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An Efficient Multi-modal Biometric Recognition System Using Artificial Bee Colony Optimization

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Abstract:

Biometrics refers to the technological means by which humans can be uniquely identified by the analysis and recognition of physical characteristics such as facial features, iris patterns, and fingerprints, among others. Biometric authentication facilitates the automatic recognition of individuals through the analysis of their behavioral or physiological features. Biometrics is widely utilized in many commercial and official identifying systems to provide automated access control. This research presents a model for multimodal biometric recognition that utilizes a feature level fusion method. The suggested method encompasses five sequential steps: pre-processing, feature extraction from all traits, feature level fusion, integrated feature space reduction, and recognition using Machine Learning. The initial stage involves the input of training images into pre-processing procedures. Consequently, the pre-processing stage is conducted for two specific features, namely iris and palmprint. Next, the process of feature extraction is conducted for each modality in order to extract the relevant features. Subsequently, the texture and phase features are derived from the pre-processed image of the palmprint and iris. Subsequently, the feature spaces derived from two distinct qualities are merged. The process of integrating many biometric data at the feature level fusion offers numerous advantages compared to other fusion strategies, albeit with the significant drawback of generating feature vectors with enormous dimensions. The primary aim of this work is to examine the challenges associated with managing high-dimensional data and explore diverse data reduction techniques applicable to multimodal biometric systems. This work proposes a strategy that utilizes Artificial Bee Colony (ABC) optimization for feature selection. The aim is to overcome the difficulties associated with combining the Iris and palmprint feature spaces at the feature level. The utilization of Machine Learning methods is employed to analyze the efficacy of ABC-based feature selection and Principal Component Analysis (PCA)-based feature space reduction techniques on the CASIA and IITD databases along with Euclidian distance based matching. Upon merging iris and palmprint evidences at the feature level, the conducted trials demonstrated a considerable reduction in the feature space by ABC in comparison to PCA. This reduction resulted in enhanced recognition accuracy.

Keywords: Artificial Bee Colony optimization, Multi-modal biometric systemsFeature Level Fusion, Palmprint, Iris,Feature selection.

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1. Introduction

Biometrics has emerged as a significant component inside contemporary security systems in recent years. Biometrics can be classified into two main categories: image-based systems and signal-based systems.

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Biometrics is a method employed to effectively distinguish individuals based on their behavioral or physical characteristics [1]. Signal-based systems encompass the recognition of Electrocardiography (ECG) as well as speaker identification. Image-based systems encompass many biometric modalities, including gestures, hand-written signature, voice, hand geometry, gait, iris recognition, and face [2,3]. The biometric system is an emerging and dynamic technology employed in automated systems to accurately and distinctively identify individuals without the reliance on memorization or physical tokens such as identification cards and passwords [4]. Multiple studies have demonstrated that the iris trait possesses several advantages over other biometric systems, such as those based on facial features [5] and fingerprints [6]. As a result, the iris system has gained widespread acceptance in numerous applications due to its accuracy and high dependability in biometric systems [4,7]. The biometric system can be classified into two main categories: multimodal biometric systems and unimodal biometric systems. The unimodal biometric framework is utilized to authenticate an individual's identity by relying on a singular source of information, such as the left iris, right iris, or face [4]. In the context of the multimodal biometric system, when the system operates in the under-identification mode, the classifier generates a list of ranks derived from the candidates, which serves as a representation of potential matches [8]. The development and execution of a multimodal biometric system necessitates consideration of several elements that have an impact on the system's overall performance [4].

Among the biometric modalities now under study, iris and palmprint identification are considered to be the primary and most dependable modalities, exhibiting a lower mistake rate [9]. Since its introduction in 1987, iris recognition has emerged as a widely adopted biometric recognition technology, as highlighted by the works of Aran and Leonard [10, 2]. Over the past two years, there has been a significant increase in research focused on iris recognition [12], making it the fastest-growing field of study [11, 12]. The primary objective of iris recognition is to acquire and analyze photographs with the intention of facilitating identification. The initial and crucial stage in iris identification involves the localization of the iris region, encompassing the determination of both the outside and inner boundaries [8, 13]. Iris recognition has been utilized in several biometric applications, such as border control for the purpose of enhancing security measures, intelligent unlocking systems, and crime screening procedures [14]. Additionally, it has also been employed in border crossing control operations [15].

In recent years, face and fingerprint biometric qualities have been identified as highly popular but have also demonstrated certain drawbacks when applied in real-world scenarios. During the COVID-19 pandemic, individuals commonly adopt the practice of wearing masks in outdoor settings and exhibit hesitancy towards utilizing contact-based biometric systems. Consequently, the efficacy of prevailing face and fingerprint identification technologies is diminished [16]. Furthermore, it is worth noting that an individual's facial features and fingerprints can be illicitly obtained through either open or contact-based means. Consequently, there has been a growing focus on the advancement of palmprint-based biometrics technology, shown by the development of Amazon One [17]. This technology is favored for its distinct discriminatory features, as well as its non-contact and sanitary data collection approach. Furthermore, the acquisition of palm photographs necessitates the active collaboration of individuals, rendering them challenging to capture and so enhancing their efficacy in safeguarding privacy.

