ISSN PRINT 2319 1775 Online 2320 7876
Research paper Volume 11, Iss 7, 2022

A Novel Framework forMulti-modal Biometric Recognition System Using Fingerprint and Palmprint

Dr. P. Aruna Kumari[1], Dr. G. Jaya Suma[2]

[1] Assistant Professor, Department of CSE, JNTU-GV, CEV, Vizianagaram, AP, India.

[2]Professor, Department of IT, JNTU-GV, CEV, Vizianagaram, AP, India.

Abstract:

In today's highly paranoid world, reliable personal authentication across a broad range of use cases is a significant technical problem. Uni-biometric systems describe the current state of the art in biometric identification methods, which rely on a single biometric attribute for verification. Spoof attacks, intra-user variability and susceptibility, noisy data, and unacceptable mistake rates are only some of the challenges that remain in person authentication using a single biometric trait despite significant progress over the past few years. These problems can be solved by multi-modal biometric systems, which combine data from a number of different biometric identifiers. The integration of evidences can be done at several levels like pixel, feature or score, etc. However, the complex feature space mapping and large dimensionality of the resulting feature space are drawbacks of feature level integration that prevent it from being used for simpler recognition tasks. In this paper, we offer a Particle Swarm Optimization (PSO) based feature selection and normalization approach to address the challenges of integrating fingerprint and palmprint characteristics at the feature level. Machine Learning algorithms are used to examine the efficacy of PSO-based feature selection and Principal Component Analysis (PCA)-based feature space reduction on the CASIA and IITD databases. After fusing iris and fingerprint characteristics at the feature level, the findings showed that PSO significantly decreased the feature space compared to PCA, leading to improved recognition accuracy.

Keywords: Particle Swarm Optimization, Feature selection, Feature Level Fusion, Palmprint, Fingerprint, Multi-modal biometric systems.

---

1. Introduction:

In present modern world, a broad range of systems need dependable person authentication techniques to authorize or decide the uniqueness of persons seeking their facilities. The objective of these safeguards is to prevent unauthorized individuals from using the provided services. Mobile phones, laptops, computers, buildings, automated teller machines, and military networks are all examples of systems that employ this technique. These technologies are vulnerable to an imposter's techniques if they do not have strong authentication procedures. For these reasons—they can't be copied or forgotten—biometrics are increasingly being used for person authentication [1]. Fingerprint recognition systems are the most common and reliable biometric authentication methods [2, 3]. Among the many biometric identifiers, fingerprints have received increased attention [2] due to the fact that they are perfectly consistent between the fingerprints and palmprint of the same person (even identical twins) [4] and do not alter [5].Because of its distinctiveness and reliability, palmprint has become widely adopted as a biometric feature for a wide range of applications [6]. It also contains a good number of features, such as ridges, wrinkles, and black palm lines, and has a number of advantages, such

ISSN PRINT 2319 1775 Online 2320 7876
Research paper Volume 11, Iss 7, 2022

as less expensive devices for acquisition, non-contact, a bigger palm area, and higher acceptability, etc. [7, 8]. These benefits have attracted greater study into palmprint-based person recognition.

The performance of a unimodal biometric system can be influenced by several factors such as noise, sample size, and spoofing assaults [9]. However, multibiometric systems have the potential to address several of these challenges by integrating information from one or more biometric traits. However, it is often observed that a significant proportion of users express dissatisfaction with the multibiometric approach due to the necessity of augmenting various resources inside biometric systems [10]. In contrast to multimodal systems that utilize diverse biometric traits, such as those incorporating multiple features from a single fingerprint [11], employing multiple classifiers [12], incorporating various impressions of a single finger [10], or involving multiple fingers [13], a significant portion of scholarly research indicates that systems relying on a single biometric trait, a solitary feature, and a lone classifier or matcher exhibit subpar performance. The implementation of multimodal systems has the potential to enhance the performance of biometric recognition.

Multimodal biometric systems offer the capability to integrate evidences at different levels, namely sensor level fusion, feature level fusion, score level fusion, and decision level fusion [14]. The performance of recognition is influenced by the score level and decision level of post-mapped procedures, which necessitate a reduced amount of information pertaining to the biometric attribute [14]. One of the pre-existing techniques is sensor level fusion, which considers the presence of noise in images and thus leads to suboptimal recognition outcomes [14]. In contrast, feature level fusion incorporates identifiable qualitative information [14] pertaining to biometric features, resulting in enhanced recognition accuracy. Nevertheless, this fusion technique also presents two significant concerns, akin to the aforementioned strategies. There are two primary concerns that need to be addressed. The first concern pertains to the compatibility [15] between two separate feature spaces, which [14] can be effectively resolved through the process of normalization. The second concern relates to the high dimensionality of the feature space [16], which undoubtedly imposes significant requirements on memory and computational resources. Consequently, it becomes necessary to develop a sophisticated classifier that can effectively operate on the fused feature space [17]. This issue can be addressed by employing either feature transformation or feature selection techniques.

Feature selection is the procedure by which a subset of features is chosen based on their significance in achieving a reliable and resilient categorization of the feature space. This methodology offers the potential to enhance the performance of classification (recognition) by eliminating redundant, noisy, and irrelevant features [18]. Feature transformation refers to the process of converting an initial feature vector space into a secondary feature space that better captures the underlying characteristics of the data.

Despite the utilization of Principal Component Analysis (PCA) [19, 20, 23, 24], Linear Discriminant Analysis (LDA) [20, 21, 16], Independent Component Analysis (ICA) [22, 24], and Kernel-based PCA (KPCA) [24] in several studies, aimed at reducing the dimensionality of diverse large-scale datasets. Feature selection approaches aim to identify the optimal number of features by optimizing an objective function. Various feature selection methods, such as Genetic Algorithms, General Sequential Forward Selection (GSFS), Sequential Forward Selection (SFS), Artificial Neural Networks (ANN), Sequential Backward Selection (SBS), Sequential Forward Floating Selection (SFFS), and Sequential Backward Floating Selection (SBFS), have been widely utilized in academic literature as effective mechanisms for feature selection [25, 26, 27].

ISSN PRINT 2319 1775 Online 2320 7876
Research paper Volume 11, Iss 7, 2022

In addition, the utilization of the Genetic Algorithm is employed in order to select the most significant features from the integrated feature space. In reference [28], the integration of eigen-features generated from a visual face picture and an infrared facial image is performed through feature level fusion. The selection of dominant features is accomplished using Genetic Algorithm. In a previous study [29], the utilization of a Genetic algorithm was observed in the process of selecting the most optimal features subsequent to the fusion of palmprint and iris at the feature level.

Despite the availability of different approaches to address the dimensionality problem, it remains a significant area of concern in the field of biometric data due to the imperative requirement for high identification rates, as well as the space and time complexity of the data.

Problem Deduction

Based on the aforementioned analysis, it is evident that the focus of research has been solely on multimodal systems that employ score level fusion. Moreover, it is well acknowledged that feature level fusion provides more comprehensive biometric inputs compared to score level fusion. However, in the context of iris recognition, the exploration of feature level fusion has been limited due to the significant challenge posed by high dimension feature space. The existing body of literature has demonstrated that the dimensionality of the feature space can be reduced by many methods, such as data transformation techniques like Principal Component Analysis (PCA) or through the utilization of feature selection procedures. Despite the existence of numerous feature space reduction methods, the process of selecting an appropriate solution necessitates a clearer understanding of the prioritization of features to be chosen from the fused feature space. Further inquiry and analysis are necessary to see whether optimization approaches may be employed to decrease the feature space, hence enhancing the performance of the recognition system.

