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Fingerprint Intramodal Biometric System Based on ABC Feature Fusion

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Unimodal biometrics system (UBS) drawbacks include noisy data, intra-class variance, inter-class similarities, non-universality, which all affect the system's classification performance. Intramodal fingerprint fusion can overcome the limitations imposed by UBS when features are fused at the feature level as it is a good approach to boost the performance of the biometric system. However, feature level fusion leads to high dimensionality of feature space which can be overcame by Feature Selection (FS). FS improves the performance of classification by selecting only relevant and useful information from extracted feature sets being an optimization problem. Artificial Bee Colony (ABC) is an optimizing algorithm that has been frequently used in solving FS problems because of its simple concept, use of few control parameters, easy implementation and good exploration characteristics. ABC was proposed for optimized feature selection prior to the classification of Fingerprint Intramodal Biometric System (FIBS). Performance evaluation of ABC-based FIBS showed the system had a Sensitivity of 97.69% and RA of 96.76%. The developed ABC optimized feature selection reduced the high dimensionality of features space prior to classification tasks thereby increasing sensitivity and recognition accuracy of FIBS.

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1. INTRODUCTION

Person authentication utilizing biometric features is commonly employed in today's security access control systems. Many countries are threatened by the existing level of insecurity, as well as the rapid increase in crime rates in a world where all tasks tend to become automatic. Identification/verification of genuine persons has become a crucial task for security in border controls, voting system, examination hall access, public or virtual sites access, and transportation system. All of the systems outlined above, which require protection against criminal activities, have increased the development of biometrics as an authentication tool for security [1].

Biometrics is pattern recognition process that uses physiological or behavioral traits of a person for authentication [2]. Physiological traits such as hand vein, ear, hand geometry, fingerprint, face, retina, iris and palmprint are used as measurements from the human body. Also, behavioral traits such as gait, keystroke, voice and signature are active measurements from human actions [3]. Fingerprint is one of the most used biometrics trait for identification and verification systems because of it distinctiveness and permanence over time [4]. Biometric systems have more advantages compared to conventional authentication systems, because a person does not have to carry credit cards or remember passwords which are either what you have-based or what you know-based [5,6].

Unimodal biometrics system (UBS) relies on single biometric information for authentication. UBS developed using fingerprints are faced with limitations such as: noise in sensed data, non-universality, intra-class variation, inter-class similarities, and spoof attacks [7]. These limitations increase the False Positive Rate (FPR) and False Negative Rate (FNR), resulting to poor performance of the biometric system [8]. It is therefore obvious that UBS is insufficient for achieving the needed performance in real-time applications, particularly the system that require robust authentication. Multibiometrics is the combination of multiple sources of biometric information for precise authentication and it is frequently regarded as a means of overcoming some of the limits of a UBS [6].

In multibiometric system, feature fusion can be put to use to merge retrieved features from the same modality (intramodal) or different modalities (intermodal). Fusion at feature level results to a curse of dimensionality due to the huge size of the integrated feature vector and may contain irrelevant or redundant information. Moreover, large feature vector also raises cost of storage and classification time [7]. Feature selection technique aids the reduction of the effect of high dimensionality by finding optimal relevant features and rejecting the irrelevant ones. This is to minimise the dimensionality of the intake to the classification stage and improve the performance of the multibiometric system. Nature inspired algorithms can be used at feature selection stage [9]. Honey bees foraging behavior influenced Artificial Bee Colony (ABC), a population-based search algorithm. Strong robustness, fast convergence and high adaptability are the advantages of ABC algorithm [10].

The objectives of this study are to extract texture features from locally acquired multiple instances of fingerprints, fused the features at feature selection stage using ABC to have an improved performance of Fingerprint Intramodal Biometric System (FIBS) and evaluate the performance of the implemented algorithm using Sensitivity, Recognition Accuracy, FPR, FNR and Recognition Time.