Several methodologies are employed in the process of iris localization, including Distance Regularized Level Set Evolution (DRLSE), integrodifferential operator, Circular Hough Transform (CHT), and Active Contour (AC). In her study, Tsai [18] employs a fuzzy matching approach in order to ascertain the distinctive characteristics of iris points.The initial development of the iris identification system by Daugman involved the

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utilization of an integro-differential operator to localize the iris and remove the eyelids [19]. In reference [20], Boles proposed an iris recognition method that is invariant to translation, rotation, and scaling. In his study, Wildes [21] employed a methodology that involved the integration of edge detection techniques with the Hough Transform algorithm to successfully identify iris patterns. In their study, the authors [22] introduced an alternative approach to the task of iris localization and pattern matching. An approach for localizing non-cooperative iris recognition has been presented, which is based on clustering [23].

However, unimodal biometric systems are encountering challenges such as spoof attacks and intra-class differences [24]. Multimodal systems have been developed to tackle the aforementioned issues [24]. These systems involve the integration of fragmented evidence obtained from numerous samples, instances, sensors, algorithms, or attributes. A potential approach to developing a reliable person recognition system involves creating a multimodal system that incorporates multiple biometric traits. The integration of evidence in multibiometric systems can occur at different stages, including the pixel level, feature level, score level, and decision level. The integration of cues at the feature level is found to provide a more comprehensive and detailed information about the biometric sample compared to other levels of integration. This has a significant impact on the recognition rate [24].

However, this fusion strategy also raises two notable issues, similar to the strategies outlined earlier. There exist two principal concerns that necessitate attention. The primary issue relates to the compatibility [25] between two distinct feature spaces, which [24] can be efficiently addressed by the normalization procedure. The second issue pertains to the elevated dimensionality of the feature space [26], which obviously necessitates substantial memory and processing resources. Therefore, it is imperative to create an advanced classifier that can efficiently function in the combined feature space [27]. This matter can be resolved by implementing either feature transformation or feature selection methodologies.Feature selection is a systematic process that involves the selection of a subset of features based on their value in attaining a robust and dependable categorization of the feature space. The utilization of this methodology presents an opportunity to improve the efficiency of classification (recognition) by eliminating superfluous, disruptive, and inconsequential features [28]. Feature transformation is the procedure of changing an original vector space of features into a subsequent feature space that more effectively reflects the fundamental attributes of the data.

In a previous study [29], Principal Component Analysis (PCA) and Independent Component Analysis (ICA) were utilized to perform iris feature extraction through the projection of a new dimensional space. Principal Component Analysis (PCA) has been widely employed in the context of palmprint and facial biometrics to effectively reduce the dimensionality of the feature space, both before to and following feature level fusion [30, 31, 32]. Numerous scholarly publications [33-36] in the field of literature have explored the topic of feature selection methods following feature level fusion, demonstrating a strong interest and motivation in this area of study. In a previous study [33], the integration of feature sets derived from the hand and face was performed at the feature level fusion. Subsequently, the SFFS feature selection method was employed to minimize the dimensionality of the feature space. The normalization and combination of the scale-invariant feature transform (SIFT) features of the face and the minutiae features of a fingerprint are performed at the feature level. The application of K-Means clustering has been utilized to pick noteworthy features from the fused feature space, as described in reference [34]. In addition, the utilization of the Genetic Algorithm is employed in order to select the most prominent features from the integrated feature space. In reference [35], the integration of eigen-features generated from a visual face picture and an infrared facial image is performed by

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feature level fusion. This integration is achieved by employing Genetic Algorithm to pick the most influential features. The utilization of a Genetic algorithm was documented in reference [37] to facilitate the selection of optimal features subsequent to the fusion of palmprint and iris at the feature level.

It is clear from the analysis above that score level fusion-based multimodal systems have been the exclusive focus of research. Furthermore, it is widely recognized that feature level fusion offers a more comprehensive set of biometric inputs in comparison to fusion at the score level. Nevertheless, the investigation of feature level fusion in the domain of iris recognition has been constrained by the formidable obstacle presented by the high-dimensional nature of the feature space. Numerous approaches have been documented in the extant literature to reduce the dimensionality of the feature space. These approaches include feature selection procedures and data transformation methods like Principal Component Analysis (PCA). Notwithstanding the abundance of feature space reduction techniques available, the procedure for determining a suitable solution requires a more comprehensive comprehension of the feature prioritization that must be achieved within the fused feature space. Additional investigation and analysis are required in order to determine whether optimization strategies can be utilized to reduce the feature space, thereby improving the recognition system's performance.