In this study, the utilization of swarm intelligence-based algorithms, such as Particle Swarm Optimization, has been explored as a means of feature selection to effectively minimize the dimensionality of the fused feature space. Boll has demonstrated that regardless of the specific methodologies employed, utilizing subsets of data consistently yields superior performance outcomes [30]. Previous studies have demonstrated the effectiveness and superiority of particle swarm optimization (PSO) based feature selection over genetic algorithms and other methods on certain extensive data sets [31, 32]. In this study, the Particle Swarm Optimization (PSO) algorithm has been utilized to address the challenge of high-dimensional feature space in the context of biometric feature level fusion. Principal Component Analysis (PCA) has been utilized as a technique for reducing the number of features in a dataset. It has been contrasted with other feature selection approaches in order to determine the effectiveness of either transformation or feature selection in addressing this issue.

This study investigates the reduction strategies for minimizing the data in multimodal systems after feature level fusion. As previously stated, experiments have been conducted on four different multi-modal biometric recognition systems, employing fingerprint and palmprint tests. The experiments utilized several databases, namely the CASIA palmprint database, the IIT Delhi palmprint database, the CASIA fingerprint database, and the FVC fingerprint database.

Organization

The structure of this document is as follows: Section 2 provides a comprehensive explanation of the unimodalpalmprint system, which incorporates the utilization of three separate feature extraction techniques.

ISSN PRINT 2319 1775 Online 2320 7876
Research paper © 2012 IJFANS. All Rights Reserved, Volume 11, Iss 7, 2022

Section 3 presents a unimodal fingerprint system that utilizes two separate feature extraction algorithms grounded in thinning approaches. Section 4 provides an explanation of feature level fusion in six multi-modal systems. The methodology employed for the PCA data transformation is expounded upon in Section 5. The proposed PSOalgorithm, which serves as a feature selection technique, is introduced in Section 6. The analysis of the experimental results is reported in Section 7. Section 8 ultimately presents a conclusive analysis.

2. UnimodalPalmprintsystem:

This section presents an analysis of two separate feature extraction algorithms utilized in unimodalpalmprint recognition systems, as depicted in Figure 1. The general palmprint system consists of several processes. First, palmprint preprocessing is performed, which involves binarization, contour extraction of the hand or palm, identification of key spots, development of a coordinate system, extraction of the region of interest (ROI), and finally, feature extraction and matching.

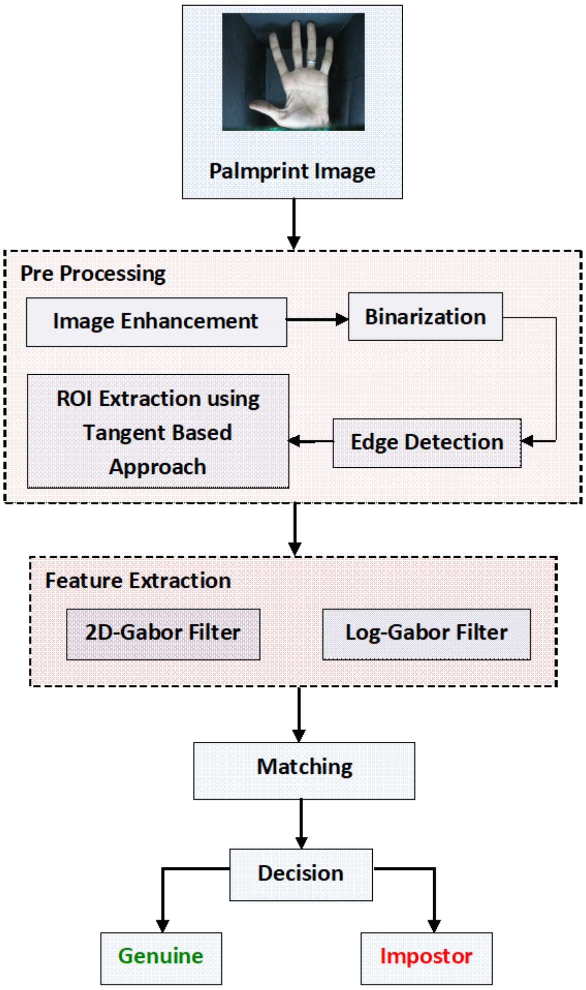

Fig 1: UnimodalPalmprint Recognition System

Preprocessing

The procedure involves the alignment of palmprint pictures and the segmentation of the central region, often known as the region of interest (ROI), for subsequent processing. One of the primary preprocessing methodologies involves the establishment of a coordinate system that is based on critical locations located

ISSN PRINT 2319 1775 Online 2320 7876
Research paper Volume 11, Iss 7, 2022

between the fingers. The preprocessing stage primarily involves five sequential steps: binarization, contour extraction of the hand or palm, identification of key spots, development of a coordinate system, and extraction of the region of interest (ROI) [33]. There is a variation in the preprocessing procedures starting from the third step onwards, until they converge and become identical [33]. Various strategies can be employed in the field of literature to identify key points [33]. The present study employed a tangent-based strategy to extract a region of interest (ROI) in the form of a square shape from a palm image.

Pre-processing is conducted on the image before to feature extraction to mitigate the presence of noise and disruptions resulting from misconnections and isolated regions. The image is initially boosted in order to augment the contrast between the various elements present in the palm. The application of a lowpass filter is indicated by the utilization of equation 1.

$$H(p,q) = \begin{cases} 1 & D(p,q) \leq D_0 \\ 0 & D(p,q) > D_0 \end{cases} \quad (1)$$

Where H is enhanced image, D is original image, $D_0$is a user specific threshold value,and $D\ (p,q) = \sqrt{p^2 + q^2}$.

The binary picture is derived from the improved image in order to facilitate the distinct identification of features. The detection of edges is achieved through the application of the Sobel filter, which assumes that edges occur at points where there is a discontinuity in the intensity function or a steep intensity gradient. The extraction of the ROI of the image is achieved by the utilization of a tangent-based technique.

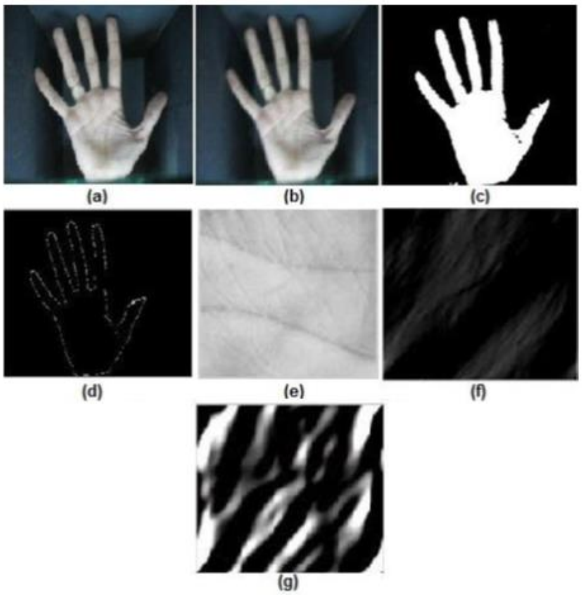

Fig 2 (a) Original Input Image (b) Image After Enhancement (c) Image AfterBinarization (d) Image After Edge Detection (e) ROI (f) 2D-Gabor Features (g)Log-Gabor Features

A. 2D - Gabor Filter

The utilization of Gabor filter bank, Gabor wavelets, and Gabor transform is widespread in the field of pattern recognition. This function accurately determines the time-frequency location and exhibits robustness against variations in visual contrast and brightness. Furthermore, this particular filter has the capability to accurately represent the receptive fields of a basic cell located in the primary visual cortex [34]. The Gabor filter bank has been employed for the purpose of extracting palmprint texture, taking into consideration the aforementioned qualities.

