GwPeSOA-based MSVNN: the multimodal biometric system for futuristic security applications

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Abstract. Biometric systems have gained considerable significance as they are highly employed in the security applications. Achieving human recognition is easier and cheaper and the single modality employed for the recognition faces a lot of challenges due to the environmental factors. Thus, the paper proposes a multimodal recognition system based on the Multi-Support Vector Neural Network (MSVNN). The algorithm proposed is the Glowworm Penguin Search Optimization Algorithm (GwPeSOA), which is a modification of the Glowworm Optimization Algorithm (GOA) with the Penguin Search Optimization Algorithm (PeSOA). The proposed method employs two modalities: the ear and the finger vein modalities; the features of the ear image are obtained using the proposed BiComp masking method of feature extraction, whereas the features from the finger vein are extracted using the Repeated Line Tracking (RLT) method. The features obtained are applied to the MSVNN classifier to recognize the person with good accuracy and the proposed BiComp Mask offers robust features for the extraction. The experimentation using the proposed method attained a better accuracy, specificity and sensitivity at a rate of 0.95, 0.95 and 0.9868, respectively.

Keywords. Multimodal biometric system; MSVNN; BiComp features; RLT; GOA.

1. Introduction

The demand for secured systems gave rise to the automatic personal verification system, named as biometrics, which has drawn huge attention from the research community and is one of the challenging tasks nowadays [1, 2]. Biometrics identifies the humans based on the features obtained from fingerprints, iris, face and so on [3]. In other words, biometrics enables the automatic recognition of humans using their physiological or behavioural characteristics [4]. Biometrics [5] is used in official and commercial identification systems and it is advantageous in terms of the accuracy, cost and noninvasive identification methods of the measured characteristics [6]. In general, the biometric system consists of the sensor module, feature extraction block, matching module and the decision block. The raw data are obtained and subjected to feature extraction. The features are matched with the database to authenticate the person [7]. Almost all the biometric systems employed in the real-world applications are unimodal that use any of the following images: fingerprint, face, voice, palm print, finger knuckle print (FKP) and so on. The unimodal systems are subject to the problems with nonuniversality, noisy data, inter-class similarities, intra-class variations and spoofing,

which provide a greater value of False Acceptance Rate (FAR) and False Rejection Rate (FRR), whereas they offer limited discrimination capability. These problems are easily tackled using multiple sources for identifying the person [8].

Multimodal biometric systems have gained more importance when compared with the unimodal biometric systems. The multimodal system uses two or more traits of a person to authenticate the individual with high security and moreover, to offer high reliability. The traits used can be any of the combinations using the iris, face, fingerprint, finger knuckle and so on, such that they provide higher acceptability, security and accuracy. The features obtained from the individual traits are fused together for the identification process [9]. The multimodal biometric system provides improved performance when compared with the unimodal system, mainly in terms of uniqueness, spoofing rate, error rate and noise [10]. The main aim of the multimodal biometric system is that even if the quality of a sample obtained from a single modality is affected, it is balanced using the other modality such that the other sample provides sufficient information for making accurate decisions [11]. The security characteristics of the biometric are improved in the multimodal biometrics. The usage of the multimodal biometric system dissuades the intruder away from intruding, and in addition enables proper

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authentication of the user [12]. Some machine learning methods [13–15] and optimization algorithms [16, 17] are utilized in biometric systems.

The finger vein patterns are advantageous over the other traditional biometrics and the finger vein patterns are applicable in the real world. The patterns in the finger vein are difficult to identify as they are unique [18]. Therefore, the patterns can be traced using infrared light, which permits contactless images, enabling convenience to the users. Due to the stability and clarity of the finger vein patterns, to click small-sized simple images from the finger vein image, a low-resolution camera is sufficient [19]. Thus, finger veins are preferred for authentication [3]. In addition to the finger veins, ear images gain remarkable significance due to their structural properties. The main reason for using the ear images is that the ear images do not change with aging, but other modalities, such as finger vein, fingerprint and so on, change in structure as the human ages. The human face alters with age, bringing a hectic challenge in face recognition systems, and the fingerprint changes with varying states of the skin [20]. These problems noted in other modalities as a result of aging are not prevalent in the ear images and the researchers confirm that ears are exclusive and can be employed for human recognition. Thus, due to the merits of choosing ear and finger vein, the biometrics are employed for the multimodal recognition system [21].

The paper proposes a multimodal biometric system using the ear and the finger vein images. The two modalities are pre-processed and subjected to feature extraction. The features from the ear image are obtained using the proposed BiComp masking procedure such that the texture features are presented. The features from the finger vein images are obtained using the adaptive thresholding procedure, which employs repeated line tracking strategy to extract the features. The features obtained are used to train the Multi-Support Vector Neural Network (MSVNN) and the score value is the output from the classifier such that the score values obtained for both the ear and vein images features are fused together. The score level fusion is brought about by the optimal score weights that fuse the scores of the two images and based on the maximum value of the score, the person is authenticated. The optimal scores are found based on the optimal values provided by the proposed Glowworm Penguin Search Optimization Algorithm (GwPeSOA).

The contribution of the paper is the following.

Proposed BiComp mask: A new texture descriptor, named BiComp mask, which generates an image with the same dimension as that of the input image, is proposed. It is advantages over the existing Local Binary Patterns (LBP) and Local Gradient Patterns (LGP) and the proposed mask transfers digital images in grey scale such that the texture features are extracted effectively.

GwPeSOA: The proposed GwPeSOA is a modification of Glowworm Optimization Algorithm (GOA) with the Penguin Search Optimization Algorithm (PeSOA). The proposed algorithm offers a greater convergence rate and

converges to the global optimal solution. Also, the proposed algorithm is adaptive to the local-decision domain that effectively locates the optimal solution. It generates a simple balance between the global and local minima even during large-sized penguin groups.