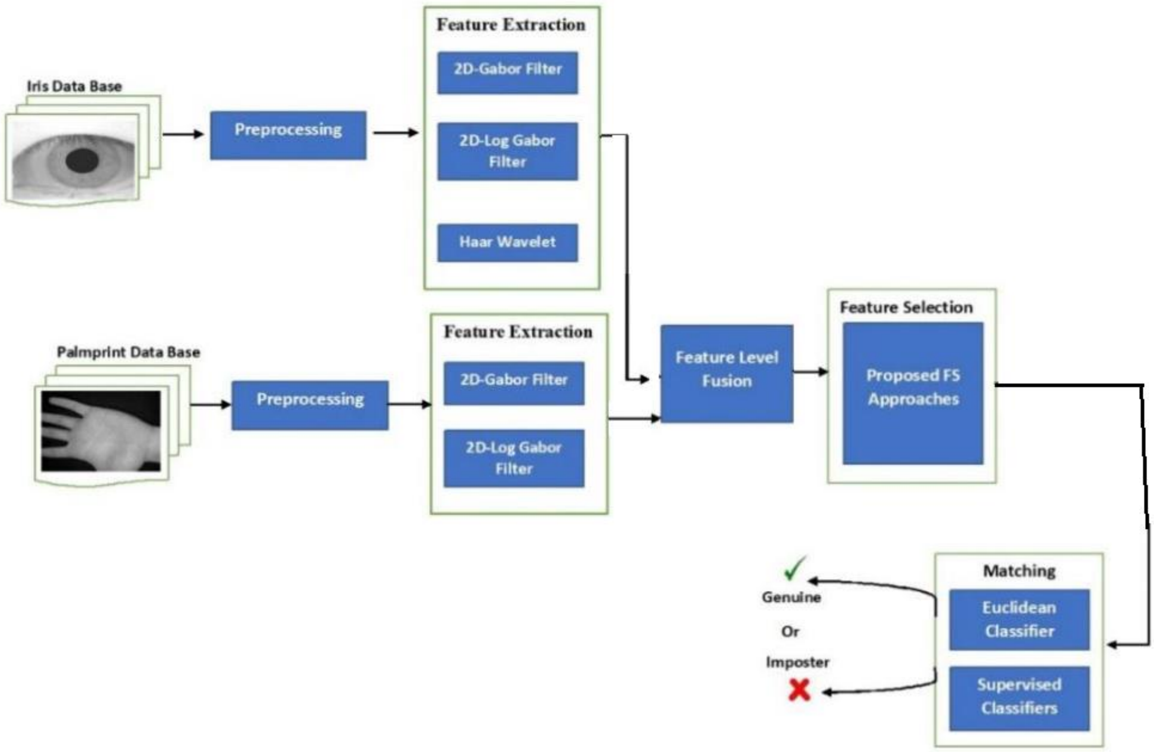

Fig 1: System Architecture

In order to tackle these issues, this study has examined swarm intelligence-based algorithms, such as the Artificial Bee Colony algorithm, as feature selection methods for reducing the fused feature space. Boll has demonstrated that performance is enhanced regardless of the procedure [38]; results based on subsets are superior. The ABC algorithm, along with its variants, has been implemented in numerous domains, including network configuration optimization [39], neural network training [40], image contrast enhancement [41], neural network image deblurring optimization [42], and iris segmentation for multilevel thresholding application [43]. The issue of biometric feature level fusion involving a high-dimensional feature space has been addressed with the implementation of ABC. Principal Component Analysis (PCA) was utilized to reduce features and was

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compared to feature selection methods in order to determine whether feature selection or transformation is superior.

As a result, the aforementioned reduction strategies to decrease the amount of data in multimodal systems following feature level fusion were examined in this article. Experiments have been conducted on six distinct multi-modal systems, as stated previously. Using feature level fusion, the 2D-Gabor, 2D-LogGabor palmprint and iris texture features, as well as Haar wavelet-based iris features, were extracted and integrated. The CASIA iris and palmprint databases and the IIT Delhi iris and palmprint databases were utilized for these experiments. The system architecture is presented in Fig 1.

The primary contribution of the research paper is the following:

• Proposed the ABC optimization algorithm, which is utilized to select the most effective features for an individual's authentication.

The structure of the paper is as follows: preprocessing and feature extraction of the iris and palmprint are discussed in Section 2. In Section 3, the integration of feature spaces is discussed. The reduction strategies implemented in the fused feature space are detailed in Section 4. Section 5 contains the results and discussion of the proposed method, while Section 6 serves as the concluding remarks of the paper.

2. Preprocessing and Feature Extraction

The procedure of readying a biometric characteristic for the purpose of extracting features is commonly referred to as preprocessing. In this study, the procedure of localizing the iris region from an eye picture was performed, followed by normalization to bring the iris regions to a standardized dimension. The technique of iris preprocessing is elaborated upon in section 2.1. The palmprint image undergoes preprocessing in order to extract the core part (ROI) of the palm, as the full image is not acceptable for the recognition process. This is achieved by a tangent-based approach, which is further described in section 2.2, where the quality of the palm image is also enhanced.The extraction of characteristics from preprocessed images is necessary in order to distinguish between real and impostor individuals. Three distinct methodologies for feature extraction have been employed to extract texture characteristics and phase features from preprocessed iris samples. These methodologies include the utilization of a 2D-Gabor filter, a 2D-Log Gabor filter, and Haar wavelets, respectively. The extraction method has been addressed in section 2.3. The extraction of textural features from the region of interest (ROI) of palmprints is accomplished through the utilization of 2D-Gabor filter and 2D-Log Gabor filter, as detailed in section 23.

2.1 Iris Preprocessing

The procedure of isolating the iris region from a provided eye image, in order to facilitate further feature extraction, is referred to as iris preprocessing. In the field of literature, researchers have employed diverse methodologies for the preparation of iris data [19-21]. The iris extraction process in this study involved several steps, as depicted in Figure 2. First, the iris was localized using the Canny operator and Hough transform. Next, normalization was performed using Daugman's Rubber Sheet Model. Finally, the quality of the normalized image was upgraded. The intricacies of this technique have been elucidated below.

Localization

Iris localization involves detecting the iris in an eye image. This step is crucial to iris identification. This can be achieved using methods like Daugman's [20], which uses an integro-differential operator. Wildes [21] suggests detecting iris by identifying edges and applying the Hough transform. Boles [20] localizes the pupil and outside

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boundary via edge detection and extracts features using the pupil as a reference. Another study [19] uses pixel intensity projections, thresholding, and circular Hough transform to identify the pupil. Many more ways have been suggested [24]. This study used an initial canny operator for edge tracking and detection. The iris and pupil boundaries were then determined using the Hough transform. Established pupil and iris radii.