ISSN PRINT 2319 1775 Online 2320 7876
Research paper Volume 11, Iss 7, 2022

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

Where,

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

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

The equation presented includes several variables that are relevant to the Gabor function. The symbol λ represents the wavelength of the sinusoidal factor, while θ denotes the orientation of the normal to parallel stripes. Additionally, φ represents the phase offset, σ corresponds to the standard deviation of the Gaussian envelope, and γ indicates the spatial aspect ratio, which determines the ellipticity of the Gabor function's support.

B. Log Gabor Filter

Extensive research has been conducted by scholars on the Log-Gabor filter for the purpose of texture extraction [35, 36]. The Log-Gabor filter possesses the advantage of exhibiting symmetry on the logarithmic frequency axis. The phenomenon exhibits invariance with respect to time, space, and frequency. The utilization of a logarithmic axis is considered the most effective method for depicting the spatial frequency response of visual cortex neurons in medium and high-pass filters.The log Gabor filter is implemented through the utilization of the subsequent mathematical expression:

$$G(\rho,\theta,a,b) = \exp\left(\frac{-1}{2}\left(\frac{\rho-\rho b}{\sigma a}\right)^2\right) + \ exp\left(\frac{-1}{2}\left(\frac{\theta-\theta_{ab}}{\sigma\theta}\right)^2\right) \qquad (3)$$

In which (ρ, θ) are the log-polar coordinates, a and bgivesorientation and scale, the pair (ρk, θ_{pk}) corresponds to the frequency center of the filters, and (σ_ρ ,σ_θ) is the angular and radial bandwidths.

Matching

The utilization of Euclidean distance for matching has been employed due to the continuous nature of the feature space. The measurement of distance is utilized to quantify the feature vectors that are both claimed and enrolled. In order to distinguish between a genuine individual and a fraudulent one, a comparative analysis is conducted by evaluating a certain threshold value that is unique to the user [30]. In order to ascertain the authenticity of the given template, many machine learning approaches like Naïve Bayes, SMO, C4.5, and Random Forest classification algorithms have been employed.

3. UnimodalFingerprint system:

This section presents an analysis of two separate preprocessing procedures employed in unimodal fingerprint recognition systems, as depicted in Figure 3. The general fingerprint system comprises the following steps: The process of fingerprint image preprocessing involves several steps, including segmentation, normalization,filtering, thinning, and Minutiae feature extraction and matching.

The presence of non-ideal surroundings introduces isolated patches and misconnections in fingerprint lines due to noise and disturbances, hence affecting the extraction of tiny information. In order to mitigate noise and improve the overall quality of the fingerprint image, it is necessary to preprocess the image by eliminating unwanted regions. Preprocessing commonly involves a series of steps, including region masking, binarization,

ISSN PRINT 2319 1775 Online 2320 7876
Research paper Volume 11, Iss 7, 2022

thinning, segmentation, filtering, ridge frequency analysis, normalization, and picture orientation adjustment [37]. The fingerprint image has undergone preprocessing techniques include segmentation based on morphological processing [38], normalization, orientation, filtering and ridge frequency analysis, region masking, and thinning.

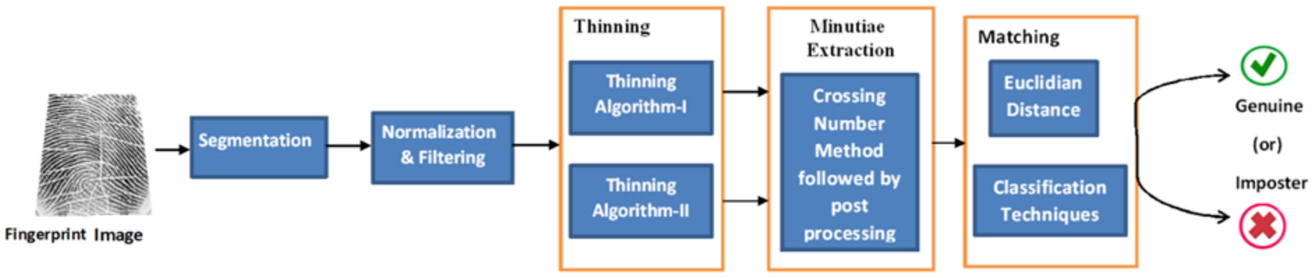

Fig 3: UnimodalFingerprint Recognition System

Normalization

The fingerprint image acquisition technique may result in variations in gray level values along the ridges and valleys of the resulting image. This scenario may arise if the finger establishes an inaccurate connection with the sensor. Therefore, it is imperative to perform a normalization phase in order to mitigate the impact of these differences by regulating the range of gray level values. The present methodology employs a predetermined mean and variance in order to standardize a finger image. The intensity values of the finger image provided and the normalized image at pixel (p, q) can be denoted as I_m (p, q) and N_m (p, q), respectively. The equation presented above is utilized for the purpose of acquiring the normalized image.

$$N_m = \begin{cases} M_0 + \sqrt{\frac{V_0(I_m(p,q)-M)^2}{V}} & if\ I_m(p,q) > M \\ M_0 - \sqrt{\frac{V_0(I_m(p,q)-M)^2}{V}} & otherwise \end{cases} \quad (4)$$

Equation 4 represents the estimated mean (M) and variance (V) of the function I_m(p, q). The target mean (M_0) and variance (V_0) values are also represented in the equation.

Segmentation

The fingerprint image typically comprises the area of interest (ROI), referred to as the foreground, which consists of ridges, bifurcations, and valleys. In addition, it may encompass a background, a rectangular bounding box, and distorted segments of a pattern referred to as the background. In order to mitigate the extraction of intricate information from the region with high levels of noise, the region of interest (ROI) of the fingerprint is separated from the background. Segmentation refers to the procedure of extracting the Region of Interest (ROI) from an image. There are multiple techniques available to carry out this procedure, including segmentation based on statistical characteristics and orientation field, segmentation based on ridge orientation and frequency features, and ROI extraction from fingerprints using a neural network-based approach. In this study, a morphological processing segmentation technique [38] was employed to extract the region of interest (ROI) from a fingerprint.

The identification of ridges should be conducted subsequent to the excision of the region of interest (ROI). The depicted image of a finger has undergone an initial process of normalization. The presence of regular orientations of ridgelines, bifurcations, and valley lines within an optimal fingerprint image facilitates the

ISSN PRINT 2319 1775 Online 2320 7876
Research paper © 2012 IJFANS. All Rights Reserved, Volume 11, Iss 7, 2022

straightforward identification of minute features. Nevertheless, in the real-world context, several elements pose challenges to the extraction of minute details. These issues include wounds on the skin, noise in sensors, insufficient image quality, skin wetness, and inadequate finger-sensor contact. The process of normalizing the image is vital in order to mitigate the extraction of inaccurate minutiae features and the potential loss of significant minutiae points, hence augmenting the overall clarity of the image. The mean and standard deviation are utilized in the process of generating the normalized image. In contemporary times, the technique of 1-D masking is employed for the purpose of identifying ridges by leveraging ridge orientation.