The paper is organized as follows. Section 1 provides an introduction to the paper, section 2 describes the related works and presents the challenges and section 3 discusses the proposed method. The results are discussed in section 4 and finally, section 5 concludes the paper.

2. Motivation

2.1 Related works

Gambhir and Shekher [9] proposed a multimodal biometric system using finger vein pattern and ear biometric that overcomes the problems caused by noisy information and irregular error rates. The advantage of the method is that it offers improved efficiency of a single or unimodal biometric system and resolves its limitations, but strict administration of data is essential during storage and transfer. Xi *et al* [22] proposed a method, termed as the Discriminative Binary Codes (DBC) learning method, for the recognition of the finger vein. Initially the subject correlation graph was developed, which was transferred to a binary template, yielding the information of the subject. Finally, these templates were employed for classification using the SVM. The merits of the DBC are that they are more discriminative and shorter, and they are generated using the relationships among subjects, which are useful to improve performance. However, the authors did not focus on developing visual attributes of finger veins. Liu *et al* [23] introduced a secure biometric template scheme based on deep learning and random projections, named FVR-DLRP. Its importance is that the method protects the user data even when the password is cracked, but never guarantees template protection. Tharwat *et al* [24] proposed a Multimodal Biometric Authentication Algorithm, for which the authentication is performed using the ear and FK images. The method provides a greater value for the recognition rate when compared with the state-of-the-art methods and computational time of the method is less, but the recognition rate is degraded when the classifiers are dependent on each other. Matsuda *et al* [3] proposed a finger vein authentication system based on deformation-tolerant feature-point matching that was found to be robust enough in matching the feature points. The method offered higher identification accuracy, and better processing than SIFT. The authentication with high usability is enabled, in which the processing time is reduced, but the processing speed of the proposed method is a bit greater than in the existing method. Ghoulmi *et al* [6] used an ear image contrast enhancement approach based on the grey-level mapping technique, and in turn, utilized Artificial Bee

Colony (ABC) algorithm. This method provided more discriminative points for identification, but the accuracy of the over-illuminated images was poor. Tahmasebi and Pourghassem [21] proposed a Robust Intra-Class Distance-Based Approach to differentiate the genuine images from the imposters. The game theory was utilized, which merged the unimodal biometrics using the optimal logistic regression weights. The recognition performance is improved, and the system performance is interestingly high, but the fusion weights are not chosen automatically and, therefore, there is no confidence in choosing the most proper weights. Banerjee and Chatterjee [25] proposed a kernel-based simultaneous sparse representation that tackled non-linearity infusion caused by pose variations and occlusions, but took longer time to converge. Sánchez *et al* [26] proposed a firefly algorithm for human recognition that reduced the recognition error, but the complexity of MGNNs architectures is the major issue. Cantó-Navarro *et al* [27] proposed the Floating-Point Biometric Accelerator (FPBA) to increase the speed of processing kernels utilized in biometric algorithms. The FPBA was part of an embedded system that was implemented on a low-cost Field Programmable Gate Array (FPGA) family from Xilinx. The benefit of this method is that it is programmed on the same hardware architecture following a software design flow. Barman *et al* [28] developed a method of fingerprint-based authentication system, in which fingerprint matching was performed using the distance of minutiae points only. This method was straightforward and it required very little space to store templates. Here, an indexing approach was used to increase the speed of the matching process.

2.2 Challenges

- The main challenge in biometric authentication is regarding the data leaks, which is the result of fake identification. In the authentication process, the problem is about automatic, quick and accurate identity [23].
- Age, facial expressions and health conditions have considerable impact with human face. The iris image is an intrusive modality as it is costly and the fingerprint for recognition differs due to some medicine, burns or ink on fingers [6].
- The performance of the unimodal systems is poor in case of multiple attempts and user-friendly and flexible biometrics [25].
- Unimodal biometric systems suffer from uniqueness, high rates of spoofing, error, non-universality and noise. Moreover, almost 2% of the population do not have a clear fingerprint and hence, it cannot be used in fingerprint biometrics system [11].
- In [6], biometric systems are based on the ABC and SIFT features of ear. They are simple, robust and easy to implement, but they lead to data loss and computational complexity.

- The techniques employed in [22] and [23] use finger vein for recognition but the recognition cannot be performed effectively with single modal consideration.

3. GwPeSOA-MSVNN classifier: proposed multimodal biometric recognition using the fusion of the ear and the finger vein images

The need for the multimodal recognition is to overcome the problems caused by the unimodal recognition. The recognition accuracy is high in the multimodal system and the usage of the ear and the finger vein images overcomes the issues caused by aging and skin texture. Thus, the proposed multimodal recognition system uses the ear images and the finger vein images for recognition. The features are extracted from the images individually using the feature extraction process and used to train the GwPeSOA-based MSVNN classifier. The outputs from the proposed classifier using the ear images and the finger vein images are fused together using optimal weights. The output of the score value of the person and the final output are compared among the persons and the person with the maximum score value is recognized as the person. Figure 1 shows a block diagram of the proposed multimodal biometric system.

Consider a database P with n number of persons, given by the relation

$$P = \{P_1, P_2, \dots, P_i, \dots, P_n\}. \quad (1)$$

The ear and the finger vein images of the i th person are denoted, respectively, as E_i and V_i and the dimension of the images is $[pq]$.

3.1 Pre-processing

The image is pre-processed so that it can be made effective for further features extraction. Initially, the image is subjected to undergo binarization and segments are formed. Out of the segments, the segments with large area undergo ROI extraction to provide a pre-processed image.