Canny Edge Detection

Canny edge detection is largely utilized in image processing and computer vision. The first Gaussian derivative and precisely predicts the operator that maximizes signal-to-noise ratio and localization [44]. Canny edge detectors use smoothing, gradient discovery, non-max suppression, and hysteresis to track edges. Convolved iris image I [a, b] with Gaussian filter G to smooth data. This reduces noise and false edges. Get smoothed S[a, b] picture. To calculate the gradient of the smoothed image array S[a, b], 2x2 first-difference estimations are used to generate two arrays, P[a, b] and Q[a, b], for the x and y partial derivative Calculate gradient magnitude array and orientation. When the gradient is large, the magnitude array has huge values. However, large ridges must be narrowed in magnitude array to locate edge points. Only the highest magnitude change is kept. Next comes non-maxima suppression. Single threshold values cannot remove erroneous edges in non-maxima suppressed image NI[a, b]. To eliminate spurious edges, hysteresis or double thresholding is used.

Segmentation

Iris segmentation detects inner and exterior boundaries [45]. Circular Hough transform was used to identify iris and pupil center coordinates and radius. Calculating the first intensity derivate in the eye image yielded an edge map. For each edge pixel in the edge map, the circle's surrounding points at different radii are taken and voted on to obtain the maximum Hough space circle parameters. Calculate centre coordinates and radius. The greatest point is the radius ‘r’, and the circle's centre coordinates (x, y) are the Hough space edge points. The Parabolic and Linear Hough Transforms may identify both top and lower eyelids. For iris-sclera border detection, derivatives (gradients) are taken in the vertical direction to lessen the influence of horizontally aligned eyelids. For eyelid detection, horizontal gradients are taken. Since Hough space considers fewer edge points (not all edge pixels), this method accurately localizes the iris boundary.

Normalization

Normalization converts the iris region into a fixed-size representation. Due to pupil dilatation produced by varying illuminations, iris photos may have dimensional anomalies. Dilatation occurs when the head and eyes or camera rotate during image capture. Using the Cartesian system representation also affects iris matching distance calculations. Another issue is that the pupil region is not necessarily concentric within the iris, having a doughnut shape [19]. A good normalization approach generates separate representations for different pictures in similar situations and maintains consistent dimensions for the same iris region across conditions. Several literature methods have been proposed [20, 21]. Daugman's rubber sheet model explains how to map each point in the iris region to polar coordinates (r, θ), where r represents distance range [0,1] and θ represents angle range [0,2π]. Normalized polar coordinates are converted from Cartesian coordinates (p, q) of iris area points.Obtained pixel coordinates for circle around iris and pupil with radial resolution as20 and angular resolution as 240.

2.2 PalmprintPreprocessing

Aligning palmprint images and segmenting the ROI for processing is the process. One of the main preprocessing steps is creating a coordinate system based on crucial locations between the fingers. Binarization, contour extraction of the hand or palm, key point identification, coordinate system construction, and ROI extraction comprise the preprocessing stage [46]. From the third stage on, preparation methods vary until they

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become identical [46]. Key points can be identified in several ways. This study extracted palm image ROIs as square forms using tangents. Pre-processing the image before feature extraction reduces noise and interruptions from misconnections and isolated regions. The image is originally enhanced to increase palm element contrast. The binary picture is created from the upgraded image to help identify distinct traits. Edges are detected using the Sobel filter, which implies edges occur at intensity function discontinuities or steep intensity gradients. Tangent-based method extract image ROIs.

Tangent Based Approach

The precision achieved in the ROI segmentation procedure from palm images significantly impacts the reliability of palm print recognition systems. The central portion of the palm is isolated by pre-processing techniques utilizing a range of algorithms. This region is then segmented into several shapes such as circles, half ellipses, or squares to facilitate the extraction of relevant features. The square region is a fundamental and often utilized geometric shape. The blurred image is acquired through the application of a low pass filter (LPF) on the clipped image. The visual quality of this image is diminished, resulting in the suppression of minor lines as well as an impact on the more obvious big lines.The ROI of the palm image is obtained by cropping the sub image which contains richfeatures.

2.3 Iris and PalmprintFeature Extraction

Various feature extraction algorithms can be employed to extract the features from normalized iris [47]. The classification of approaches primarily includes Phase and Texture-Based methods, Zero-crossing Representation, Key point Descriptors, and Intensity Variation Analysis [47]. The utilization of Gabor filter-based feature extraction has demonstrated its effectiveness in achieving a high level of recognition accuracy, as evidenced by studies [19, 20]. Additionally, in the context of iris feature extraction, study [23] successfully employed Haar Wavelet and achieved exceptional accuracy while minimizing computational complexity. The utilization of Phase and Texture-based methods for iris feature extraction has been motivated by the advantages offered by Gabor filters and Haar Wavelets. Three distinct approaches, namely Haar wavelet [49], 2D-Gabor filter [48], and 2D-LogGabor filter [48], have been employed for this purpose.

A. Haar Wavelets

Phase characteristics from the iris have been extracted using the Haar wavelet transform [22]. Using a five level decomposition, the iris feature pattern was reduced to a single vector by taking approximation coefficients into account; this vector is referred to as the feature vector [23].

B. 2D - Gabor Filter

The literature demonstrates that Gabor-based feature extraction has been widely utilized in several applications of pattern recognition. The Gabor function is more effective in managing the instability of visual contrast and brightness, as it accurately determines the precise time frequency position [48]. The Gabor filter bank has been utilized forpalmprintand iris texture extraction due to its advantageous features [30, 31].