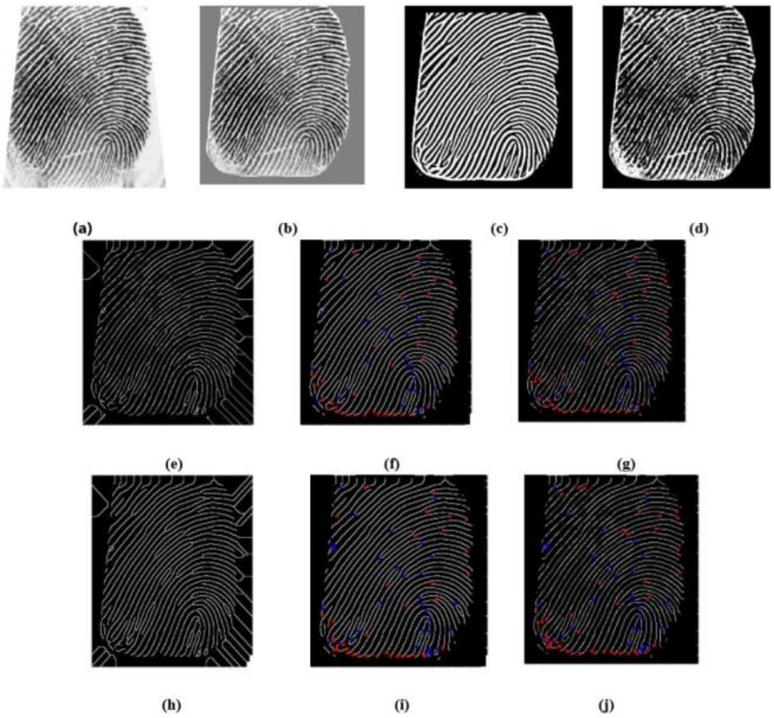

Fig 4 (a) Input Image (b) Segmented Image (c) Normalized Image (d) Binary Image (e) Thinned Image1 (f) Minutiae extraction1 (g) Post processing1 (h) Thinned Image2 (i) Minutiae extraction2 (j) Post processing2

Thinning

The process of thinning involves the elimination of extraneous edge pixels while maintaining the connectedness of the initial ridge patterns. This technique effectively reduces the width of ridgelines to a single pixel. The primary objective of this morphological process is to achieve skeletonization. The thinning procedure results in the production of a thinned image, commonly referred to as a skeleton image, which serves as a simplified representation of a given pattern [2]. The thinning method employed by the preprocessing module facilitates the study and recognition of higher-level features in a diverse range of applications, such as optical character recognition, fingerprint analysis, and picture understanding. Thinning has been accomplished by the utilization of two distinct algorithms, namely the Zhang Suen thinning algorithm and the Sentiford Thinning algorithm. The Zhang Suen thinning algorithm, as described in reference [39], is a very efficient and parallel thinning technique that consists of two sub-iterations. The Stentiford thinning algorithm [40] is an iterative method for skeletonization that relies on the concept of a mask.

ISSN PRINT 2319 1775 Online 2320 7876
Research paper Volume 11, Iss 7, 2022

Minutiae Extraction

The accurate extraction of minutiae features determines the consistency of thefingerprint recognition. The CN approach is widely applied for extraction minutiaepoints from fingerprint. In [41], Rutovitz's defined crossing number of apixel as

P_4	P_3	P_2
P_5	P	P_1
P_6	P_7	P_8

$$CN = 0.5 \sum_{i=1}^{8} |P_i - P_{i+1}|$$

Where $P_i$is the neighborhood binary pixel value of P with P_i= (0 or 1) and $P_1 = P_9$.

According to the definition provided in reference [41], the characteristics of CN are employed for the purpose of detecting even the most minute details from the thinned image. In the context of analyzing a thinned image, it is determined that a pixel qualifies as a bifurcation point inside a 3x3 window if its central pixel value is 1 and all three of its adjacent pixels possess an identical value. The presence of a ridge ending is indicated when all adjacent pixels possess a value of 1, and the pixel in the center also possesses a value of 1. The determination of truth and false minutiae points is based on the preprocessed, acquired fingerprint, notwithstanding this fact. The postprocessing step serves to remove these inaccurate data points.

Post-processing

The minutiae features extracted from the preprocessed binary fingerprint image encompass both genuine and spurious minutiae points. Post-processing is utilized in order to get the actual minute details. This methodology examines the local vicinity encompassing a given place and verifies the minuscule points inside the thinned image. The measurement of the distance between the termination and bifurcation locations is conducted utilizing the Euclidean distance method. The inclusion of incorrect and insignificant details will result in an increase in the False Acceptance Rate (FAR) and False Rejection Rate (FRR) of fingerprint matching. The algorithm is employed to identify bifurcation points and ridge endpoints with the purpose of eliminating these erroneous minutiae points.

4.Feature Level Fusion

This section provides an explanation of the integration of various features obtained from the palmprint image and fingerprint picture at the feature level. The texture features obtained from palmprint by the utilization of 2D-Gabor filter and 2D-Log Gabor filter exhibit incompatibility with the minutiae features of fingerprints. The texture analysis of a 100×100 region of interest (ROI) palmprint image is conducted by applying both a 2D-Gabor filter and a 2D-Log Gabor filter. This process results in the generation of 12 distinct images, each with a size of 100×100. To consolidate this texture information, horizontal and vertical downsampling techniques are employed, resulting in the creation of a single image with dimensions of 100×100. Moreover, it is transformed into a feature vector consisting of 10,000 rows.

The size of the fingerprint minutiae feature vector exhibits variation among different fingerprint databases, ranging from 52 to 112. The feature spaces of palmprints and fingerprints are normalized in order to align them within a common domain. The integration of these feature spaces involves a simple concatenation process, resulting in a fused feature space. The size of this fused feature space varies between 10112 and 10052, depending on the fingerprint databases employed.

ISSN PRINT 2319 1775 Online 2320 7876
 Volume 11, Iss 7, 2022

In this study, four multi-modal systems utilizing fingerprint and palmprint biometric data are developed, namely

MM_Finger_Palm_sys1 – which is a multi-modal system developed based on integration of Log-Gabor features of Palmprint with minutiae features extracted from thinned fingerprint image obtained from Zhang Suen thinning algorithm.

MM_Finger_Palm_sys2 – which is a multi-modal system developed based on integration of Log-Gabor features of Palmprint with minutiae features extracted from thinned fingerprint image obtained from Stentiford thinning algorithm.

MM_Finger_Palm_sys3 – which is a multi-modal system developed based on integration of Gabor features of Palmprint with minutiae features extracted from thinned fingerprint image obtained from Zhang Suen thinning algorithm.

MM_Finger_Palm_sys4 – which is a multi-modal system developed based on integration of Gabor features of Palmprint with minutiae features extracted from thinned fingerprint image obtained from Stentiford thinning algorithm.

5. Features Space Reduction Using PCA

Principal Component Analysis (PCA) is a widely used technique in the field of image processing for the purpose of dimensionality reduction and subspace projection. It has proven to be effective in addressing challenges related to picture compression and recognition. Principal Component Analysis (PCA) has predominantly been employed in the field of biometrics for the purpose of feature extraction from facial images [20,42], palmprint data [43], and footprint data [44]. The authors of [45] employed a combination of Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) to effectively decrease the dimensionality of distinct biometric characteristics, including fingerprints, faces, and signatures, prior to classification. Principal Component Analysis (PCA) has been employed as a technique to reduce the dimensionality of vectors with the aim of enhancing picture recognition [46]. Principal Component Analysis (PCA) is a commonly employed methodology for the detection and characterization of patterns in datasets with a high number of dimensions [47]. PCA has been employed as a method for reducing dimensionality in three distinct multi-biometric systems that incorporate eye, palm, and finger prints, subsequent to feature level fusion [48].