1.1 Theorectical Background

Fusion is a technique for combining of evidence from multiple biometric data. Biometric fusion refers to the process of combining data from two or more biometric sources which are divided into two: pre-mapping fusion and post-mapping fusion. Fusion at Sensor level and feature level are two types of pre-mapping fusion [11]. Sensor level fusion integrates raw data from two or more sensors measuring the same or distinct biometric features. Feature Level Fusion is the process of combining the features that are generated from raw data into a single feature set that is being sent to the classification stage

Fusion at feature level can be performed during the feature extraction or feature selection stages [12]. Fusion can be accomplished at the feature extraction stage using weighted summation or feature concatenation methods, and at the feature selection stage using nature-inspired algorithms [9].

Score level and Decision level fusion are the two basic categories of post-mapping fusion (Praveen and Tessamma, 2012). The features from various biometric data are processed separately in Score level fusion, and an individual matching score is discovered. To get a new match score, the match scores from various biometric matchers are merged. Each modality is pre-classified independently in decision level fusion, and then the final classification is based on the fusion of the outputs of the several classifiers [9].

Feature-level fusion model includes 2 layers: intra-modal and inter-modal, respectively. In both cases the fusion is based on a functional combination of the feature vectors, preserving the dimensionality as resulted from the feature space transforms and feature selection operations. The intermodal fusion technique combines feature sets from various biometrics to create a single feature vector that incorporates all of the information needed for many human traits. Multimodal systems use this fusion [13].

Intramodal feature fusion is a technique for combining extracted feature subsets from many algorithms, samples, sensors, or instances obtained from the same biometric modality (human trait) [13]. In comparison to unimodal biometric systems, a multi-instance biometric system based on intramodal feature fusion provides numerous advantages [14,15].

Fusion at feature level results to a curse of dimensionality due to the huge size of integrated feature vector and may contain irrelevant or redundant information. Moreover, large feature vector also raises cost of storage and classification time [7]. Feature selection technique aids the reduction of the effect of high dimensionality by finding optimal relevant features and rejecting the irrelevant ones. This is to minimize the dimensionality of the intake to the classification stage and improve the performance of the multibiometric system. Nature inspired algorithms can be used at feature selection stage [9].

Feature selection is the process of selecting the most relevant features from a set of features that form patterns in a dataset. Irrelevant and redundant data in a dataset can have a negative impact on the performance of a biometric system. The subset should be able to describe target concepts while still accurately representing the original features. The purpose of feature subset selection is to reduce the computational complexity of a high-dimensional dataset by reducing the number of features used to characterize it, in order to improve the performance of a learning algorithm on a particular task [16].

The process of feature selection is an NP-hard problem since it requires selecting an optimal subset of features without losing classification quality. Meta-heuristics are one of the most effective methods for determining the best subset of features in the shortest period of time [17]. For feature selection, swarm intelligent algorithms (SI), a type of meta-heuristic technique, was applied. The algorithms address an optimization problem and search for the best solutions across a number of iterations using primitive mechanisms and procedures [18].

The algorithms begin with a population of random solutions and improve their optimality with each iteration step. Most meta-heuristic algorithms start by randomly generating a set of initial solutions, and then using a fitness function to determine the optimality of the generated population's individual solutions. A new generation of production will begin if none of the termination criteria are met. This cycle continues until one of the termination criteria has been met [19,20].

ABC is a population-based, nature-inspired algorithm that mimics honey bee swarm foraging behavior. Almost every field today prefers the ABC optimization technique for artificial intelligence challenges. It is an extremely effective global optimization strategy. In order to maximize the amount of nectar stored in the hive, each bee in the colony has a specific role. ABC has been widely used in numerical domain and feature selection optimization because of its ease of implementation, flexibility, ease of conversion to other methods, and rapid convergence [21].

The employed bee phase, selection probabilistic step, onlooker bee phase, and scout bee phase are the major components of the ABC method. The ABC method has the advantage of having fewer parameters, which are the number of food sources (SN): this equals the Number of Employed bees (NE) or Number of Onlooker bees (NO), and the number of trails after which the food source is presumed to have abandoned is determined using parameter limit. The sole constraint considered in the ABC algorithm is that the number of employed bees is equal to the number of food sources, that is, one employed bee for each food source. Fig. 1 illustrate the ABC flowchart.