3.2 Feature extraction using the proposed BiComp Mask on the input ear image

This section presents the extraction of texture features using the proposed BiComp masking. The texture features extracted using the Scattering Wavelet Transform, Gabor filters and Discrete Wavelet Transform (DWT) are applied to the proposed BiComp mask, which generates the image with the same dimension as that of the input ear image. The proposed BiComp output undergoes convolution to form an output image of the same dimension. The proposed BiComp is advantageous over the methods like the LBP

Figure 1. Block diagram of the proposed multimodal biometric recognition system.

and the LGP. The proposed method of patterns transforms the digital image and provides an image with the same dimension as that of the input image. It yields better texture features for recognition using the classifier. Figure 2 shows the feature extraction steps.

Step 1: Gabor features

The Gabor features are extracted using the Gabor filters with variable orientation and frequency that provide useful and significant features. The ear image is provided to the Gabor filter to provide the Gabor-transformed image, which is of dimension $[p \times q]$, given as

$$g_i = G[E_i] \quad (2)$$

where g_i is the Gabor-transformed image.

Step 2: Wavelet features

The DWT provides wavelets, which are the high- and the low-frequency bands containing the information of

frequency and location. The application of the wavelet transform is given as follows:

$$[e_i^1 \ e_i^2 \ e_i^3 \ e_i^4] = W[E_i] \quad (3)$$

where e_i^1 , e_i^2 , e_i^3 and e_i^4 are the wavelets corresponding to the LL, LH, HL and HH bands, respectively. The LH and HL bands are selected for the further processes as they enable the feature extraction horizontally and vertically.

Step 3: Scattering Wavelet Transform

The Scattering Wavelet Transform [29] is used to extract the texture features using the Morlet wavelet at multiple scales and orientations. The scattering transform develops non-linear invariants from wavelet coefficients, with the modulus and the average pooling functions. Following are the steps involved in the scattering transform. Initially, the 2-D input image E_i is convoluted with the average filter to form a local affine transformation that preserves the image

Figure 2. Texture feature extraction using the ear modality.

from any deformations. The filter used is a low-pass filter in the frequency domain that is controlled using a scaling factor. The affine transformation rejects the high-frequency component of the image and thus, to capture the high-frequency components, bandpass filters are applied. The Morlet filters are employed and the wavelet modulus is the output from the individual bandpass filters (Morlet filters) and the average filters. The high-frequency components are obtained by taking space average over these wavelet modulus coefficients. In turn, the first-order scattering coefficients yield the complementary high-frequency wavelet coefficients and the first-order coefficients are obtained using the second wavelet modulus transform on the wavelet modulus coefficients. Following this, the second-order scattering coefficients are obtained by averaging the first-order coefficients with the low-pass filter. The second-order coefficients are obtained by applying the third wavelet transform that convolutes the wavelet modulus coefficients and the newly generated wavelets with different scale and orientation. The other layers are formed by repeating the same processes and the scattering transform is applied to any order by employing a constant wavelet bank at the individual steps. Thus, the higher order scattering coefficients yield the robust features that remain stable to affine deformations and they are locally invariant:

$$s_i = S[E_i] \quad (4)$$

where s_i is the transformed image using the scattering transform.

Step 4: Proposed BiComp masking

The proposed BiComp masking is the texture descriptor that labels the image pixels through thresholding its neighbouring pixels, and the result of thresholding is the binary number that is converted to decimal. The centre pixel is fixed and the surrounding pixels are valued based on the difference in the intensities. The proposed BiComp thresholding is described in Eq. (5). The centre pixel is fixed as (X_C, Y_C) and the intensities of the surrounding pixel located at the location H are interpreted. If the difference in the intensities between the centre pixel and the neighbouring pixel exceeds zero, then mark the pixel value as '1'; otherwise, the pixel value becomes '0'. The pixel values so obtained are converted to a decimal, whose value varies between 0 and 255. The proposed BiComp masking is based on the following formula:

$$\text{BiComp}(X_C, Y_C) = \sum_{j=0}^{|H|-1} J_{X_C, Y_C} \times 2^j \quad (5)$$

where

$$J_{X_C, Y_C} = \begin{cases} 0 & \text{if } [P_{X_C, Y_C} - P_{(X_C + H_j^1 Y_C + H_j^2)}] < 0, \\ 1 & \text{otherwise.} \end{cases} \quad (6)$$

Now

$$H = \{(-2, 0), (-1, 0), (0, 1), (0, 2), (1, 0), (2, 0), (0, -1), (0, -2)\}. \quad (7)$$

Applying the proposed BiComp to texture features: The proposed BiComp masking converts a digital image into grey-scale image for extracting the features like the shape, colour, etc., of the object in the image. The Gabor features with pixel centre (X_C, Y_C) are applied to the proposed BiComp mask:

$$y_1 = \text{BiComp}[g_i]; \quad g_i \in (X_C, Y_C) \quad (8)$$

Similarly, the proposed BiComp mask applied to the scattering-transformed image, the wavelet outputs and the original ear image E_i is given as

$$y_2 = \text{BiComp}[s_i]; \quad s_i \in (X_C, Y_C), \quad (9)$$

$$y_3 = \text{BiComp}[e_i^2]; \quad e_i \in (X_C, Y_C), \quad (10)$$

$$y_4 = \text{BiComp}[e_i^3]; \quad e_i \in (X_C, Y_C), \quad (11)$$

$$y_5 = \text{BiComp}[E_i]; \quad E_i \in (X_C, Y_C). \quad (12)$$

The results of the proposed BiComp masking the Gabor features, scattering features and wavelet features are given as y_1 , y_2 , y_3 and y_4 , respectively. The outputs of the proposed BiComp mask y_1 and y_2 are convoluted to form x_1 . The convoluted outputs x_1 and y_3 form x_2 , while x_3 is formed by convoluting x_2 and y_4 . The convolution of x_3 and y_5 yields x_4 . The importance of applying convolution is that convolution yields the required features regardless of the position of the image.