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

Where,

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

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

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θsignifies the orientation of the normal to parallel stripes of a Gabor function, φ is the phase offset, λ specifies the sinusoidal factor wavelength, σ is the standard deviation of the Gaussian envelope and γ is the spatial aspect ratio [48].

C.2D-Log Gabor Filter

The Log-Gabor filter has been extensively studied and utilized for the purpose of texture-based feature extraction due to its properties of time/space and frequency invariance, as well as symmetry on the log frequency axis [51]. The Log Gabor filter is applied for palmprint and iris feature extraction using the formula presented in reference [50].

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

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.

3. Feature Vectors Integration

This section outlines the amalgamation of iris characteristics with palmprint features. The Haar wavelet decomposition of a 20×240 iris picture has resulted in a 1×114 Haar feature vector. The iris image's Gabor characteristics, namely the 2D-LogGabor or 2D-Gabor, consist of a set of 12 distinct images denoted as G. Each image in G has dimensions of 20×240. The image GF has been resized to dimensions of 20×240 by the process of horizontal and vertical downsampling. The data has been transformed into a one-dimensional vector with a length of 4800.

The texture features extracted from palmprints using the 2D-Gabor filter and 2D-Log Gabor filter demonstrate a lack of comparability with the minutiae features found in fingerprints. The analysis of texture in a specific region of interest (ROI) palmprint image is performed by utilizing two different filters, namely a 2D-Gabor filter and a 2D-Log Gabor filter. The aforementioned procedure yields a total of twelve unique photos, each possessing dimensions of 100×100. In order to combine the texture information, the utilization of horizontal and vertical downsampling techniques is implemented, leading to the generation of a unified image with dimensions of 100×100. Additionally, the data is converted into a feature vector including 10,000 rows.

Gabor values and Haar values exhibit variations across multiple scales, hence rendering them distinct from one another. Classifier normalization has been implemented to mitigate the issue of disparate domain ranges, hence preventing the dominance of one group of data. This normalization process ensures that all values are brought into a standardized domain.

Here, six multi-modal systems based on iris and palmprint are designed namely

MM_Iris_Palm_sys1 – which is a multi-modal system developed based on integration of Log-Gabor features of Palmprint with Log-Gabor features of iris.

MM_Iris_Palm_sys2 – which is a multi-modal system developed based on integration of Log-Gabor features of Palmprint with Gabor features of iris.

MM_Iris_Palm_sys3 – which is a multi-modal system developed based on integration of Log-Gabor features of Palmprint with Haar features of iris.

MM_Iris_Palm_sys4– which is a multi-modal system developed based on integration of Gabor features of Palmprint with Log-Gabor features of iris.

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MM_Iris_Palm_sys5– which is a multi-modal system developed based on integration of Gabor features of Palmprint with Gabor features of iris.

MM_Iris_Palm_sys6– which is a multi-modal system developed based on integration of Gabor features of Palmprint with Haar features of iris.

4. Features Space Reduction

The literature shows that feature selection or reduction improves classifier prediction, scalability, and generalization. Knowledge discovery relies on feature reduction to reduce computing complexity, storage, and cost.This work applied both feature extraction based on PCA and ABC based feature selection method for reducing high dimensional fused feature space.

4.1 PCA based Feature Space Reduction

Image processing often uses PCA to reduce dimensionality and project into a subspace. This method has solved photo compression and recognition problems. PCA is mostly used in biometrics to extract features from facial photographs [52], palmprint data [53], and footprint data [54]. Before classifying fingerprints, faces, and signatures, [55] researchers used a hybrid approach combining PCA and LDA to reduce their dimensionality. According to [56], PCA reduces vector dimensionality to improve image identification. PCA is commonly used to find and describe patterns in multidimensional datasets [57]. After feature fusion, PCA was used to minimize dimensionality in three multi-biometric systems that incorporate eye, palm, and finger prints [48].

A linear data reduction method is PCA. It includes projecting data into a new space where the most variable directions describe it. PCA is a mathematical method that converts visual data into principle components. In picture data, these orthogonal PCs are ordered in descending variance.

PCA measures iris and fingerprint feature vector variability across orientations [48]. Let T be the training dataset with p iris and fingerprint templates. One-dimensional templates are 1 x q. The dataset T (p×q) is reduced in dimension using the PCA algorithm. The new dataset T' has dimensions p×k, where k is less than or equal to q. This algorithm uses eigen() to solve equation 5 and find eigen vectors and values.

$$[cov - \lambda I]e = 0 \tag{3}$$

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 $\lambda_1, \lambda_2, \ldots, \lambda_q$.

4.2Artificial Bee Colony Algorithm based Feature Selection

Karaboga [58] and Basturk devised the popular meta-heuristic optimization method Artificial Bee Colony algorithm, inspired by honey bees' sophisticated foraging [60]. Its performance has been studied [59]. ABC works well compared to other methods. The ABC method features fast convergence, few parameters, high flexibility, and strong robustness [61]. Modification rate (MR) eliminates premature convergence in this algorithm [62].

ABC has employee, bystander, and scout bees. Half of the bee population is employee and half is spectator [60]. The worker bees explore food sources and carry nectar to the hive and tell onlookers with waggle

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dances. Onlooker bees choose food based on quality. High-quality food attracts more bees. Scout bees randomly look for food based on external or internal information.

