A Robust Method for Multi-algorithmic Palmprint Recognition Using Exponential Genetic Algorithm-Based Feature Selection

Aruna Kumari Palisetty and Jaya Suma Gogulamanda

Abstract Biometrics is widely used in authentication systems to improve their security. One of the leading traits is palmprint thanks to its extensive user's acceptability, accuracy, security as well as to its relatively inexpensive cost. Although palmprint authentication systems know certain maturity, still some challenging tasks need more researches. The integration of multiple representations of palmprint at the representation level provides highly accurate information about palm which led to robust palmprint recognition. This integration creates a problem of substantial dimensional feature space which consumes recognition time, space, and sometimes the accuracy. Feature selection addresses this problem effectively. Therefore, this paper mainly concentrates on the improvement of the Genetic Algorithm (GA)-based feature selection approach for a robust palmprint recognition by including exponential function in the searching process and altering the fitness function, which includes recognition rate, the impact of selected and non-selected features. Experiments on CASIA and IITD databases have shown significant improvement in recognition accuracy along with the reduction of space and time requirements with the proposed Exponential Genetic Algorithm(EGA) compared with GA and Principal Component Algorithm (PCA).

1 Introduction

Multibiometric system, a system based on either different modalities or various samples of the same trait or several instances of a single modality or different representations of single modality, seems to be the best way to overcome the problems caused by unimodal systems [1]. Indeed it restricts from forgery of the modalities to breach the security. A robust authentication is required against frauds with the

A. K. Palisetty (✉) · J. S. Gogulamanda
JNTUK University College of Engineering, Viziangaram, Vizianagaram, AP, India
e-mail: arunakumarip.cse@jntukucev.ac.in

J. S. Gogulamanda
e-mail: gjsuma.it@jntukucev.ac.in

S. C. Satapathy et al. (eds.), *Communication Software and Networks*, Lecture Notes in Networks and Systems 134, https://doi.org/10.1007/978-981-15-5397-4_61

improved performance of the system for most of the security applications. Among various modalities, palmprint gains more focus because of its high user acceptance, steady line shreds of evidence, low insensitivity, and low-resolution imaging [2]. A robust palmprint-based multibiometric authentication system can be developed by considering the different representations of palmprint; these representations are obtained by applying various feature extraction algorithms on palmprint. The pieces of evidence collected from palmprint should be integrated at various stages, namely, pixel level, representation level, score level, and decision level.

The representation or feature-level integration gives highly qualitative information of biometric modality against the rest of the levels, which is useful in constructing a robust system [1]. But in this integration stage, the different representations to be combined may contain heterogeneous feature space which is incompatible for integration. Normalizing the varied feature space produces new feature spaces which are compatible for integration [1]. In addition to this incompatibility, this stage provides ample dimensional feature space after integration which creates problems like increase in time and space requirements and sometimes reduces the system performance instead of improvement. This can be handled by applying dimensionality reduction methods which can be broadly classified as feature extraction and feature selection [3, 4]. It is important to distinguish between both notions. While feature selection methods output a subset of the original features without any further change, feature extraction algorithms transform the input features into a completely different space. Although the feature extraction is more general and the transformation mapping may provide features with better discriminatory ability than the best subset of the input features, new features may not have clear (physical) interpretation. The feature selection is beneficial especially for problems where some sensory inputs are likely to carry a little of useful information for the class discrimination, or if there are very strong correlations between sets of input observables so that very similar information is repeated in several variables, or if measurements on an examined object (or process) are costly and it is advisable to reduce their number. Furthermore, features keep their original physical meaning because no transformation of data is made. This may be important for a better problem understanding in some applications (e.g., in medicine) as only relevant information is analyzed.

The literature has studied various feature extraction, and feature selection approaches in different fields of applications. Feature extraction methods like PCA, Linear Discriminant Analysis (LDA), and Independent Component Analysis (ICA) are investigated in several applications including biometric recognition [5–7]. The feature subset selection approaches like sequential floating forward selection and backward selection methods, sequential forward and backward approaches, exhaustive search, branch and bound search method are suffering from problems like nesting effect, local optimum, and moreover not suitable for large datasets like palm biometric data [8–10]. A robust feature selection method for large scale data like biometric data is needed without any problems as mentioned earlier approaches. Evolutionary Computation (EC) approaches are able to address this feature selection problem in biometric data as it has robust global searching mechanisms [11, 12].