Individual initialization begins with randomly created food sources for all employed bees. The position of food source i^{th} that corresponds to the solutions in the search space are represented as $X_i = (x_{i1}, x_{i2}, ..., x_{iD})$, and is produced by Equation (1).

$$x_{ij} = lb_j + rand \times (ub_j - lb_j) \quad (1)$$

where i = 1, 2, …, SN, j = 1, 2, …, D. The number of food sources is SN, and the dimension of the search space is D; rand is a random number in the range of [0, 1] and ub_j and lb_j are the upper and lower bounds for the j^{th} dimension respectively. Food sources are randomly assigned to bees, then employed and onlooker bees are supposed to exploit food sources, while the scout bee is supposed to explore new sources.

During the employed bee phase, each employed bee exploits a new solution in the nearby area of the food source of its current position, based on local information stored in their memory, and then assesses its quality (fitness). Equation (2.2) is used to exploit a new food supply.

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \quad (2)$$

Here v_i is the new food source in the region of x_i; k ∈ 1, 2, …, SN where k ≠ i and $j \in 1,2,...,D$ are randomly picked values. ϕ_{ij} is uniformly distributed random number between –1 and 1. After generating v_i, for a minimization problem, a fitness value fit_i related to i^{th} bee food source is defined as follows:

$$fit_i = \begin{cases} 1/(1+f_i), if\ f \geq 0 \\ 1 + abs(f_i),\ if\ f < 0 \end{cases} \quad (3)$$

After obtaining the new solution, a greedy selection mechanism is used to choose between the old and new candidate solutions, that is, x_i and v_i; the better one is then chosen based on fitness values, while the rest is discarded. If the source at v_i is more profitable than the previous one x_i, the employed bee remembers the new one and forgets the old one. Aside from that, the former position is retained.

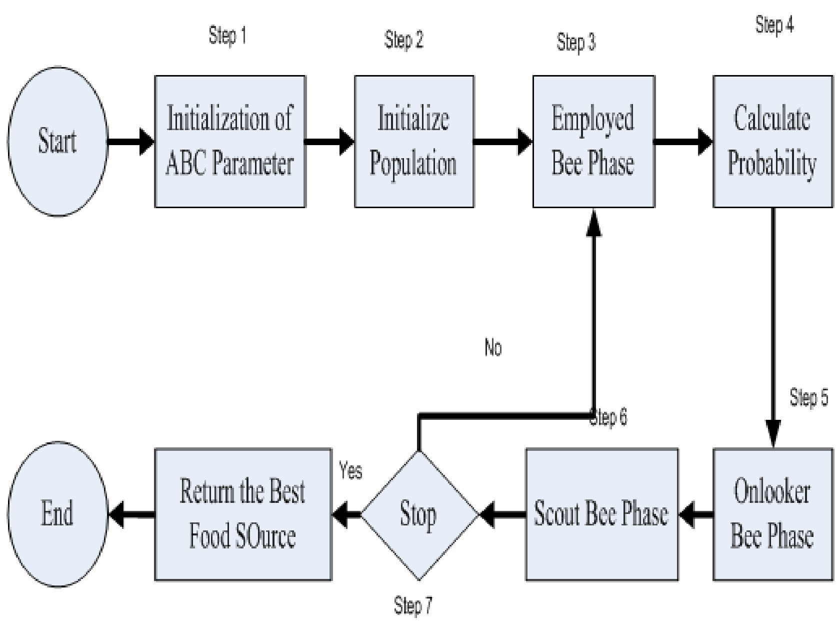

Fig. 1. Flowchart of artificial bee colony (Source: [22]

When all of the employed bees have finished foraging, they carry out various dances to communicate nectar amounts and the location of their sources to the observer bees on the dance floor [23]. An onlooker bee attentively watches the nectar information from all employed bees and chooses a food source location with a probability proportionate to its nectar amount, and this probabilistic selection is based on population fitness values. The roulette wheel fitness-based selection strategy was implemented in ABC.