$$x_1 = y_1 \otimes y_2, \quad (13)$$

$$x_2 = x_1 \otimes y_3, \quad (14)$$

$$x_3 = x_2 \otimes y_4, \quad (15)$$

$$x_4 = x_3 \otimes y_5. \quad (16)$$

Thus, x_4 is the final output of convolution and it is applied to the histogram. The transformed image x_4 is of dimension $[p \times q]$, and the result from the histogram descriptor is the feature vector of the ear image of dimension $[1 \times k]$, where k is the number of bins and is equal to 255.

$$\{f_1^E, f_2^E, \dots, f_k^E\} = \text{Hist}[x_4]. \quad (17)$$

These features represent the significant features of the ear image and they are subjected to fusion using the proposed GwPeSOA-based SVNN classifier. The output from the MSVNN using the ear images is given as O_i^E , which is the output of the MSVNN classifier of the i th person using the ear images.

3.3 Input finger vein image feature extraction using adaptive thresholding

The finger vein image is subjected to adaptive thresholding using repeated line tracking. The vein image V_i is subjected to the adaptive thresholding [30]. Initially, the repeated line tracking determines the starting point of the tracking and finds the moving direction attribute. In the second step, the direction of the dark line and the movement of the tracking line are identified and the points tracked in the locus space are counted. Finally, the finger vein patterns are generated from the finger vein image. The result of the adaptive thresholding, denoted as M , is of dimension $[pq]$. The image M obtained as a result of adaptive thresholding is split into ' h ' grids; the value of each grids is '1' whenever the vein is detected in the grid; otherwise, the grid value is '0'. The grids are of dimension $[1 \times h]$. Thus, the features obtained from the image M are given as

$$M = \{f_1^V, f_2^V, \dots, f_h^V\} \quad (18)$$

where h refers to the number of grids and is equal to 625. The features are fed to the MSVNN classifier to provide the output O_i^V , which is the output of the i th person obtained using the finger vein features.

3.4 MSVNN classifier for score level computation

In this section, score level computation using the MSVNN is presented, which offers the score level of the person using the ear and the finger vein features. In the MSVNN layered approach, there are $(n - 1)$ classifiers employed in performing the classification. The $(n - 1)$ classifiers are trained with the features of the $(n - 1)$ number of persons such that the first SVNN recognizes the first person, second SVNN recognizes the second person and so on. During the process of the training, the first SVNN is trained using the features corresponding to the first person or in other words, the features of the first person are kept as the positive samples, while all other samples are referred to as negative samples. Similarly, the features of the second person are considered as the positive samples and the features of all other persons are used as negative samples, which is used to train the second SVNN such that the second SVNN is trained using the features of the second person. The process is repeated, where the features of third person are used to train the third SVNN and so on. Finally, the features of the $(n-1)$ th person are used to train the $(n-1)$ th SVNN. Thus, during the testing process, the first SVNN recognizes the first person P_1 , second SVNN recognizes the second person P_2 and finally, the $(n-1)$ th SVNN recognizes the $(n-1)$ th person, and if any of the $(n-1)$ th SVNN does not recognize the person, it ensures that the person is the n th person.

3.4a Architecture of SVNN classifier: The architecture of the SVNN is depicted in figure 3. The SVNN comprises the

Figure 3. Architecture of the MSVNN classifier.

input layer, hidden layer and the output layer. The features from the ear or the finger vein are fed to the input layers and the training is carried out. The output from the MSVNN is the ‘ n ’ number of outputs that are the score value of the ‘ n ’ number of persons. The score value provided by the SVNN ensures recognition of the person. The features corresponding to a person gaining maximum score value are authenticated. Figure 4 depicts the working principle of the SVNN classifier.

The output of the SVNN is given as

$$O_i^{\mathfrak{R}} = \left[w_2 \times \log \text{sig} \left[\left(\sum_{\substack{m=1 \\ \mathfrak{R} \in \{E_i, V_i\}}}^k f_m^{\mathfrak{R}} \times w_m^1 \right) + b_1 \right] + b_2 \right] \quad (19)$$

where $\mathfrak{R} = \{E_i, V_i\}$. The weights of the input layer are

$$w_m^1 = \{w_1^1, w_2^1, \dots, w_k^1\} \quad (20)$$

where, $w_1^1, w_2^1, \dots, w_k^1$ denote the weights of the individual input layers and k denotes the total number of input

Figure 4. Architecture of SVNN.

features. The value of k is 255 when the ear features are used to train the SVNN classifier, and the value of k is 625 when the finger vein features are employed for training the SVNN. The input features are denoted as f_m , and the value range of m is $(1 \leq m \leq k)$; w_2 and b_2 are, respectively, the weight and bias of the output layer.

a) Training the SVNN using Genetic Algorithm (GA)

The main aim of the training is to determine the optimal weights to train the SVNN classifier and the steps are briefed here.

Initialization: The weights are initialized in the first step; the weights are given as w_τ , where τ represents the total number of chromosomes and the optimal weights are determined based on the GA concept [31–34].

Fitness computation: The fitness of the individual chromosomes is selected based on the accuracy or minimum error value. The chromosomes are ranked and the best-ranked chromosomes are selected for the generation of the new population. The fitness is given in Eq. (23).

Generation of new population based on crossover: The parents are selected randomly based on their rank and the new population is generated. The process is repeated until the optimal weights are found.

3.5 Optimal score level fusion using the scores obtained using the MSVNN classifier

In the multimodal system, the features extracted from the two modalities, such as ear and finger vein, are used to train the MSVNN and score values obtained are fused together using the optimal score weights. The score level fusion enables better recognition of the person with a better accuracy.

$$O_i^{final} = \alpha O_i^E + \beta O_i^V \quad (21)$$

where, α and β are the score weights and they are determined optimally using the proposed GwPeSOA. The output O_i^{final} is the score value of the i th person and it should be maximum for recognition.