A multi-tree Genetic Programming (GP) method with classification has shown better performance than filter and wrapper methods [13]. GA with fuzzy objective function has investigated for feature selection [14]. For the selection of optimal features from Microarray gene expression data has been applied in [15], which concentrated on reducing computational complexity and fast convergence. A combination of filter and wrapper approaches based on GA has been proposed where three strategies called greedy, sequential, and improvement first strategies are examined and shown that GA produces the best results than remaining methods. The literature shows that GA is producing the best results as a feature selection in various applications [16].

This paper aimed to gain the advantages of representation-level fusion to build robust multi-algorithmic palmprint recognition system with EGA-based feature selection to overcome challenges in representation-level integration. Gayatri and Ramamoorthy [17] proposed a palmprint recognition using the feature-level fusion of four features, namely, energy, contrast, homogeneity, correlation extracted using Gabor Wavelet. But texture features of palmprint contains more discriminative data for better classification compared to the above four features. Zhang et al. [18] proposed palmprint recognition using feature-level integration of 2D-Gabor filter and 2D-Log Gabor filter, where the shreds of evidence extracted from filters are divided into sub-images and calculated the standard deviation (SD) of each sub-image. These SD's of all sub-images of texture image forms feature vector. Even though this approach has produced better results than the unimodal system, due to the calculation of SD, it losses advantage of qualitative and highly discriminative information about palmprint. Hence this work attempted to integrate texture features of palmprint at the representation level.

The proposed system architecture has shown in Fig. 1. The claimed palmprint image has been preprocessed to get fixed dimension palmprint Region of Interest (ROI) image. Then two different approaches based on 2D-Gabor filter and 2D-Log Gabor filter have been applied to obtain different feature representations from ROI. The extracted feature vectors have integrated at the representation level. Three feature reduction approaches called PCA, GA, and proposed EGA have applied. The reduced feature vector has been matched with the stored palmprint template database using

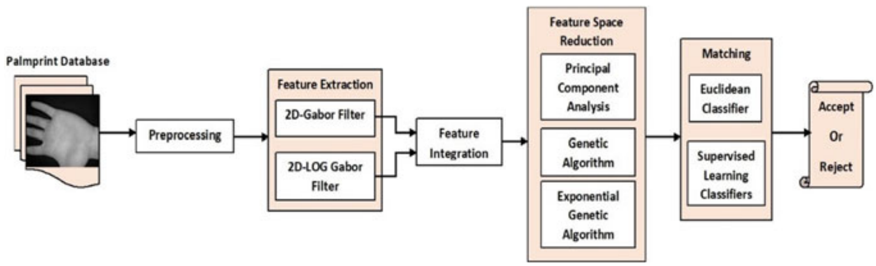

Fig. 1 Proposed system architecture

either Euclidean distance-based classifier or supervised learning classifiers to detect genuine or imposter claim.

This paper has planned as follows: Sect. 2 gives how preprocessing of palmprint image has been carried to get ROI image. Different feature extraction algorithms applied to the ROI image has presented in Sect. 3. The integration of different obtained feature spaces has presented in Sect. 4. The process of dimensionality reduction by PCA, GA, and proposed EGA is presented in Sect. 5. The experimental setup, results, and analysis have discussed in Sect. 6. The work has concluded in Sect. 7.

2 Preprocessing

It is the process of aligning various palmprint images and segmenting middle region (ROI) for further process. Major preprocessing approaches establishes a coordinate system based on key points between fingers. This preprocessing mainly consists of five steps Binarization, Contour extraction of hand/palm, Key points identification, Coordinate system establishment, and Extraction of ROI [19]. All preprocessing algorithms differ from third step onwards until they are all the same [19]. Key points can be identified using tangent-based approach [18], bisector-based approach (midpoint) approach [20], wavelet-based approach [21].