Scout bees search for new food sources when one cycle of this cyclic process is completed, that is, after all employed and onlooker bees have completed their searches; the algorithm is designed to assess if any exhausted food sources need to be abandoned. A bee's abandoned food supply is replaced by a scout's discovery of a new food source. This is accomplished by creating a site location at random and then replacing it with an abandoned one. This procedure is equivalent to the process of introducing new food sources to a worker bee.

1.2 Review of Related Works

Krishneswari and Arumugam [24] proposed fusion at feature level for palmprint verification and identification system using the combination of two palmprint features. Using a Particle Swarm Optimization (PSO) based feature fusion technique backed by Principal Component Analysis (PCA), the extracted texture and Line features from the preprocessed palmprint images were fused. Aranuwa [4] developed a Fingerprint Recognition System (FRS) using multiple representation based on minutiae and texture representations for reliable and efficient FRS. The image enhancement and texture features extraction were done using Fourier Fingerprint Transform (FFT) and Spatial Grey Level Dependence Matrix (SGDLM) approach respectively. The minutia matching and fusion were carried out utilizing the Rutovitz concept of crossing number algorithm matching score level using linear summation rule technique accordingly. The texture-based algorithms outperform the minutiae-based algorithms in terms of speed. Latha and Prasad [8] presented intramodal palmprint recognition using texture feature. Preprocessing, feature extraction, feature fusion, and matching were all part of the proposed system, which had a database size of 7752. The Haralick, 2D-Gabor, and 2D-log Gabor filters were used to retrieve texture feature from the palmprint. By concatenating the extracted features, the three extracted features were fused at the feature level. The palmprint verification was carried out by using the Pearson correlation coefficient to apply the matching algorithm to the input palmprint image and the palmprints in the database. The results demonstrated that the created intramodal feature fusion increased the performance of a palmprint recognition system compared to Haralick, Gabor, and log-Gabor approaches.

Alasadi and Jaffar [25] presented Fingerprint Verification System based on Active Forgery Techniques. There are four groups of images in the database. Each database contains images of eighty (80) different fingers, each with eight (8) fingerprint impressions. For reducing the time consuming, the eight images for each person were merged into one image. Scale Invariant Feature Transform (SIFT) was used for representation and extraction of features. After that, Random Sample Consensus (RANSAC) algorithm was used for determining the matching area exactly. A matching was performed for each keypoint with the nearest neighbor correspondent by measuring Euclidean distance. Experimental result of 92% sensitivity and 86% of recognition accuracy was obtained.

In Schiezaro and Pedrini [26], an ABC-based data feature selection was proposed to improve the classification accuracy. In this method, when the feature selection problem was represented as a binary vector, the classification accuracy in the classifier was used as a fitness function. In Wang *et al.* [27], an ABC-based feature selection was proposed by integrating of multi-objective optimization algorithm with a sample reduction strategy. This proposed method both increased classification accuracy and reduced computational complexity. Hancer *et al.* 2018, presented a feature selection approach is proposed based on multi-objective artificial bee colony algorithm integrated with non-dominated sorting procedure and genetic operators. Two different implementations of the proposed approach are developed: ABC with binary representation and ABC with continuous representation. Their performance are examined on 12 benchmark datasets and the results are compared with those of linear forward selection, greedy stepwise backward selection, two single objective ABC algorithms and three well-known multi-objective evolutionary computation algorithms. The results show that the proposed approach with the binary representation outperformed the other methods in terms of both the dimensionality reduction and the classification accuracy. .

1.3 Research Gap

From these literatures, intramodal biometric system with fusion at feature level has achieved a better performance with a level of redundancy of features. However, existing fusion at feature level was done at the feature extraction (concatenation) and this led to high dimensionality of data which affect the classification sensitivity, accuracy, false error rate and recognition time of the biometric system. Fusion at the feature selection phase deals with the selection and combination of features to remove redundant and irrelevant features, the objective is to reduce the computational burden of feature concatenation by choosing optimal subsets of features from the original features extracted from each modality[6].

Also existing algorithms of feature selection for classification are often evaluated through classification accuracy. However, the sensitivity of algorithms is also an important consideration when developing feature selection methods. Developing algorithms of feature selection for classification with high classification accuracy and stability is still challenging [28]. This paper presents feature selection stage fusion using ABC to select features from extracted texture features from multiple instances of the locally acquired fingerprints to improve the sensitivity, accuracy, FPR, FNR and reduced recognition time of the biometric system.