3.5a Testing phase to identify the person: Whenever a new person requires to be authenticated, the MSVNN classifier matches the features of the person with the features in the database and provides a score value individually using the ear image and the finger vein image. The features obtained from ear and finger vein are matched to the entire database to yield the corresponding score values. The score values obtained using the two modalities are fused together using the optimal weights to yield the final score value. The score values of the proposed classifier for all the persons are compared; the person who attained the maximum score value during the feature matching using the proposed MSVNN is finalized as the incoming person and is authenticated.

$$O_i^{final} = \arg \max_i (O_i^{final}) \quad (22)$$

3.6 Optimal fusion scores using the proposed GwPeSOA

The proposed GwPeSOA is the proposed optimization algorithm developed based on the Glowworm Swarm Optimization (GSO) [35] and the PeSOA [36]. The advantage of the proposed algorithm is that it inherits the merits of both the optimizations. The GSO is modified with the PeSOA in the position update step of the GSO. The convergence is faster and is adaptive. The advantage of the GSO [35] over the other optimization algorithms is that it is adaptive to the local-decision domain that effectively locates the optimal solution. The GSO algorithm begins the search mechanism through the distribution of the swarm of agents randomly in search space. Glowworms possess luciferin, a pigment that emits luminance, and this is used as the fitness measure. In other words, the glowworms follow the other neighbouring glowworms with greater intensity, for which the glowworms use the probabilistic mechanism. The level of luciferin in the glowworm does not reduce with increasing distance, which is the assumption of the GSO. For identifying the neighbours, the glowworm uses the adaptive neighbourhood approach that is based on the local-decision domain. Thus, the decision for movement of the glowworm is based on the local-decision domain and selective neighbour interaction that ensures the formation of the glowworm subgroups to attain the objective function. The meta-heuristic, called PeSOA [36], is based on the hunting mechanism of the penguins. The penguins dive in different directions until they have oxygen reserves; the purpose of dive is to locate the availability of food and they gather together in an iceberg to

share the availability of the food so that they feed on the food. The significance of the PeSOA is that the optimization is robust and it provides a simple balance between the global and local minima even in large-sized penguin groups.

3.6a Solution encoding: The solution encoding aims to picture the solution vector of the proposed algorithm. The score weights α and β are tuned optimally using the proposed algorithm such that the optimal fusion of the features enables better recognition of the person. The solution vector is of dimension $[1 \times 2]$.

3.6b Objective function: The objective function aims at the maximum value and the objective function depends on the eigenvalues [37], regularization factor and the error. The error defines the accuracy factor and it is obtained as the difference between the network output and the ground value. The maximum value of the fitness provides the best score value and the person is authenticated. The objective function is given as

$$F_i = \lambda_{\max} + \lambda_{\min} + \frac{cr}{U} \quad (23)$$

where $\lambda = \text{eigen}(w \times w^T)$.

$$\lambda_{\max} = \max(\lambda) \quad (24)$$

$$\lambda_{\min} = \min(\lambda) \quad (25)$$

where c is the regularization factor, U is the cardinality of the training dataset and r is calculated based on the accuracy as given by the relation

$$r = \|O_i - T\|^2 \quad (1 \leq i \leq n) \quad (26)$$

where O_i indicates the output of the i th person obtained using the MSVNN and T denotes the ground truth.

3.6c Algorithmic steps of the proposed GwPeSOA: The algorithmic steps of the proposed GwPeSOA are discussed in this section. The assumption made is that the luciferin (L_0) present in the beginning of the optimization is the same for all the glowworms present in the population and the algorithm includes three phases: luciferin update phase, movement phase and neighbourhood range update phase.

1. Initialization: The population of the glowworms is initialized in the first step as

$$Q = \{Q_1, Q_2, \dots, Q_a\} \quad (27)$$

where a is the total number of the glowworms present in the population.

2. Luciferin update phase: The luciferin update is based on the function value of the individual glowworms. During the luciferin update in the current phase, the luciferin level in the previous iteration is added to the luciferin level of the current iteration such that the so-obtained luciferin quantity

is directly proportional to the objective function of the present iteration. The luciferin level decays with the iteration. The luciferin update is given as

$$L_u^{t+1} = (1 - \gamma) L_u^t + \kappa F[z_u^{t+1}] \quad (28)$$

where L_u^t is the luciferin level of the u th glowworm at the t th iteration, γ denotes the decay constant and the value of the decay constant lies between 0 and 1. The luciferin enhancement constant is notated as κ . $F[z_u^{t+1}]$ is the fitness function of the u th glowworm at the $(t + 1)$ th iteration.

3. Movement phase: The probabilistic mechanism is employed by the glowworms that select the glowworm with higher luciferin and follow them. The probability of the u th glowworm to move towards the v th glowworm is given by

$$\rho_{u,v}^t = \frac{L_v^t - L_u^t}{\sum_{K \in N_u^t} (L_K^t - L_u^t)} \quad (29)$$

where $v \in N_u^t$. The neighbours of the u th glowworm at time t is given by

$$N_u^t = \left\{ v : \hat{d}_{u,v}^t < v_u^t ; L_u^t < L_v^t \right\} \quad (30)$$

where $\hat{d}_{u,v}^t$ denotes the Euclidean distance between the u th and the v th glowworm at time t and v_u^t denotes the variable neighbour range of the u th glowworm at time t . The position update equation of the GSO is given by the relation

$$z_u^{t+1} = z_u^t + l \left(\frac{z_v^t - z_u^t}{\|z_v^t - z_u^t\|} \right). \quad (31)$$