Principal Component Analysis (PCA) is a linear method used for data reduction. It involves projecting data into a new space, where it is represented by the directions that exhibit the highest variability. Principal Component Analysis (PCA) is a mathematical technique used to transform the original image data into a set of principle components (PCs). These PCs are orthogonal to each other and arranged in descending order of variance within the image data.

Principal Component Analysis (PCA) quantifies the extent of variability present in the feature vectors of iris and fingerprint pictures across different orientations [48]. Let T denote the training dataset, which comprises p iris and fingerprint templates. These templates are one-dimensional and have dimensions of 1 x q. The dataset T, which has dimensions p×q, undergoes dimensionality reduction using the Principal Component Analysis (PCA) algorithm. This results in a new dataset T', which has dimensions p×k, where k is less than or

ISSN PRINT 2319 1775 Online 2320 7876
Research paper © 2012 IJFANS. All Rights Reserved, Volume 11, Iss 7, 2022

equal to q. The function eigen() in this algorithm is utilized to answer the equation 5 and ascertain the eigen vectors and eigen values.

$$[cov - \lambda \mathrm{I}]e = 0 \tag{5}$$

cov is the covariance matrix in this case. The eigen vectors (e1, e2, e3,...,eq) are given by the identity matrix I, the eigen value λ, and the eigen vector e. The eigen vectors e1, e2, e3,...eq are sorted by the Sort() function in decreasing order of their associated eigen values $\lambda_1, \lambda_2, \ldots, \lambda_q$.

6. Feature Selection using Particle Swarm Optimization

The Particle Swarm Optimization (PSO) method is a population-based and stochastic optimization strategy that was initially proposed by Kennedy and Eberhart in 1995 [49]. Its primary purpose is to effectively address optimization problems. The foundational concept of Particle Swarm Optimization (PSO) is derived from investigations into the collective behavior of birds in synchronous flocking. The presented program explores a multidimensional space by controlling the paths of population vectors, referred to as particles, which are represented as mobile points inside the search space. Every individual particle is stochastically attracted towards the positions corresponding to their own and their neighbor's previously achieved optimal performance [50].

In the field of literature, a wide range of feature selection algorithms have been utilized in the context of biometric systems. This study utilizes binary Particle Swarm Optimization (PSO) [49] to perform feature selection within an integrated feature space that combines palmprint characteristics and fingerprint features.

Working and implementation aspects of PSO

PSO initializes each particle of the fixed-size population with a random position in n-dimensional feature space as a possible solution for the n-dimensional optimization problem. Feature selection is affected by population size; empirically evaluated 5 to 30 population sizes at an interval of 2 and chose 25 as the population size where performance changes noticeably. As the k^{th} particle moves in a search space, its trajectories, position P_k, and velocity V_k change.

$$P_k = \{ p_1, p_2, \ldots, p_n \}$$
$$V_k = \{ v_{k1}, v_{k2}, \ldots, v_{kn} \}$$

A particle's position is a binary vector with n binary values and n feature space dimensions. One in position vector denotes selected features and zero represents non-selected features at that index which are randomly initialized. The following equation6 initializes the k^{th}particle's velocity:

$$V_k = V_{min} + (V_{max} - V_{min})^* \text{ rand} \tag{6}$$

Small or large V_{max} values push the algorithm to local or global exploration. In this work, the value was empirically chosen as 6. A random number between (0,1) is rand. Each particle additionally has a best position 'lbest' that is changed each iteration based on its fitness. Particle fitness is assessed using the optimal fitness function. The population's global best position 'gbest' is determined by fitness value and updated each cycle. Each iteration, the particle changes position and velocity using these equations [49]:

ISSN PRINT 2319 1775 Online 2320 7876
Research paper Volume 11, Iss 7, 2022

At iteration y+1:

$$V_j^{y+1} = \alpha * \underbrace{V_j^y}_{\text{Diversification}} + \underbrace{C_1 * rand_1 * (lbest_j^y - P_j^y)}_{\text{Cognition}} + \underbrace{C_2 * rand_2 * (gbest - P_j^y)}_{\text{Social}} \quad (7)$$

$$P_k^{y+1} = P_k^y + V_k^{y+1} \quad (8)$$

Where kbe the particle index, α be the inertia weight, C_1 and C_2 be cognitive and social factors, and $rand_1$ and $rand_2$ be uniform random values between 0 and 1. Diversification momentum defines the particle's memory and chooses the best answer while seeking for a new solution. The particle moves toward its optimum place after cognition. The particle moves to the best population site due to sociality. Excellent inertia weight value selection produces an optimal solution in less number of iterations and balances local and global search space inquiry. This parameter starts at 0.7. The equation [51] shows that its value fluctuates from 0.9 to 0.4 in different iterations.

$$\alpha = (\alpha - 0.4) \times ((max\_iter - curr\_iter))/((max\_iter + 0.4)) \quad (9)$$

In this work, max_iter is 50 and curr_iter is the current iteration. Each particle is driven towards its 'lbest' and 'gbest' by acceleration parameters C_1 and C_2, which govern algorithm convergence speed. The literature recommended 2 [49] for acceleration parameters, however some works found good convergence with C_1=0.7, C_2=1.2 and 0.5 [52, 53]. Experiments with varying C_1 and C_2 values yield 1.7. After updating velocity to V_k, n, the following equation updates particle locations:

$$Sig(V_{j,n}) = {}^{1}\!/_{\left(1 + e^{-V_{j,n}}\right)} \quad (10)$$

$$P_{j,n} = \begin{cases} 1 & Sig(V_{j,n}) > rand \\ 0 & otherwise \end{cases}$$

Sig(V_i, n) is a sigmoid function, and 'rand' is a random number from (0,1).Equations 7, 8 update particle velocity and locations in each iteration, then the fitness value is calculated. Update 'gbest' and 'lbest' based on particle fitness. If fitness values are equivalent, 'gbest' and 'lbest' are changed based on feature selection. After all algorithm iterations or convergence, 'gbest' produces the best features.

Fitness Function

Fitness function construction is crucial to feature selection. In our iris-based recognition system, recognition accuracy (RA) is calculated by computing the distances between all database samples with the provided iris sample and then obtaining match scores. C4.5 decision trees classify this data. True positives t_p, true negatives t_n, false positives f_p, and false negatives f_n are confusion matrix classification results.RA = $(t_p + t_n)/(f_p + f_n + t_p + t_n)$. The fitness of particle P_i is calculated as follows:

$$fit(P_i) = RA + n_{selected} * \left(\frac{N_{DB}}{n}\right) \quad (11)$$

Where,$n_{selected}$ is the particle P_i's selected feature count. N_{DB} is the database's biometric sample count.

ISSN PRINT 2319 1775 Online 2320 7876
Research paper Volume 11, Iss 7, 2022

7. Experimental Results

This section discusses multi-modal recognition system installation results with and without reduction techniques. Results focus on recognition rate, computation time to process dataset, and feature space reduction following feature level fusion. At FAR = 0.01%, recognition is considered. To determine recognition rate, two Euclidean distance matching schemes and four classification algorithmsSMO, C4.5, NB, RF were used.

The experiments use two fingerprint databases: the Fingerprint Image Database (CASIA Version 1.0), which comprises 100 left- and right-hand fingerprints. Four samples are obtained from each hand's four fingers. Studies use two fingers from each hand—two left and two right—because each finger is unique. Each of 400 subjects is evaluated with four samples. The trials use 10 human fingerprints from the FVC 2004 DB1_B database. Six finger samples are taken from each person.