2. RESEARCH METHODOLOGY

A fingerprint-based biometric system is a pattern matching system that determines the genuineness of a person's fingerprint. The biometric system includes stages such as image acquisition, pre-processing, extraction of features, feature fusion, and classification.

The image acquisition stage is the first step in any vision system. Hardware is required for image acquisition. It is at this stage that the multi-instance fingerprint biometric information database is created. The majority of the databases available online were taken in controlled environments and their images were aimed at a specific algorithmic goal. However, when the datasets used in the algorithms change due to variances in the conditions under which the images were acquired, the performance of biometric systems varies. This necessitates the creation of a fingerprint database that was collected in an uncontrolled environment.

The second stage is preprocessing, which is a set of image enhancement operations performed on the acquired fingerprint to increase the clarity of the print pattern structure and localize the prints grid. The accuracy of fingerprint identification is determined by the quality of the fingerprints and the effectiveness of the preprocessing mechanism. Image enhancing techniques include image cropping and downsizing to keep only the fingerprints Region of Interest (ROI). To reduce illumination effects, boost contrast, and improve visual quality, and also to generate a consistent histogram of the images, histogram equalization was used.

The quantify of minutiae, singularities, points, and textural qualities in terms of a set of descriptors or quantitative feature measurements, commonly referred to as a feature vector, is the basis of feature extraction. In this paper, texture-based features were retrieved from the fingerprint's central point using Discrete Cosine Transform (DCT). The feature selection procedure was then carried out using ABC algorithm, which comprises selecting a subset of features to improve classification performance on a training set of feature vectors.

Each unknown pattern is allocated to a class in the classification stage of any image-processing system. Back Propagation Neural Network (BPNN), a type of ANN, was adopted. BPNN Algorithm is a multi-layer feed forward, supervised learning network using the gradient descent learning rule, and it is a variant of the ANN.

2.1 Performance Evaluation Metrics

The aim of performance evaluation is to provide some quantitative metrics of biometric system efficiency. The performance metrics employed in this paper were sensitivity, RA, FPR, FNR, and RT. The percentage of correctly detected positive cases is known as sensitivity.

$$SEN = \frac{TP}{TP + FN} \tag{4}$$

The fraction of correct classifications over the total number of samples is known as recognition accuracy.

$$RA = \frac{TP + TN}{TP + FP + FN + TN} \quad (5)$$

False Positive Rate (FPR): This is the rate at which the system accepts an unauthorized user as a valid user, allowing an impostor to have access to the system

$$FPR = \frac{FP}{TN + FP} \quad (6)$$

False Negative Rate (FNR): This is the rate at which the system accepts an authorized individual as an imposter user, that is, when the system refuses to grant a legitimate person access to the system.

$$FNR = \frac{FN}{TP + FN} \quad (7)$$

where TP represent True Positive, which indicates to the number of images which have been classified as correct and are actually correct.

FP represents False Positive, which indicates to the number of images which have been classified as correct but are actually incorrect.

TN represent True Negative, which indicates to the number of images classified as incorrect or out of classification that are, in fact, incorrect or out of classification.

FN represents False Negative, which indicates to the number of images which have been classified as incorrect or out of categorization but are actually right [29].

The recognition time is the time it takes the system to recognize an image that has been tested.

3. RESULTS AND DISCUSSIONS

3.1 Evaluation of Result of FIBS using ABC Feature Selection

The evaluation results of FIBS for ABC as shown in Table 1 shows that the system had SEN of 97.91, 97.84, 97.76 and 97.69%, RA of 96.54, 96.59, 96.65 and 96.76%, FPR of 7.29, 6.88, 6.46 and 5.83%, FNR of 2.09, 2.21, 2.24 and 2.31% and RT of 280, 297, 282 and 216sec, respectively at the different thresholds.