The tangent-based method considers two boundaries- one from point finger and middle finger and the other from ring finger and last finger—as two convex curves. The intersections are considered as two key points for establishing the coordinate system. This approach gives many advantages. They depend on a very short boundary around the bottom of fingers. Therefore it is robust to incomplete fingers and the presence of rings [19]. Because of these advantages, the tangent-based method has applied to extract ROI from palmprint image. To simplify the further processing and for uniform template size, ROI has cropped to 100×100 pixels.

3 Feature Extraction

This section discusses the process of feature extraction of palm ROI image. The Gabor filter is previously applied in biometrics to extract texture information from palmprint [7, 22–24], fingerprint [7, 15], and iris [7]. The texture extraction from palm using Gabor filter comprises principle lines, ridges, and wrinkles, etc. Because of this reason, it has widely applied in palmprint feature extraction [25].

3.1 2D—Gabor Filter

The literature shows Gabor-based feature extraction that has extensively used in various application of pattern recognition. Unstable contrast and brightness of images are better handled by the Gabor function and gives the location of time-frequency exactly [24, 26]. Because of these advantages, the following Gabor filter bank has applied to iris texture extraction [7, 26]:

$$g(a, b; \theta, \varphi, \sigma, \gamma, \lambda) = \exp\left(\frac{a^2 + \gamma^2 b^2}{2\sigma^2}\right) + \exp\left(i\left(2\pi\frac{a}{\lambda} + \varphi\right)\right) \tag{1}$$

where

$$a = a\cos\theta + b\sin\theta$$

$$b = -a\sin\theta + b\cos\theta$$

θ signifies the orientation of the normal to parallel stripes of a Gabor function, φ is the phase offset, λ specifies the sinusoidal factor wavelength, α is the standard deviation of the Gaussian envelope, and γ is the spatial aspect ratio [26].

3.2 2D-Log Gabor Filter

Because of time/space and frequency invariance, symmetry on the log frequency axis, Log Gabor filter has systematically investigated and applied for texture-based feature extraction [27]. The Log Gabor filter has applied by using the following formula [7, 24]:

$$G(\rho, \theta, a, b) = \exp\left(\frac{-1}{2}\left(\frac{\rho - \rho b}{\sigma a}\right)^2\right) + \exp\left(\frac{-1}{2}\left(\frac{\theta - \theta_{ab}}{\sigma\theta}\right)^2\right) \tag{2}$$

In which (ρ, θ) are the log-polar coordinates, a and b gives orientation and scale, the pair $(\rho k, \theta pk)$ corresponds to the frequency center of the filters, and $(\sigma\rho, \sigma\theta)$ is the angular and radial bandwidths.

4 Integration of Feature Spaces

This section explains how the different features collected from the palmprint image by applying two distinct feature extraction approaches have integrated at the feature level. The texture features extracted from palmprint by using 2D-Gabor filter and 2D-Log Gabor filter are compatible with each other. The texture analysis of 100 × 100 palmprint ROI image obtained by applying 2D-Gabor filter and 2D-Log Gabor filter produces 12 different images of size 100 × 100 each; this texture has brought to a single image of size 100 × 100 by using horizontal and vertical downsampling. Further, it converted into a row feature vector of size 10000. The weighted average of feature vectors produces integrated feature space, as shown below:

$$\text{featurevector}_{\text{integrated}} = \frac{\left(w_1 \times \text{featurevector}_{\text{gabor}}\right) + \left(w_2 \times \text{featurevector}_{\text{loggab}}\right)}{2} \tag{3}$$

Here, $\text{featurevector}_{\text{integrated}}$ represents the feature vector after integration, $\text{featurevector}_{\text{gabor}}$ indicates the feature vector formed from the 2D-Gabor feature extraction, $\text{featurevector}_{\text{loggab}}$ indicates the feature vector created from the 2D-Log Gabor feature extraction. w_1 and w_2 are the weights assigned for Gabor features and log Gabor features. Experimentally these weights w_1 and w_2 are fixed to 0.6 and 0.4, respectively.

5 Reduction of High Dimensional Integrated Feature Space

The integration of two feature vectors at the representation level creates the dimensionality problem. This work solves this problem with existing PCA, GA, with new fitness function approaches and proposed EGA method.

