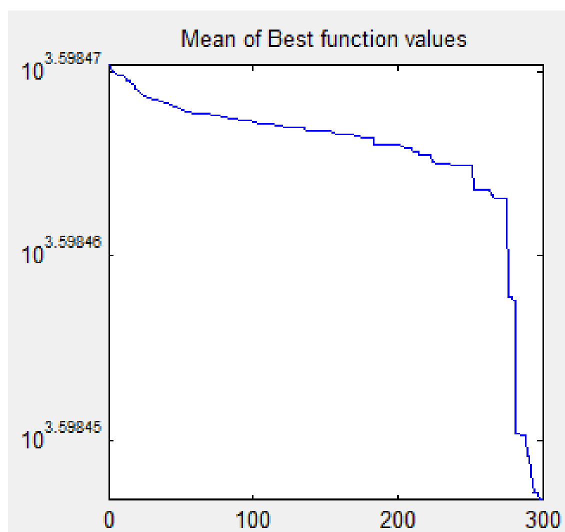


Fig. 5.Graph illustrating results of ABC classification with cycle number in x-axis and error in y-axis

The employer bee searches for the best food source within the neighbourhood of the old food source. This information is passed to the onlooker bee which calculates the neighbouring food source using the formula:

$$S_{nj} = Z_{nj} + \Phi_{nj}(Z_{nj} - Z_{kj}) \quad (11)$$

where,

Z_k= randomly selected food source
J= randomly chosen parameter
Φ= randomly chosen number in the range [-1,1]

In palmprint recognition, with the train dataset representing the colony and the test data set representing the employer bees, test dataset is compared with the train dataset to sort out the appropriate classification group. This is achieved through a number of iterations as described above until it reaches the maximum number of iterations which is predefined. From fig.6 that as iteration number increases, mean square error decreases, thus leading to absolute accuracy.

5. Experimental Results

We test the proposed feature extraction and classification methods on the Chinese Academy of Sciences' Institute of Automation (CASIA) open palmprint database to prove the effectiveness of the approach.

```
ABC:Interate Cycle = 1
    obj.Val = 3967.08
ABC:Interate Cycle = 2
    obj.Val = 3967.08
ABC:Interate Cycle = 3
    obj.Val = 3967.07
ABC:Interate Cycle = 4
    obj.Val = 3967.07
ABC:Interate Cycle = 5
    obj.Val = 3967.07
ABC:Interate Cycle = 6
    obj.Val = 3967.07
ABC:Interate Cycle = 7
    obj.Val = 3967.07
ABC:Interate Cycle = 8
    obj.Val = 3967.07
ABC:Interate Cycle = 9
    obj.Val = 3967.07
ABC:Interate Cycle = 10
    obj.Val = 3967.07
```

Fig.6.Illustration of mean square error obtained in first ten iterations of classification algorithm

5.1 Database

The CASIA database consists of 5502 images of palmprint captured from 312 subjects. Images from this database undergo ROI extraction. The ROI extracted images are then processed to extract multiple features of palmprint. The images are then classified within the database. Matching is done to check for the accuracy of the proposed method. This is done by comparing each palmprint image with the database images.

5.2 Authentication Experiments

This section puts forward the experiments conducted to evaluate the performance of morphological based minutiae extraction, RLTP, novel ridge detection method and artificial bee colony classification on palm print database. Here, considering 4 images for each subject, three are used for training and the remaining one is used for testing purpose. The performance of this authentication system is evaluated.

5.3 Verification Experiments

The final step deals with performing verification experiments for testing the method proposed in this paper. In order to identify the test image, classification of all the images in the database is necessary. Templates are generated for each class. The sample images are compared with all the template classes and the results are produced. By seeing the results, we get to know that the proposed method leads to absolute accuracy.

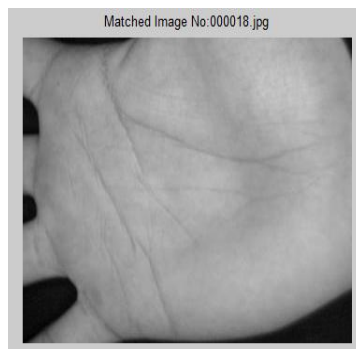


Fig. 7.Verification for matched image

6. Conclusion

This paper presented a novel approach for personal authentication using palmprint images. We propose RLTP for texture feature extraction, minutiae extraction using morphological operators and a novel ridge detection algorithm which overcomes the shortcomings of algorithms proposed earlier in the literature. The use of artificial bee colony algorithm for effective classification is also presented in this paper. The performances of the proposed algorithms on palm print database are compared and discussed in this paper. It has been proven through experimental results that the presented method is the most apt one as far as palm print recognition is concerned. The efficiency of palm print recognition system can be further improved by adopting multimodal biometrics. For instance, palm print may be used in combination with hand vein/palm vein to further enhance the authentication accuracy.

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