3.2 Results of Unimodal Biometric System

Table 2 showed UBS at the different thresholds that the system had SEN of 96.04, 95.97, 95.90 and 95.82%, RA of 93.79, 93.85, 93.90 and 94.01%, FPR of 12.50, 12.08, 11.67 and 11.04%, FNR of 3.96, 4.03, 4.10 and 4.18 % and RT of 142, 108, 126 and 166s, respectively. At the threshold values, the sensitivity increased by 1.87, 1.87, 1.86, and 1.87%, RA increased 2.75, 2.74, 2.75, and 2.75%, FPR reduced by 5.21, 5.2, 5.21, and 5.21%, FNR reduced by 1.87, 1.82, 1.86, and 1.87% and RT increased by 138, 189, 156, and 50s, respectively for ABC-based FIBS with respect to UBS values.

Table 1. Results of FIBS using ABC-Based feature selection

Threshold	TP	FN	FP	TN	SEN (%)	RA (%)	FPR (%)	FNR (%)	RT (Sec)
0.2	1312	28	35	445	97.91	96.54	7.29	2.09	280
0.35	1311	29	33	447	97.84	96.59	6.88	2.21	297
0.5	1310	30	31	449	97.76	96.65	6.46	2.24	282
0.75	1309	31	28	452	97.69	96.76	5.83	2.31	216

Table 2. Results of UBS

Threshold	TP	FN	FP	TN	SEN (%)	RA (%)	FPR (%)	FNR (%)	RT (s)
0.2	1287	53	60	420	96.04	93.79	12.50	3.96	142
0.35	1286	54	58	422	95.97	93.85	12.08	4.03	108
0.5	1285	55	56	424	95.90	93.90	11.67	4.10	126
0.75	1284	56	53	427	95.82	94.01	11.04	4.18	166

From the results, sensitivity and recognition accuracy of the FIBS based on ABC feature selection was higher than that of UBS. This implied that FIBS had reduced feature space that contained relevant texture features used for classification than UBS. Also, feature selection of FIBS of the same biometric trait can increase the RA of a system in alignment with Adedeji *et al.,* 2019.

Also, FIBS using feature selection algorithm showed the system had reduced FPR and FNR. This showed that feature selection yielded minimum classification error by selecting optimal feature subsets which are significantly correlated within class but uncorrelated with other classes, resulting in a system with good prediction ability. The results obtained showed that the sensitivity increased by 5.69%, RA increased by 7.76%, respectively for ABC-based FIBS with respect to Alasadi and Jaffar [25] results. The RA increased by 16.76%, FPR reduced by 19.17%, FNR reduced by 17.69%, respectively for ABC-based FIBS with respect to Aranuwa [4] values. Also, there was 1.17% increase of accuracy for ABC-based FIBS with respect to Krishneswari and Arumugam [24] evaluation.

The reduced low recognition time of FIBS compared to UBS implied that feature selection resulted into reduce feature space due to the removal of redundant features that are not relevant for classification of the images thereby reducing its implementation time [4]. The results showed significant improvement between FIBS and UBS due to removal of redundant and irrelevant features in extracted features of fingerprint images using ABC. Integrating texture features of multiple instances of the same biometric trait using an effective feature selection scheme significantly gives better performance than single instances.

4. CONCLUSIONS

In this paper, ABC algorithm for feature selection of texture features extracted from multiple instances of fingerprint was used to improve the performance of fingerprint intramodal biometric system (FIBS). At the threshold values, the sensitivity increased by 1.87%, RA increased 2.75%, FPR reduced by 5.21%, FNR reduced by 1.87% and RT increased by 50s, respectively for ABC-based FIBS with respect to UBS values. The results showed significant improvement between FIBS and UBS in relation to sensitivity, recognition accuracy, FPR and FNR performance while reducing the number of features of the system. The improvements were due to removal of redundant and irrelevant features in extracted features of fingerprint images. However, FIBS based on ABC algorithm took more recognition time due to having more features to select and classify. Despite the fact that ABC is an effective algorithm, there is need for improvement in terms of exploitation capability by hybridizing ABC with local search algorithm to optimize feature selection in order to enhance sensitivity and accuracy of fingerprint intramodal biometric system.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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