5.1 Principal Component Analysis

PCA is a dimensionality reduction approach based on subspace projection and widely applied for image compression and recognition problems [28]. PCA has been used for extracting features from face [29–31] and enforced as a reduction strategy in various biometric recognition like face, signature, fingerprint, palm print before matching [7, 32, 33]. PCA is a linear data reduction technique and projects the original data into new dimensional space with maximum variability. The projected data is a collection of principal components which represents new dimensions of the data.

5.2 Exponential Genetic Algorithm-Based Feature Space Reduction

Genetic Algorithm is a population-based search algorithm applied in various applications like feature selection [34], routing protocol [35], parameter selection [36], etc. The main motto behind GA selection is that it is simple which requires less computation time, even though a large number of dimensions are present it identifies optimal features with limited time, mutation operation provides flexibility of small changes which cause good results, the number of parameters to be selected are less, and finally it applies probabilistic selection rather than deterministic.

GA mimics the evolution of man and which includes fitness, reproduction, mutation, and crossover [37]. The set of chromosomes known as population denotes solutions. For the selection of essential features from integrated palm feature space, chromosomes are represented in a binary form with a size equivalent to the number of dimensions in the integrated feature space. Here, 1 in chromosome denotes the selected feature, and 0 indicates a non-selected feature. Initially, chromosomes have randomly initialized, and then the evolution process continues as generations. In each generation, chromosomes are selected based on the selection method, and then the quality of the selected chromosomes are computed as fitness value. Based on the quality the selected chromosomes undergoes crossover and mutation operations to generate a new set of chromosomes and forms a new population. This process continues for either a fixed number of generations or some criteria. In the end, the chromosome with the best quality presents the optimum features for robust palmprint recognition.

This work has adopted GA for reducing fused feature space. Each palmprint template after feature-level fusion has encoded as chromosome, where each feature has encoded as genes. Randomly, the initial population of random size has initialized.

Fitness Function

The fitness of each chromosome has evaluated by using Eq. (4). Here, the Recognition Accuracy (RA) of the dataset formed by considering the selected features from the chromosome Chi has calculated by applying the C4.5 classification algorithm.

$$\operatorname{fit}(Ch_i) = RA + n_{\text{selected}} * \left(\frac{N_{DB}}{n}\right) \tag{4}$$

where n_{selected} is the number of selected features in the given chromosome Ch_i. N_{DB} represents the total number of iris samples in dataset and n represents the number of dimensions or features in the dataset. By applying the Roulette Wheel selection method and then using a single-point crossover, mutation operations new population has generated.

New Solution Based on Exponential Order

The chromosomes produced after mutation are further undergone exponential order-based process to produce a new solution. The moto behind the inclusion of exponential function in GA is it provides a reliable solution, causes a quick way of finding optimality because of exponential weights, improves the diversity of solution.

$$\mathrm{Exp}(f) = n^{(p-1)} \tag{5}$$

where p indicates the chromosome rank based on its quality, n denotes the fitness value of each chromosome is how many times greater than in earlier chromosome.

The exponential function is multiplied with each chromosome. Before multiplication, each gene of the chromosome is converted to an integer by mapping "0" to a random number between (0, 0.5) and "1" to a random number between (0.51, 1). New solution after multiplication is converted to binary vector as in initialization process. The new solution is now replaced with the old one.

6 Experimental Results and Analysis

This section describes the experimental environment in which the proposed systems have tested evaluated. The experiments are performed on two different databases, namely, the CASIA palmprint database and Indian Institute of Technology Delhi (IITD) palmprint database. CASIA database consists of palmprint images collected from 312 individual persons. For each person, 8 images have captured for each hand. From this database, 6 samples have been selected from each hand of an individual person to evaluate the proposed system. The IITD database contains palmprint images of left and right hands collected from 230 different persons. From each user, 5 to 6 samples from the left and the right hand have captured. Since each hand of the same person contains utterly different pattern from another hand of the same person, here the samples from each hand has been considered as samples individual subjects; 460 subjects have selected, and from each subject 3 samples were chosen for the evaluation process. The experiments carried on a system with i7 processor CPU @1.8 GHz;16 GB RAM and implemented with Matlab 9.5.