The investigation used two palmprint datasets. First, the CASIA Version 1.0 palmprint image database has 756 images from 108 people. Each person has seven images taken in two sessions, with three palmprint samples in the first and four in the second. Six samples were taken from each database user. IITD's palmprint image database version 1.0 is the second. The database has 2240 images from 224 users. Ten palmprint samples are acquired from each user, five from the left and five from the right. We treated a user's left and right palmprint as two individual users in our experiment because each is unique. Three samples per person are chosen from 448 subjects.

Table 1 Number of Features Selected in Multi-Modal System Based on PalmprintAndFingerprint for Various DB's

Databases	Multi-modal Systems	Without FS	PCA	PSO
CASIA DB & CASIA DB	MM_Palm_Finger_Sys1	10060	3012	2757
	MM_Palm_Finger_Sys2	10060	3015	2759
	MM_Palm_Finger_Sys3	10050	2986	2331
	MM_Palm_Finger_Sys4	10050	2989	2335
FVC DB & IITD DB	MM_Palm_Finger_Sys1	10052	2997	2615
	MM_Palm_Finger_Sys2	10052	2999	2617
	MM_Palm_Finger_Sys3	10048	2992	2311
	MM_Palm_Finger_Sys4	10048	2989	2309
CASIA DB & IITD DB	MM_Palm_Finger_Sys1	10060	2808	2582
	MM_Palm_Finger_Sys2	10060	2810	2585
	MM_Palm_Finger_Sys3	10050	2997	2374
	MM_Palm_Finger_Sys4	10050	2994	2371
FVC DB & CASIA DB	MM_Palm_Finger_Sys1	10052	2997	2574
	MM_Palm_Finger_Sys2	10052	2999	2576
	MM_Palm_Finger_Sys3	10048	2984	2215
	MM_Palm_Finger_Sys4	10048	2981	2212

Each virtual person in our multi-modal biometric databases has one biometric feature from one database and another from another. Each virtual human was built by selecting one fingerprint sample from the Fingerprint CASIA DB and one palmprint sample from the palmprinnt CASIA DB while building a multimodal database using fingerprint and palmprint data. For multimodal systems, another database was created.

ISSN PRINT 2319 1775 Online 2320 7876
Research paper Volume 11, Iss 7, 2022

Combining fingerprints from the Fingerprint FVC DB and palmprints from the iris IITD DB creates each virtual person in this database. The above method produces multi-modal biometric datasets.

All of the experiments were done on a PC with a 1.8 GHz i7 processor, 16 GB RAM, and Windows 10. Two reduction methodologies are tested on multi-modal systems to find the best one namely PCA and PSO. The functionality of the suggested systems can determine the efficiency of these two tactics. We utilize a Euclidean distance metric and supervised algorithm-based measure to calculate true and false positive rates. The suggested systems use four supervised algorithms: C4.5 decision tree, Random Forest, SMO, and Naive Bayes.

Result Analysis

We present the results of fingerprint and palmprintbased multimodal systems with and without reduction. These calculations focus on recognition rates, dataset processing times, and feature space reductions from feature level fusion.

Table 2 Recognition Accuracy using Euclidean Distance Measure In Multi-Modal Systems Based On PalmprintAnd Fingerprint For Various DB's

Databases	Multi-modal Systems	Without FS	PCA	PSO
CASIA DB & CASIA DB	MM_Palm_Finger_Sys1	81.7	84.5	91.3
	MM_Palm_Finger_Sys2	81.5	84.4	91.2
	MM_Palm_Finger_Sys3	80.8	83.6	90.6
	MM_Palm_Finger_Sys4	80.9	83.8	90.8
FVC DB & IITD DB	MM_Palm_Finger_Sys1	79.8	83.6	91.4
	MM_Palm_Finger_Sys2	79.7	83.4	91.5
	MM_Palm_Finger_Sys3	79.2	83.5	91.6
	MM_Palm_Finger_Sys4	79.02	83.4	91.8
CASIA DB & IITD DB	MM_Palm_Finger_Sys1	81.3	85.2	91.7
	MM_Palm_Finger_Sys2	81.4	85.5	91.9
	MM_Palm_Finger_Sys3	80.8	84.5	92.3
	MM_Palm_Finger_Sys4	80.7	84.3	92.1
FVC DB & CASIA DB	MM_Palm_Finger_Sys1	79.4	83.8	92.01
	MM_Palm_Finger_Sys2	79.5	83.9	92.1
	MM_Palm_Finger_Sys3	79.6	83.7	92.1
	MM_Palm_Finger_Sys4	79.9	83.9	92.2

The results of matching multimodal systems using Euclidean distance across all reduction procedures are presented first. Table2 shows the recognition rate for four systems and two datasets using data reduction methods. Considering that, we set FAR = 0.01% recognition rate. PCA processes faster than PSO but has a slightly lower recognition rate across all six systems. Compared to PCA, PSO had a greater recognition rate. The results show that PSO performs better on huge datasets.

Table 1 lists the number of reduced features in eigen space PCA, PSO for section 4's fingerprint and palmprint-based multi-modal systems. Table 2 exhibits PCA, PSO Euclidean distance performance. Good recognition rate and feature space reduction are essential in any system. Tables 2 and 1 show that while PCA reduces feature space better than PSO, it does not enhance recognition accuracy, which PSO achieves better.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper Volume 11, Iss 7, 2022

Table 3 Recognition Accuracy using Various Classifiers in Multi-Modal System Based on Palmprint and Fingerprint for Various DB's

Databases	Multi-Modal Systems	Classifiers	Without FS	PCA	PSO
CASIA DB & CASIA DB	MM_Palm_Finger_Sys1	SMO	84.2	85.1	94.6
		C4.5	84.1	85.07	94.7
		NB	82.5	83.2	91.2
		RF	83.2	84.1	92.4
	MM_Palm_Finger_Sys2	SMO	84.1	85.2	94.5
		C4.5	84.2	85.1	94.6
		NB	82.4	83.1	91.1
		RF	83.1	84.01	92.3
	MM_Palm_Finger_Sys3	SMO	82.2	84.7	93.8
		C4.5	81.7	84.6	93.7
		NB	80.4	82.4	91.2
		RF	82.5	83.8	92.5
	MM_Palm_Finger_Sys4	SMO	82.1	84.8	93.9
		C4.5	81.6	84.2	93.8
		NB	80.3	82.5	91.4
		RF	82.3	83.7	92.7
FVC DB & IITD DB	MM_Palm_Finger_Sys1	SMO	85.3	86.8	94.8
		C4.5	85.2	87.1	94.9
		NB	82.4	84.7	92.7
		RF	84.6	85.8	93.6
	MM_Palm_Finger_Sys2	SMO	85.2	86.8	94.7
		C4.5	85.4	87.01	94.8
		NB	82.2	84.5	92.6
		RF	84.5	85.6	93.5
	MM_Palm_Finger_Sys3	SMO	85.8	87.5	95.01
		C4.5	85.8	87.6	94.91
		NB	81.1	83.6	92.2
		RF	84.8	85.6	93.6
	MM_Palm_Finger_Sys4	SMO	86.1	87.6	95.1
		C4.5	85.9	87.5	94.2
		NB	81.2	83.8	92.1
		RF	84.9	85.7	93.4
CASIA DB & IITD DB	MM_Palm_Finger_Sys1	SMO	85.9	86.7	94.9
		C4.5	85.8	86.6	94.6
		NB	81.7	83.5	92.4
		RF	82.8	84.7	93.6
	MM_Palm_Finger_Sys2	SMO	85.7	86.6	94.6
		C4.5	85.6	86.4	94.5
		NB	81.5	83.3	92.3
		RF	82.6	84.6	93.5
	MM_Palm_Finger_Sys3	SMO	85.3	87.3	95.1
		C4.5	85.4	87.2	95.2
		NB	82.01	84.3	92.1
		RF	84.6	85.6	94.2
	MM_Palm_Finger_Sys4	SMO	85.4	87.5	95.2
		C4.5	85.5	87.4	95.3
		NB	82.1	84.5	92.2
		RF	84.8	85.7	94.1
FVC DB & CASIA DB	MM_Palm_Finger_Sys1	SMO	85.8	87.5	95.3
		C4.5	85.7	87.4	95.1
		NB	82.3	84.5	93.2
		RF	84.2	85.6	94.1
	MM_Palm_Finger_Sys2	SMO	85.6	87.3	95.1
		C4.5	85.5	87.5	95.2
		NB	82.1	84.4	93.04
		RF	84.1	85.4	94.2
	MM_Palm_Finger_Sys3	SMO	86.1	88.6	95.2
		C4.5	86.2	88.7	95.1
		NB	82.7	84.5	93.4
		RF	84.7	86.4	94.3
	MM_Palm_Finger_Sys4	SMO	86.2	88.7	95.1
		C4.5	86.01	88.8	95.2
		NB	82.8	84.7	93.5
		RF	84.9	86.3	94.2