The position update step is modified using the PeSOA and the modified position update equation is discussed here. The newly obtained position update equation offers better convergence and converges to the optimal global solution. Equation (31) is rearranged as

$$z_u^t = z_u^{t+1} - l \left(\frac{z_v^t - z_u^t}{\|z_v^t - z_u^t\|} \right) \quad (32)$$

where $\|\cdot\|$ denotes the Euclidean norm operator, and the step size is denoted as l ; z_u^t is the position of the u th glowworm at time t and z_u^{t+1} is the position of the u th glowworm at the next iteration. The position update equation of the PeSOA is given as

$$z_u^{t+1} = z_u^* + R|z_d - z_u^t|. \quad (33)$$

When $(z_d > z_u^t)$, $|z_d - z_u^t| = z_d - z_u^t$; therefore, Eq. (33) yields

$$z_u^{t+1} = z_u^* + R(z_d - z_u^t). \quad (34)$$

On substituting Eq. (32) in Eq. (34), it becomes

$$z_u^{t+1} = z_u^* + R \left(z_d - z_u^{t+1} + l \left(\frac{z_v^t - z_u^t}{\|z_v^t - z_u^t\|} \right) \right), \quad (35)$$

$$z_u^{t+1} = z_u^* + R z_d - R z_u^{t+1} + R \times l \left(\frac{z_v^t - z_u^t}{\|z_v^t - z_u^t\|} \right), \quad (36)$$

$$z_u^{t+1} + R z_u^{t+1} = z_u^* + R z_d + R \times l \left(\frac{z_v^t - z_u^t}{\|z_v^t - z_u^t\|} \right), \quad (37)$$

$$z_u^{t+1} (1 + R) = z_u^* + R \left[z_d + l \left(\frac{z_v^t - z_u^t}{\|z_v^t - z_u^t\|} \right) \right], \quad (38)$$

$$z_u^{t+1} = \frac{1}{(1 + R)} \left\{ z_u^* + R \left[z_d + l \left(\frac{z_v^t - z_u^t}{\|z_v^t - z_u^t\|} \right) \right] \right\}. \quad (39)$$

The position update equation of the proposed GwPeSOA is given by Eq. (39).

4. Update the range of the neighbourhood: The range of the individual glowworm is dynamic because when the glowworms depend on the local information for their movement, the number of the peaks attained is a function of the radial sensor range. If the sensor range of all the glowworms covers the entire search space, all the glowworms converge at the global optima rather than the local minima. Thus, the adaptive neighbourhood is used to identify the peaks in the multimodal function. The neighbourhood is updated based on the relation

$$v_u^{t+1} = \min \{ v_{\varpi}, \max \{ 0, v_u^t + \aleph(\chi - N_u^t) \} \} \quad (40)$$

where $\aleph$ is a constant and χ is the parameter that controls the neighbours. Thus, γ , κ , ϖ , $\aleph$, χ and L_o are the control parameters in the algorithm.

5. Termination: The steps are repeated until the maximum number of iterations.

Algorithm 1 explains the proposed GePeSOA, which aims at determining the optimal position of the glowworm. The glowworm follows the other glowworms that possess greater brightness. The best position obtained using the proposed optimization offers the optimal weights for the effective feature fusion.

Algorithm 1. Pseudo-code of the proposed GwPeSOA.

GwPeSOA	
1	Input: Glowworm population
2	Output: Global optimal position of Glowworm, z_u^{t+1} (Tuning optimal weights)
3	Begin
4	Read the control parameters: $\gamma, \kappa, \varpi, \aleph, \chi$ and L_o
5	*/Population initialization.*/
6	For ($u \leq a$)
7	{
8	Update L_o and $v_u' = 0$.
9	}
10	For ($u \leq \text{max. no. of iterations}$)
11	{
12	Update L_u^{t+1} .
13	}
14	For the u th glowworm
15	{
16	$N_u' = \{v: \partial_{u,v}' < v_u'; L_u' < L_v'\}$
17	For the v th glowworm, $v \in N_u'$.
18	{
19	$\rho_{u,v}' = \frac{L_v' - L_u'}{\sum_{K \in N_u'} (L_K' - L_u')}$
20	$z_u^{t+1} = \frac{1}{(1+R)} \left\{ z_u^* + R \left[z_d + l \left(\frac{z_v' - z_u'}{\ z_v' - z_u'\ } \right) \right] \right\}$
21	$v_u^{t+1} = \text{Min} \{ v_\varpi, \max \{ 0, v_u^t + \aleph (\chi - N_u') \} \}.$
22	}
23	$t = t + 1$
24	}
25	End

4. Results and discussion

This section presents the results and discussion of the multimodal biometric recognition system and the comparative results are deliberated to prove the effectiveness of the proposed method.

4.1 Experimental set-up

The experimentation of the proposed technique of authenticating the person is done in a system with 2 GB RAM, an Intel core processor and Windows 10 Operating System. The technique is implemented using the software tool MATLAB.

4.2 Dataset description

For the experimentation, finger vein database from SDUMLA-HMT [38] and AMI ear database [39] are used. The AMI ear database is developed from the students, teachers and staff belonging to the Computer Science Department; the images are taken in an indoor environment and the database is obtained from 100 different subjects. Similarly, the SDUMLA-HMT database possesses the face images, finger vein images, gait videos, view angles, iris images and fingerprint images. The database includes real multimodal data from 106 individuals. The device employed to capture finger vein images is modelled by Joint Lab of Intelligent Computing and Intelligent Systems of Wuhan University. At the time of capturing the finger vein images, individuals gave the images of their index finger, middle finger and ring finger of both hands, and the collection for each of the 6 fingers is repeated 6 times to obtain 36 finger vein images for each volunteer. Therefore, the finger vein database is composed of 3,816 images.