Working principle of ABC

In the context of an optimization problem with n dimensions, the Artificial Bee Colony (ABC) algorithm employs a random initialization strategy to determine the positions of N food sources within an n-dimensional solution space. The quality of each food source is indicative of the fitness level associated with the respective solution. According to the cited source [60], there is a one-to-one correspondence between employee bees and food sources, indicating that the quantity of food sources is equivalent to the quantity of employee bees. Moreover, the number of employee bees corresponds to the potential solutions inside the population space [59]. Each food source, P_i, is represented as an n-dimensional vector, p_{i1}, p_{i2}, p_{i3}, …, p_{in}, and is initialized randomly within a preset range of values, as depicted in equation (4).

$$p_{ik} = p_k^{min} + rand(0,1)\left(p_k^{max} - p_k^{min}\right) \tag{4}$$

Where i represents the range of food sources from 1 to N, and k represents the range of optimization parameters from 1 to n. In addition to the provision of food sources, the counters responsible for tracking the quantity of solution trails are initialized to a value of zero [62].

The current state involves the population of food sources (solutions) undergoing many iterations of search procedures carried out by worker bees, observer bees, and scout bees [62]. The termination criteria for the algorithm might be defined as either reaching the maximum number of iterations (max_iter) or meeting a specified error threshold. The search iteration consists of three steps: firstly, the employee bees are dispatched to their respective food sources and the quantities of nectar they collect are determined; secondly, the nectar information from the food sources is communicated among the bees, and the onlooker bees choose food source regions while also calculating the quantities of nectar available in these sources. employing the method of identifying scout bees and subsequently dispatching them in a random manner to explore potential food sources [63].

As previously stated, individual worker bees exhibit a dynamic behavior in relocating food sources by relying on local knowledge. This is achieved through the utilization of equation (5) to identify and assess surrounding food sources in terms of their quality.

$$v_{ij} = \begin{cases} p_{ij} + \emptyset_{ij}\left(p_{ij} - p_{kj}\right) & if\ R_{ij} < MR \\ p_{ij} & otherwise \end{cases} \tag{5}$$

To determine the neighborhood food source v_i of a food source p_i, alter one of its parameters. The equation uses j as a randomly picked integer from [1,n] and k as any food source from N other than i. Ø_ij is a random real number between [-1,1]. To counteract slow convergence, MR is set between o and 1[62]. Random integer R_{ij} is between 0 and 1. New food source values can be set to acceptable values if they exceed boundary values. Fit_i, a new food source, is then calculated using a fitness function. Compare x_i (fitness value $prev\_fit_i$) and v_i to their quality. Employee bee remembers the new FS position and leaves the old one if v_i is qualitative. If x_i does not improve, its trail_count is incremented by 1 [60, 62]. Otherwise, it is reset to 0.

The dissemination of information pertaining to nectar quantities and the locations of food sources is facilitated by worker bees to observer bees. Subsequently, the observer bees engage in the process of food source selection, wherein their choices are influenced by the probabilities associated with the respective nectar quantities. The fitness-based selection approach encompasses several selection mechanisms, such as roulette

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wheel tournament selection, rank-based selection, and other similar processes. The present study utilizes the roulette wheel selection method to determine the probability pr_i as, as depicted in equation (6).

$$pr_i = \frac{fit_i}{\sum_{i=1}^{N} fit_i} \quad (6)$$

In the current process, a stochastic value is generated within the range of 0 to 1 for each food source, and subsequently compared with its respective likelihood. If the likelihood exceeds the randomly produced value, it indicates that the position of the food source has been altered by observer bees, following the same equation (5) used by employee bees. Subsequently, spectator bees retain in their memory either the recent location or the previous location of the food source, as determined by the fitness values. If there is no improvement in the value of p_i, then the trail_count associated with it is increased by 1; otherwise, the trail_count is reset to 0.

After each iteration, once all employee bees and observer bees have completed their searches, it is necessary to assess the availability of depleted food sources. In order to determine the food source that is to be abandoned, it is necessary to compare the updated trail_count value obtained during the search process with the control parameter "limit". If the count of trails exceeds the specified limit, the food source is relinquished by the bee and then substituted with a new source that has been found by a scout bee. If the number of trail counts that exceed the "limit" value is greater than one, the maximum value among them is chosen.

Selection of parameters and representation

The process of feature selection in this study involved the utilization of a modified version of the ABC method, as described in previous works [64, 65]. In the context of optimization problems, it is common practice to represent each food source or potential solution as a vector composed of real numbers. In the context of the feature selection issue, it is common to describe each potential answer as a binary vector with a length of n, where n corresponds to the total number of features. A value of 1 at a specific place signifies that the corresponding feature is included in the feature subset to be chosen. Alternatively, if the value is 0, it is excluded from the feature subset. The population or colony size refers to the quantity of bees, encompassing both worker bees and observer bees, denoted as N. This factor significantly impacts the computational expenses and effectiveness of feature selection. The method was subjected to experimental evaluation across a range of population sizes, namely ranging from 10 to 50 in increments of 5. Finally, the amount was adjusted to 30 due to the observed discernible impact on performance when the value exceeds 30. Following a series of experimental iterations involving several values, the control parameter "limit" has been established at a value of 0.3.The parameter MR, which has been assigned a value of 0.5, governs the frequency of the perturbation.