ISSN PRINT 2319 1775 Online 2320 7876
Research paper Volume 11, Iss 7, 2022

Table 1 illustrates the number of decreased PCA,PSO features in eigen space for section 4's fingerprint-palmprint multi-modal systems. Table 2 demonstrates Euclidean distance performance in PCA, PSO. Good recognition rate and feature space reduction are essential in any system. Tables 1 and 2 show that while PCA reduces feature space better than PSO, it does not enhance recognition accuracy, which PSO achieves better than the other techniques. Table 3 shows supervised learning classifier accuracy for proposed multi-modal systems. Tables 2 and 3 show that supervised classifiers outperformed distance measure in recognition. In our work, the PSO approach improves performance as much as the global scheme while reducing the amount of features, demonstrating that PSO keeps the most discriminant characteristics throughout reduction.

Table 3 shows fingerprint-palmprint results for four multi-modal systems. These Table 3 shows that in all multi-modal systems, SMO and C4.5 classifiers have extremely close and high recognition accuracy relative to NB and RF. NB outperforms distance measure, although it performs poorly with continuous data in supervised classifiers. 94.9% accuracy in MM_Palm_Finger_sys1, 94.8% recognition accuracy in MM_Palm_Finger_sys2, and 95.2% recognition rate in MM_Palm_Finger_sys3, 95.3% recognition rate in MM_Palm_Finger_sys4. These results are for multimodal database created using fingerprint CASIA DB, FVC DB, plamprint, IITD DB, CASIA DB.

PCA had lower recognition rates than the suggested PSO in all multi-modal systems. PCA reduces feature space by 90% but has a low recognition rate compared to suggested algorithms. With 95.3% recognition, PSO decreases feature space to over 82%. Any biometric authentication system's performance depends on space recognition rate. Due of this limitation, PSO outperforms PCA.

Analysis of Computation Time: All FS techniques PCA, PSO are tested on the same databases and environment. Although PSO takes longer to train than other algorithms, it takes less time to test. Biometric systems require one offline training at enrolling. The testing is different. In these biometric systems, testing time matters more than training time. As the proposed method generates fewer characteristics than others, it always classifies the test biometric template as genuine or imposter faster.

8. Conclusion

This work used PSO to minimize feature space after integrating biometric features from various modalities. Principal component analysis (PCA) can manage large datasets, however it may miss essential features every time. This led us to create PSO, which efficiently solves this problem by expanding feature space exploration using an exponential function. PSO outperforms PCA in feature space reduction on fingerprint and plamprint benchmark datasets CASIA, IITD, and FVC.

PSO performed well in all cases, including feature space reduction, distance measure identification accuracy, and supervised classifier performance. In all section 4 multi-modal systems, PSO outperforms PCA in recognition accuracy. Using supervised classifiers, PCA produces88.8% accuracy and PSO 95.3%. It would make it easier to find distinguishing features, improving classification accuracy. The results show that supervised algorithms match more accurately than Euclidean distance.

ISSN PRINT 2319 1775 Online 2320 7876
Research paper Volume 11, Iss 7, 2022

References

[1] Anil K Jain, Arun Ross, SalilPrabhakar, An Introduction to Biometric Recognition, IEEE Transactions on Circuits and Systems For Video Technology, 14(1) (2004).

[2] Maltoni D, Maio D, Jain AK, Prabhakar S (2009) Hand book of fingerprint recognition, Springer, Berlin.

[3] J. Daugman, How Iris Recognitin Works, IEEE Transactions on CSVT, 14(1) (2004) 21-30.

[4] A. K. Jain, S. Prabhakar, S. Pankanti, On the similarity of identical twin fingerprints, Pattern Recognition35(11) (2002) 2653-2663.

[5] S. Pankanti, S. Prabhakar, A. K. Jain, On the individuality of fingerprints, IEEE Transactions on PatternAnalysis and Machine Intelligence, 24(8) (2002) 1010-1025.

[6] J. You, W. Li, D. Zhang, Hierarchical palmprint identification via multiple feature extraction, Pattern Recognition,35pp.847-859 (2002).

[7] Wu, X., Zhang, D., Wang, K.: Palm Line Extraction and Matching for Personal authentication. IEEE Transactions onSystems Man and Cybernetics Part A: Systems and Humans 36, 978–987 (2006).

[8] Kumar, A., Wong, D.C.M., Shen, H.C., Jain, A.K.: Personal Verification using Palmprint and Hand Geometry Biometric.In: Kittler, J., Nixon, M.S. (eds.) AVBPA 2003. LNCS, vol. 2688, pp. 668–678. Springer, Heidelberg (2003).

[9] Cui FF, Yang GP (2011) Score level fusion of fingerprint and finger vein recognition. Journal of Computer Information Systems 7:5723–5731.

[10] ChunxiaoRen, Yilong Yin, Jun Ma, Gongping Yang, A Novel Method of Score Level Fusion UsingMultiple Impressions for Fingerprint Verification, Proceedings of the 2009 IEEE International Conference on
Systems, Man, and Cybernetics, (2009) 5196-5201.

[11] A. K. Jain, A. Ross, and S. Prabhakar, A hybrid fingerprint matching using minutiae and texture features,Proceedings of the international conference on Image Processing (ICIP 2001) 282-285.

[12] A. Ross, A. K. Jain, and J. Reisman, A hybrid fingerprint matcher, Proceedings of International Conferenceon Pattern Recognition (ICPR), (2002) 795-798.

[13] A. K. Jain, S. Prabhakar, and A. Ross, Fingerprint Matching: data acquisition and performance evaluation,MSU Technical Report TR99-14, 1999.

[14] Ross AA, Nandakumar K, Jain AK (2006) Handbook of multibiometrics, Springer, Berlin.

[15] U. Park, S. Pankanti, A. K. Jain, Fingerprint Verification using SIFT features, Proceedings of SPIE Defenseand Security Symposium, pp. 69440K-69440K-9 (2008).