4.3 Competing methods

The methods taken for comparing the performances with the proposed Ear (BICOM) + Finger Vein (RLT) with GwPeSOA-MSVNN are the Ear (SIFT) with MultiSVM [6], Ear(BICOM) with KNN [40], Finger vein (RLT) with DBN [23] and the Ear (LBP) with MultiSVM [9].

4.4 Performance metrics

The metrics used for the experimentation are described in this section, as follows.

4.4a Accuracy: It is the measure of correctness of the detection, given by the relation

$$TPR = \frac{TP + TN}{TP + FP + FN + TN} \quad (41)$$

where TP is true positive, TN is true negative, FN is false negative and FP is false positive.

4.4b Sensitivity: The sensitivity or the true positive rate (TPR) is defined as the number of positives identified correctly.

$$TPR = \frac{TP}{TP + FN}. \quad (42)$$

4.4c Specificity: The specificity or the true negative rate (TNR) is defined as the number of negatives identified correctly.

$$TNR = \frac{TN}{TN + FP}. \quad (43)$$

4.5 Comparative analysis

Figure 5 depicts a comparative analysis of accuracy, sensitivity and specificity of the methods using dataset 1 with the images of size 256×256 . The accuracy of the comparative methods is shown in figure 5a. When the training percentage is 0.9, the accuracy of the methods Ear (BICOM) + Finger Vein (RLT) with GwPeSOA-MSVNN, Ear (SIFT) with MultiSVM, Ear(BICOM) with KNN, Finger vein (RLT) with DBN and Ear (LBP) with MultiSVM is 0.92115, 0.8191, 0.8191, 0.8082 and 0.6644, respectively. The sensitivity of the comparative methods is shown in figure 5b. The sensitivity is analysed based on

the training percentage and the training percentages considered are 0.4–0.9. When the training percentage is 0.9, the sensitivity of the methods Ear (BICOM) + Finger Vein (RLT) with GwPeSOA-MSVNN, Ear (SIFT) with MultiSVM, Ear(BICOM) with KNN, Finger vein (RLT) with DBN and Ear (LBP) with MultiSVM are 0.9202, 0.9081, 0.8581, 0.8578 and 0.8542, respectively. The specificity of the comparative methods is shown in figure 5c. The specificity is analysed based on the training percentage and the training percentages taken are 0.4–0.9. When the training percentage is 0.9, the specificity of the methods Ear (BICOM) + Finger Vein (RLT) with GwPeSOA-MSVNN, Ear (SIFT) with MultiSVM,

Figure 5. Analysis using database1 with images of size 256×256 based on (a) accuracy, (b) sensitivity and (c) specificity.

Ear(BICOM) with KNN, Finger vein (RLT) with DBN and Ear (LBP) with MultiSVM are, respectively, 0.9545, 0.8993, 0.8948, 0.8948 and 0.8945. Thus, it is clear from figure 5 that the accuracy, sensitivity and specificity increase with the increase in the training percentages and it is evident that the proposed method attains greater values.

Figure 6 depicts a comparative analysis of accuracy, sensitivity and specificity of the methods using dataset 1 with images of size 128×128 . The accuracy analysis result is plotted in figure 6a, for the competing methods. When the training percentage is 0.9, the accuracy of the methods Ear (BICOM) + Finger Vein (RLT) with

GwPeSOA-MSVNN, Ear (SIFT) with MultiSVM, Ear(BICOM) with KNN, Finger vein (RLT) with DBN, and Ear (LBP) with MultiSVM are 0.95, 0.9337, 0.8444, 0.8331 and 0.6771, respectively. The sensitivity of the comparative methods is shown in figure 6b. When the training percentage is 0.9, the sensitivity of the methods Ear (BICOM) + Finger Vein (RLT) with GwPeSOA-MSVNN, Ear (SIFT) with MultiSVM, Ear(BICOM) with KNN, Finger vein (RLT) with DBN and Ear (LBP) with MultiSVM are, respectively, 0.95, 0.9263, 0.9190, 0.8765 and 0.8762. The specificity of the comparative methods is shown in figure 6c. The specificity is analysed based on the training percentage and the training percentages taken are

Figure 6. Analysis using database1 with images of size 128×128 based on (a) accuracy, (b) sensitivity and (c) specificity.

0.4–0.9. When the training percentage is 0.9, the specificity of the methods Ear (BICOM) + Finger Vein (RLT) with GwPeSOA-MSVNN, Ear (SIFT) with MultiSVM, Ear(BICOM) with KNN, Finger vein (RLT) with DBN and Ear (LBP) with MultiSVM are 0.9868, 0.93, 0.9292, 0.9253 and 0.9251, respectively. Thus, it is clear from figure 6 that the accuracy, sensitivity and specificity of the proposed method attain better values.

Figure 7 depicts a comparative analysis of accuracy, sensitivity and specificity of the methods using dataset 2 with the images of size 256×256 . Figure 7a pictures the accuracy analysis graph. When the training percentage is 0.9, the accuracy of the methods Ear (BICOM) + Finger Vein (RLT) with GwPeSOA-MSVNN, Ear (SIFT) with

MultiSVM, Ear(BICOM) with KNN, Finger vein (RLT) with DBN and Ear (LBP) with MultiSVM are 0.9215, 0.8995, 0.8849, 0.8182 and 0.485, respectively, as depicted in figure 7a. The sensitivity of the comparative methods is shown in figure 7b. When the training percentage is 0.9, the sensitivity of the methods Ear (BICOM) + Finger Vein (RLT) with GwPeSOA-MSVNN, Ear (SIFT) with MultiSVM, Ear(BICOM) with KNN, Finger vein (RLT) with DBN and Ear (LBP) with MultiSVM are 0.9202, 0.9036, 0.8941, 0.8542 and 0.8161, respectively. The specificity of the comparative methods is shown in figure 7c. The specificity is analysed based on the training percentage and the training percentages considered are 0.4–0.9. When the training percentage is 0.9, the specificity of the methods Ear

Figure 7. Analysis using database2 with images of size 256×256 based on (a) accuracy, (b) sensitivity and (c) specificity.