Table 1 presents the recognition accuracy and the reduced number of features without and with different reduction strategies. These results have taken at FAR = 0.01% for the two databases—the results have shown that any reduction approach is giving an improvement in the recognition rate. PCA is producing better reduction compared to the other two. But, along with the amount of reduction recognition rate must be acceptable. Because of this reason, the proposed EGA-based reduction approach is given both adequate reductions in feature space and recognition rate.

Table 1 Recognition accuracy and computation time for processing dataset with euclidian classifier without and with different reduction strategies

Reduction approach	Recognition accuracy		Reduced number of features	
	IITD DB	CASIA DB	IITD DB	CASIA DB
Without reduction	80.2	81.5	10000	10000
PCA	83.4	85.6	1590	1982
GA	89.5	90.1	2458	2698
Proposed EGA	91.7	92.03	2190	2206

Figures 2 and 3 give the performance of the palmprint system with and without reduction approach on four different classification algorithms, namely SMO, C4.5, Naïve Bayes, and Random Forest. Figure 2 gives the classification accuracy on IITD database; Fig. 3 presents classification performance on CASIA database; on CASIA and IITD databases multi-algorithmic palmprint system using EGA as feature selection method has produced the best accuracies of 98.2%, 97.9% with SMO classifier and C4.5 classifier, respectively. In two databases SMO and C4.5 are giving best with very close classification accuracies. When compared to Euclidean classifier, supervised learning classifiers has produced the best accuracy results with and without reduction strategies. As already mentioned, the amount of reduction with reasonable

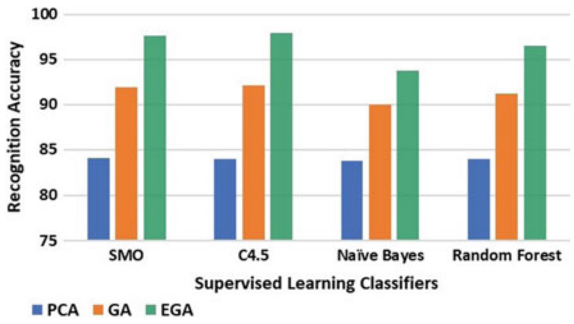

Fig. 2 Classification performance of multi-algorithmic palmprint system with and without applying reduction strategies for IITD DB

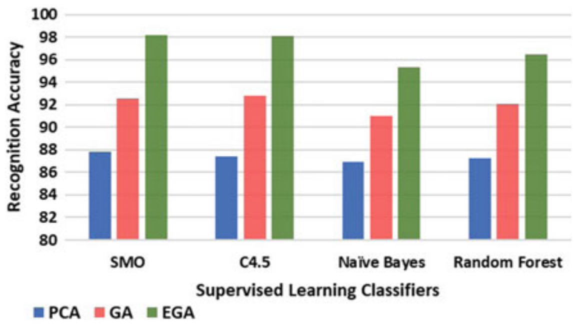

Fig. 3 Classification Performance of multi-algorithmic palmprint system with and without applying reduction strategies for CASIA DB

recognition rate is acceptable. So, EGA-based reduction strategy has given noticeable results in terms of both the amount of reduction and recognition accuracy.

7 Conclusion

Multibiometric systems produce robust recognition systems based on representation-level fusion with a solution to high dimensional feature space after fusion. This work has addressed this solution in terms of presenting different feature space reduction approaches after feature-level fusion in the multi-algorithmic palmprint recognition system. This work proposed EGA to find essential features for robust palmprint recognition. And a new fitness function was designed by including the recognition performance with selected features in chromosome and contribution of non-selected features along with database size. Basic GA with new fitness function has produced better performance than PCA, and the proposed EGA when effectively combined with designed fitness function generated best results compared to PCA and GA. The results showing improvement discrimination of genuine and an imposter in both Euclidean and supervised learning classifiers with EGA. Even though PCA producing more than 85% reduction EGA generated more than 75% reduction in feature space with 98.2% recognition accuracy. Among supervised learning classifiers SMO and C4.5 algorithms, discriminated palmprints efficiently compared to the other two. In the future, this can be improved with the inclusion of mathematical powers like calculus in GA.

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