[16] Y. S. Moon, H. W. Yeung, K. C. Chan, S. O. Chan, Template synthesis and image mosaicking forfingerprint registration: an experimental study, Proceedings of IEEE International Conference on Acoustics,Speech, and Signal Proceedings 2004 (ICASSP"04) vol.5, pp. 409-412, 2004.

[17] Faundez-Zanuy M, Data Fusion in biometrics, In IEEE Aerospace and Electronic Systems Magzine, 20(2005) 34-48.

[18] Chen. Y, Li. Y, Cheng. X, Guo. L, Survey and Taxonomy of Feature Selection Algorithms in IntrusionDetection System, In Lipmaa H., Yung M., Lin D. (eds) Information Security and Cryptology. Inscrypt2006.Lecture Notes in Computer Science, vol 4318. Springer, Berlin, Heidelberg.

[19] D. Swets and J. Weng: "Using discriminant eigenfeatures for image retrieval," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 8, no. 8, pp.831–836, 1996.

ISSN PRINT 2319 1775 Online 2320 7876
Research paper Volume 11, Iss 7, 2022

[20] M.Turk, A. Pentland, Eigenfaces for Recognition, Journal of Cognitive Neuroscience, Vol. 3, no. 1, pp. 71-86, 1991.

[21] B. Son, Y. Lee, Biometric Authentication systems using Reduced Joint Feature Vector of iris and face, AVBPA 2005, LNCS 3456, pp. 513-522, 2005.

[22] G.R. Naik et al., An Overview of Independent Component Analysis and its Applications, Informatica 35(2011) 63-81.

[23] T. Chen, Y. Jessie Hsu, X. Liu, W. Zhang, Principle Component Analysis and its Variants for Biometrics, IEEE ICIP 2002, pp.61-64,2002.

[24] D. Zhang, X. Jing, J. Yang, Biometric image discrimination (BID) technologies, IGP/IRM Press edition, 2006.

[25] D. Zongker, A. Jain, Algorithms for Feature Selection: An Evaluation, IEEE proceedings of ICPR'96, 1996.

[26] P. Pudil et al., Floating search methods in feature selection, Pattern Recognition Letters 15 (1994) 1119-1125.

[27] G. Feng, K. Dong, D. Hu, D. Zhang, When faces are combined with palmprints: a novel biometric fusion strategy, in: First International Conference on Biometric Authentication (ICBA), 2004, pp.701-707.

[28] S. Singh, G. Gyaourova and I. Pavlidis, Infrared and visible image fusion for face recognition, SPIE Defence and Security Symposium, pp. 585-596,2004.

[29] A.A. Altun, H.E. Kocer, N. Allahverdi, Genetic algorithm based feature selection level fusion using fingerprint and iris biometrics, International Journal of Pattern Recognition and Artificial intelligence (IJPRAI) 22(3) (2008) 585-600.

[30] R. M. Bolle, N. K. Ratha, S. Pankanti, An Evaluation of error confidence interval estimation methods, in: Proceedings of International conference on pattern recognition ICRP-04, Cambridge, UK, 2004, pp. 103-106.

[31] J.Garcia-Nieto, E.G. Talbi, E. Alba, L.Jourdan, A comparison between Genetic Algorithm and PSO approaches for Gene selection and classification of Microarray data, in: ACM (CECCO-07), 2007, pp. 427-429.

[32] X. Wang, J. Yang, X. Teng, W. Xia, B. Jensen, Feature selection based on rough sets and particle swarm optimization, Pattern Recognition Letters, 28(2007) 459-471.

[33] A. Kong, D. Zhang, and M. Kamel, "A survey of palmprint recognition," Pattern Recognition Letters, vol. 42, pp. 1408–1418, 2009.

[34] W. K. Kong, D. Zhang, W. Li, Palmprint feature extraction using 2-D Gabor filters, Pattern Recognition 36 pp. 2339-2347(2003).

[35] M.V.N.K. Prasad, I. Kavati, and B. Adinarayana, Palmprint Recognition Using Fusion of 2D-Gabor and 2D Log-GaborFeatures, pp. 202-210, Springer (2014).

[36] P. Zheng, N. Sang, Using Phase and Directional Line Features for Efficient Palmprint Authentication, 2nd InternationalConference on Image and Signal Processing (CISP), pp.1-5,(2009).

[37] Letian Cao, Yazhou Wang, Fingerprint image enhancement and minutiae extraction algorithm, 2016.

[38] M. F. Fahmy, M. A. Thabet, A Fingerprint Segmentation Technique Based on Morphological Processing, ISSPIT, 2013.

[39] T. Y. Zhang, C. Y. Suen, A Fast Parallel Algorithm for Thinning Digital Patterns, Image Processing and Computer Vision, 27(3) (1984) 236-239.

ISSN PRINT 2319 1775 Online 2320 7876
Research paper Volume 11, Iss 7, 2022

[40] Stentiford. F. W. M, Mortimer. R. G, Some new heuristics for thinning binary handprinted characters for OCR, IEEE Transactions on Systems, Man, and Cybernetics, SMC-13(1) (1983) 81-84.

[41] D. Rutovitz, Pattern recognition, J. Roy. Stat. Soc. 129 (1966) 504–530.

[42] Jamal Hussain Shah, Muhammad Sharif, MudassarRaza, and Aisha Azeem, A Survey: Linear and Nonlinear PCA Based Face Recognition Techniques, The International Arab Journal of Information Technology, Vol. 10, No. 6, November 2013.

[43] MithunaBehera et al,Palm print Authentication Using PCA Technique, International Journal of Computer Science and Information Technologies, Vol. 5 (3), 2014, 3638-3640.

[44] RohitKhokher, Ram Chandra Singh, Rahul Kumar, Footprint Recognition with Principal Component Analysis and Independent Component Analysis, Macromol. Symp. 2015, 347, 16–26.

[45] NittayaKerdprasop, RatipornChanklan, AnusaraHirunyawanakul, KittisakKerdprasop, An Empirical Study of Dimensionality Reduction Methods for Biometric Recognition, 7th International Conference on Security Technology IEEE 2014 26-29.

[46] Z. Wang and X. Li, Face Recognition Based on Improved PCA Reconstruction, in Intelligent Control and Automation (WCICA), 2010 8th World Congress on, 2010, pp. 6272-6276.

[47] J. Meng and Y. Yang, Symmetrical Two-Dimensional PCA with Image Measures in Face Recognition, Int J Adv Robotic Sy, Vol. 9, 2012.

[48] P. ArunaKumari, G. Jaya Suma, An Experimental Study of Feature Reduction Using PCA in Multi-Biometric Systems Based on Feature Level Fusion, 2016 International Conference on Advances in Electrical, Electronic and System Engineering, 14-16 Nov 2016, Putrajaya, Malaysia.

[49] J.Kennedy, R.C.Eberhart, Particle swarm optimization, in: IEEE International Conference on Neural Networks, Perth, Australlia, 1995, pp. 1942-1948.

[50] Clerc M, Kennedy J, The particle swarm-Explosion, stability, and convergence in a multidimensional complex space, IEEE Trans SystCybern, vol 13, pp. 815-826,2002.

[51] X. Wang, J. Yang, X. Teng, W. Xia and B. Jensen, Feature selection based on rough sets and particle swarm optimization, Pattern Recognition Letters 28(2007) 459-471.

[52] J. kennedy, R.C. Eberhart, Y. H. Shi, Swarm intelligence, Morgan Kaufmann edition, 2001.

[53] C.J. Tu, L.Y.Chuang, J.Y. Chang, C.H. Yang, Feature selection using PSO-SVM, International journal of computer science (IJCS) 33(1) (2007) 138-143.