Fitness function

The creation of a fitness function plays a vital role in the process of feature selection. The iris-based recognition system employs a methodology wherein the recognition accuracy (RA) is determined by evaluating the distances between the iris sample provided and all samples in the database, followed by the computation of match scores. The data is classified using C4.5 decision trees. 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:

$$fit(P_i) = RA + n_{selected} * \left(\frac{N_{DB}}{n}\right) \quad (7)$$

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

5. Discussion of results

This section presents the experimental results of a multi-modal recognition system, comparing the outcomes with and without the implementation of reduction approaches. The results of the study primarily centeraround three key aspects: the recognition rate, the computation time required to process the dataset, and the reduction in feature space resulting from feature level fusion. Recognition is deemed when the false alarm rate (FAR) is at 0.01%. In order to ascertain the recognition rate, two matching systems based on Euclidean distance were employed, along with four classification algorithms, namely SMO, C4.5, NB, and RF.

The experiment was conducted using two distinct databases. One example of an iris database is CASIA Version 1.0 [78], which comprises a total of 756 iris images obtained from 108 distinct eyes. In each session, a total of seven images are acquired for each individual eye. The first session involves the collection of three iris samples, while the second session involves the collection of four samples. From this database, we have selected six samples from each individual eye. Another example is the iris image database version 1.0 of the Indian Institute of Technology Delhi (IITD) [79]. The collection comprises a total of 2240 photos, sourced from 224 distinct individuals. A total of 10 eye samples are obtained from each user, with the first five samples taken from the left eye and the remaining five samples taken from the right eye. In our experimental setup, the left eye and right eye of a single participant are considered as distinct entities due to the inherent dissimilarities between each eye inside an individual. A total of 448 distinct participants were selected, with three samples being picked for each subject.

The studies were conducted using the CASIA and IIT Delhi palmprint databases, consisting of 100 objects. For each object, a total of 5 samples were collected, resulting in a total of 500 samples.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 twelve distinct images, each with a size of 100×100. To consolidate this texture information, horizontal and vertical downsampling techniques are employed, resulting in a final single image of size 100×100. Moreover, it is transformed into a one-dimensional feature vector with a dimensionality of 10,000.

Each virtual individual within our multi-modal biometric databases possesses a distinct biometric characteristic sourced from one database, in conjunction with another characteristic obtained from a separate database. During the construction of a multimodal database using iris and palmprint data, each virtual human was created by carefully picking one irissample from the iris CASIA DB and one palmprint sample from the palmprint CASIA DB. Another database was established for multimodal systems. The process of generating virtual individuals inside this database involves the integration of iris data taken from the iris IITD DB with palmprint data obtained from the palmprint IITD DB. The aforementioned approach generates datasets that encompass many modes of biometric information.

The studies were conducted using a personal computer equipped with a 1.8 GHz i7 processor, 16 GB of RAM, and running the Windows 10 operating system. Two reduction approaches, namely PCA and ABC, are evaluated on multi-modal systems to determine the most effective approach. The efficiency of these two methods can be determined by the functionality of the suggested systems. A Euclidean distance metric and a

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supervised algorithm-based measure are employed to compute the rates of true positives and false positives. The proposed systems employ four supervised algorithms, including the C4.5 decision tree, Random Forest, SMO, and Naive Bayes.

Result Analysis

In this study, we describe the findings of our investigation into multimodal systems utilizing iris and palmprint biometric data, both with and without reduction techniques. The calculations in question mostly pertain to the rates of recognition, processing times of datasets, and reductions in feature space resulting from the fusion of features at the feature level.

Firstly, the present study presents the outcomes of matching multimodal systems utilizing Euclidean distance across all reduction strategies. Table 2 presents the recognition rate achieved by six systems on two datasets, employing data reduction techniques. Given the parameters, we establish a false acceptance rate (FAR) of 0.01% for the recognition rate. PCA processes faster than ABC but has a slightly lower recognition rate across all six systems. In terms of recognition rate, ABC exhibited a higher performance compared to PCA. The findings indicate that ABC has superior performance when used to large-scale datasets.

Table 1 Number of Features Selected in Multi-Modal System Based on Iris and Palmprintfor Various DB's

Multi-modal Systems	Databases	Without FS	PCA	ABC
MM_Palm_Iris_Sys4		14800	3201	3304
MM_Palm_Iris_Sys5		14800	3211	3196
MM_Palm_Iris_Sys6	CASIA DB & CASIA DB	10114	2327	2296
MM_Palm_Iris_Sys4		14800	3217	3286
MM_Palm_Iris_Sys5		14800	3218	3287
MM_Palm_Iris_Sys6	IITD DB & IITD DB	10114	2318	2216
MM_Palm_Iris_Sys1	CASIA DB & CASIA DB	14800	3211	3313
MM_Palm_Iris_Sys2		14800	3245	3198
MM_Palm_Iris_Sys3		10114	2312	2297
MM_Palm_Iris_Sys1	IITD DB & IITD DB	14800	3203	3281
MM_Palm_Iris_Sys2		14800	3208	3292
MM_Palm_Iris_Sys3		10114	2312	2219

Table 1 presents the quantity of diminished characteristics in the eigen space PCA, ABC, for both the iris and palmprint-based multi-modal systems in section 3. Table 2 presents the results of the PCA and the ABC Euclidean distance performance. Achieving a high identification rate and effectively reducing the feature space are crucial components of any system. The results presented in Tables 2 and 1 demonstrate that PCA exhibits superior performance in reducing the feature space compared to ABC. However, it is important to note that PCA does not yield an improvement in recognition accuracy, whereas ABC produces superior results in this regard.