(BICOM) + Finger Vein (RLT) with GwPeSOA-MSVNN, Ear (SIFT) with MultiSVM, Ear(BICOM) with KNN, Finger vein (RLT) with DBN and Ear (LBP) with MultiSVM are 0.9441, 0.8993, 0.8984, 0.8978 and 0.8947, respectively. Thus, it is clear from figure 7 that the proposed method has better accuracy, sensitivity and specificity than that of the other techniques compared.

Figure 8 depicts a comparative analysis of accuracy, sensitivity and specificity of the methods using dataset 2 with the images of size 128×128 . Figure 8a presents an accuracy analysis plot of the comparative methods. When the training percentage is 0.9, the accuracy of the methods

Ear (BICOM) + Finger Vein (RLT) with GwPeSOA-MSVNN, Ear (SIFT) with MultiSVM, Ear(BICOM) with KNN, Finger vein (RLT) with DBN and Ear (LBP) with MultiSVM are 0.95, 0.9418, 0.9273, 0.9123 and 0.5, respectively. The sensitivity of the comparative methods is shown in figure 8b. When the training percentage is 0.9, the sensitivity of the methods Ear (BICOM) + Finger Vein (RLT) with GwPeSOA-MSVNN, Ear (SIFT) with MultiSVM, Ear(BICOM) with KNN, Finger vein (RLT) with DBN and Ear (LBP) with MultiSVM are, respectively, 0.95, 0.94, 0.9331, 0.9229 and 0.9133. The specificity of the comparative methods is shown in figure 8c. When the

Figure 8. Analysis using database2 with images of size 128×128 based on (a) accuracy, (b) sensitivity and (c) specificity.

Figure 9. ROC curve.

training percentage is 0.9, the specificity of the methods Ear (BICOM) + Finger Vein (RLT) with GwPeSOA-MSVNN, Ear (SIFT) with MultiSVM, Ear(BICOM) with KNN, Finger vein (RLT) with DBN and Ear (LBP) with MultiSVM are 0.9363, 0.93, 0.9296, 0.9290 and 0.9284, respectively. Thus, it is obvious from figure 8 that the metrics increase with the increase in the training percentages and it is clear that the proposed method attains greater percentages of specificity.

Figure 9 depicts the ROC curve of the methods like the Ear (BICOM) + Finger Vein (RLT) with GwPeSOA-MSVNN, Ear (SIFT) with MultiSVM, Ear (BICOM) with KNN, Finger vein (RLT) with DBN and Ear (LBP) with MultiSVM. When the false positive rate (specificity) is at a minimum value of 0.1, the *TPR* (sensitivity) is 0.9.

4.6 Comparative discussion

Table 1 shows a comparative analysis of the recognition methods. The accuracy, sensitivity and specificity of the proposed method are better than those of all other methods with both the datasets. The accuracy of the proposed method is 0.95 for both the datasets. Similarly, the specificity and sensitivity of the proposed method are 0.94, 0.9868 and 0.95, 0.9363, respectively, for the two datasets. It is clear that the proposed method of multi-modal recognition offers better recognition accuracy when compared with the other methods. The accuracies of the existing methods Ear (SIFT) with MultiSVM, Ear (BICOM) with KNN, Finger vein (RLT) with DBN and Ear (LBP) with MultiSVM are 0.9337, 0.8444, 0.8331 and 0.6771, respectively, for dataset 1, which are low compared with that of the proposed method of recognition. In addition, the results convey that the person recognition using the multiple modalities is highly accurate and effective.

5. Conclusion

The proposed method of recognition using the multiple modalities is effective and the work employed the ear and the finger vein images. The proposed method of GwPeSOA-MSVNN is employed to identify and authenticate the person. The proposed method of recognition using the ear and the finger vein images is subjected to feature extraction using the proposed BiComp and the repeated line tracking. The features are generated individually and fed to the proposed classifier for classification, and the role of the classifier is to authenticate the person. This method proves to be effective as the other modalities, such as face, fingerprint and so on, fade with age, whereas ear finger vein

Table 1. Comparative discussion using the methods.

Training percentage = 0.9				
Methods		Accuracy	Specificity	Sensitivity
Dataset 1				
(Image size 128×128) Proposed Ear (BICOM) + Finger Vein (RLT) with GwPeSOA-MSVNN		0.95	0.986808	0.94
Ear (SIFT) with MultiSVM		0.933761	0.93	0.926377
Ear (BICOM) with KNN		0.844444	0.929278	0.919048
Finger vein (RLT) with DBN		0.833197	0.92537	0.876587
Ear (LBP) with MultiSVM		0.677165	0.925104	0.876263
Training percentage = 0.9				
Dataset 2				
(Image size 128×128) Proposed Ear (BICOM) + Finger Vein (RLT) with GwPeSOA-MSVNN		0.95	0.936333	0.95
Ear (SIFT) with MultiSVM		0.94181	0.93	0.94
Ear (BICOM) with KNN		0.927381	0.929636	0.933188
Finger vein (RLT) with DBN		0.912302	0.929085	0.92299
Ear (LBP) with MultiSVM		0.5	0.928475	0.913367

images offer robust features for classification. The experimentation is performed using two datasets and proves that the multimodal recognition system has good accuracy. The proposed method attained a better accuracy, specificity and sensitivity at the rate of 0.95, 0.95 and 0.9868, respectively. The proposed method overcomes most of the issues that arise in the single modality recognition system and the multimodality is found to be effective in recognizing the persons.

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