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The findings for six multi-modal systems utilizing palmprint and iris are displayed in Table 3. In the context of multi-modal systems, it was shown that the SMO and C4.5 classifiers exhibited significantly higher levels of recognition accuracy when compared to the NB and RF classifiers. Among the various classifiers examined, the NB classifier has demonstrated superior performance compared to distance measures. However, it exhibits subpar performance among supervised classifiers due to its limitations in effectively handling continuous data. The SMO and C4.5 classifiers demonstrated the greatest accuracy rates of 96.5% and 96.3%, respectively, among all multi-modal datasets of palmprint and palmprint. These results were superior to those achieved by the other classifiers utilized in the proposed ABC algorithm.

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

Multi-modal Systems	Databases	Without FS	PCA	ABC
MM_Palm_Iris_Sys4	CASIA DB & CASIA DB	81.6	85.8	94.5
MM_Palm_Iris_Sys5		80.7	84.7	94.6
MM_Palm_Iris_Sys6		82.1	86.1	95.1
MM_Palm_Iris_Sys4	IITD DB & IITD DB	80..8	84.7	95.2
MM_Palm_Iris_Sys5		81.7	85.8	95.6
MM_Palm_Iris_Sys6		80.8	84.9	95.7
MM_Palm_Iris_Sys1	CASIA DB & CASIA DB	81.8	86.1	95.3
MM_Palm_Iris_Sys2		81.2	85.1	95.4
MM_Palm_Iris_Sys3		82.1	85.8	95.6
MM_Palm_Iris_Sys1	IITD DB & IITD DB	81.3	85.9	95.4
MM_Palm_Iris_Sys2		80.7	85.3	96.1
MM_Palm_Iris_Sys3		80.8	85.1	95.9

The MM_Palm_Iris_sys1 system achieved an accuracy of 95.3% using the SMO algorithm. In the MM_Palm_Iris_sys2 system, the C4.5 algorithm achieved a recognition accuracy of 95.6%. Similarly, the MM_Palm_Iris_sys3 system achieved an accuracy of 95.3% using the C4.5 algorithm. The MM_Palm_Iris_sys4 system attained a recognition rate of 94.9% using both the SMO and C4.5 algorithms. In the MM_Finger_Palm_sys5 system, the SMO algorithm produced an accuracy of 96.5%. Lastly, the SMO algorithm achieved a recognition level of 96.3% in the MM_Finger_Palm_sys6 system.

Analysis of Computation Time: The Feature Selection techniques, namely PCA and ABC were employed in the tests using identical databases and conducted within a consistent context. Despite the fact that the algorithm ABC requires a longer training time compared to the other algorithms, it yields the least testing time. In the context of biometric systems, the training process is often conducted during the enrollment phase and is performed offline. However, the nature of the testing process differs from what has been described. In the

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context of biometric systems, the duration of testing exhibits a greater influence when juxtaposed with the duration of training. Due to its ability to create a reduced amount of characteristics in comparison to alternative algorithms, the suggested approach consistently exhibits a shorter processing time for classifying the test biometric template as either genuine or imposter.

Table 3 Recognition Accuracy using Various Classifiers in Multi-modal System Based on Iris and Palmprintfor Various DB's

Multi-modal Systems	Classifiers	Without FS	PCA	ABC
MM_Palm_Iris_Sys1	SMO	84.3	85.2	95.3
	C4.5	84.2	85.1	95.1
	NB	82.6	83.01	92.5
	RF	83.3	84.4	93.7
MM_Palm_Iris_Sys4	SMO	82.2	85.1	94.9
	C4.5	81.6	85.2	94.9
	NB	80.4	82.6	92.7
	RF	82.1	83.9	93.9.
MM_Palm_Iris_Sys2	SMO	85.5	87.1	95.5
	C4.5	85.4	87.2	95.6
	NB	82.1	84.8	93.3
	RF	84.7	85.9	94.9
MM_Palm_Iris_Sys5	SMO	86.2	87.8	96.5
	C4.5	86.1	87.7	96.01
	NB	81.9	83.8	93.7
	RF	84.8	85.9	94.9
MM_Palm_Iris_Sys3	SMO	85.6	86.1	95.2
	C4.5	85.5	86.9	95.3
	NB	81.4	83.8	93.9
	RF	82.5	84.2	94.9
MM_Palm_Iris_Sys6	SMO	84.7	86.3	96.2
	C4.5	84.8	86.8	96.3
	NB	81.8	83.9	93.9
	RF	82.6	84.9	95.3

6.Conclusion

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The present study employed the ABC algorithm to reduce the dimensionality of the feature space following the integration of biometric features derived from multiple modalities. Principal component analysis (PCA) has the capability to handle big datasets; yet, it may fail to capture crucial information on each occasion. As a result of this, the development of ABC was undertaken, which effectively addresses this issue through the utilization of an exponential function to broaden the exploration of feature space. The performance of ABC is superior to that of PCA in reducing the feature space of iris and plamprint benchmark datasets, specifically CASIA and IITD.

ABC demonstrated strong performance across various scenarios, encompassing feature space reduction, accuracy in identifying distance measures, and the effectiveness of supervised classifiers. In the context of section 3 multi-modal systems, it can be observed that ABC has superior performance in terms of recognition accuracy compared to PCA. When employing supervised classifiers, PCA yields an accuracy rate of 87.8%, whereas the ABC classifier achieves a higher accuracy rate of 96.3%. Enhanced identification of distinctive characteristics would facilitate the enhancement of categorization precision. The findings indicate that supervised algorithms exhibit a higher degree of accuracy compared to the use of Euclidean distance.

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