CLONAL SELECTION ALGORITHM FOR FEATURE LEVEL FUSION OF MULTIBIOMETRIC SYSTEMS

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ABSTRACT: Multimodal biometric makes use of two or more biometric modalities to overcome some of the limitations of unimodal biometric system. Feature level fusion has been shown to provide a more secured recognition system with higher performance accuracy. However, associated with feature level fusion is the problem of high dimensionality of the combined feature, therefore in this paper, Discrete Wavelet Transform (DWT) is used for feature extraction while fusion is performed at the feature selection phase using Clonal Selection Algorithm (CSA). The performances of the bimodal systems indicate increase in recognition accuracy comparedto their unimodal counterparts.

KEYWORD: Biometrics, Fusion, Multimodal, Discrete Wavelet Transform, Clonal Selection Algorithm.

1. INTRODUCTION

The term biometrics can be seen as a scientific discipline which measure unique characteristics of individuals. Biometrics is the science of establishing the identity of an individual based on the physical, chemical or behavioural attributes of the person [KA12]. Physical characteristics include features like fingerprints, face, iris, and they are the most common used traits for human identification. A biometric system is essentially a pattern-recognition system that recognizes a person based on these characteristics [VK14]. Biometric systems are advantageous because they do not require a person to carry cards or remember information unlike conventional authentication systems, which are either possession-based or knowledge-based [Omi06, K+12]. These conventional methods are unreliable because keys and cards can be lost or stolen, likewise passwords can be compromised, forged or hacked [Fal06]. Therefore, biometric system has been adopted in many applications [K+12]. However, these systems still have to contend with a variety of problems such as noisy data, inter-class similarities, intra-class variations to mention a few. Also, research has shown that unimodal biometric system has difficulties in eliminating spoof attacks by the impostor which could results in poor performance [RJ04]. It is therefore apparent that unibiometrics is not sufficient to achieve the desired performance in real world applications especially those that demands strong authentication [SJ13]. For higher security requirement system, where the limitations of unimodal biometrics are unacceptable, multimodal biometrics present an alternative solution [A+13]. The design of Multimodal biometric systems can be in two ways; serial and parallel architecture. For serial architecture, the different modalities are processed sequentially. In this way, the output of the first modalities affects the processing of the other trait. As such the system can be much faster compared to the parallel design in a case when the first modality provides a high level of confidence output such that the second is disregarded. However, the design is considered as less secured as there is a possibility of it being dependent on only one biometric trait. In parallel architecture on the other hand, all the inputs from the biometric traits are processed simultaneously. The output from the processing are then fused at a certain level. Therefore, the system accuracy depends on the performances of all the traits. This makes parallel architecture a preferable choice where higher security identification is required.

In multimodal biometrics, the data are independent of each other; it is therefore expected that spoofing such system would pose more difficulty as compared to unimodal system. However, the problem of suitable fusion technique arises when dealing with multimodal biometric. There are various level of fusion in multimodal biometrics namely sensor level, feature level, match score level and decision level. From literature, score level fusion is the most popular, this is not unconnected to the fact it is easy to implement. However, the information obtained for fusion at this level is limited compared to feature level fusion and may result in inferior performance [A+13, A+15]. Fusion at feature level is more advantageous because it contains richer information about the image, thus it is believed to contribute to better recognition accuracy of the system.

2. RELATED WORKS

Unimodal biometric systems that are based on utilizing a single biometric trait often face practical limitations that negatively influence their overall performance. This is expected due to a variety of reasons such as noisy data, intra-class variability, low distinctiveness, non-universality and unacceptable error rates due the nature of the biometric traits. Multibiometrics, that is the integration of more than one sources of biometric information for accurate authentication, is often seen as a way to solve some of the aforementioned limitations. In this direction, many researchers have worked on different fusion approaches both at the pre-mapping stage and post-mapping stage.

[F+04] combined face and palmprint for recognition, which are both image based by concatenating the features extracted using Principle Component Analysis (PCA) and Independent Component Analysis (ICA) with the nearest neighbor classifier (NNC) and support vector machine (SVM) as the classifier. [W+09] proposed complex vector as the fusion technique of face and iris after the implementation of z-score normalization whereby classifier is Fisher Discriminant Analysis (FDA) with Equal Error Rate (EER) of 0.07% and 2.9% for Olivetti Research Laboratory (ORL) and Yale's database respectively.

[R+06] implemented face and fingerprint bimodal system with Scale Invariant Feature Transform Features (SIFT) applied for face feature extraction and minutiae matching technique for fingerprint. The features are fused by simple concatenation while Delaunay triangulation technique is applied as the matching algorithm with an accuracy of 97.41%.

[K+12] presented a multimodal framework based on face and ear modalities. The features were extracted using Haar wavelet and Scale Invariant Feature Transform (SIFT). Integration of their ranks was done with modified Borda count and Logistic regression method. According to their report, logistic regression gave a better result. [NP13] developed a multimodal biometric system using iris and ear, features were extracted from both modalities using Principal Component Analysis and the features were normalized and concatenated. The system showed an improvement over unimodal systems, attaining 93% success rate. [K+12] proposed a multimodal biometric system that combines the recognition of the face and both irises to enhance the performance based on Support Vector Machine. Their results showed that the proposed system performs better than face and irises in isolation, and it was also discovered that both irises differ in their performances; hence, could be treated as different biometrics. Intramodal feature level fusion of texture and line features of palmprint was carried by Krishneswari and Arumugam [KA12] using PSO based technique. The resulting feature vector was further reduced via PCA. Experimental results illustrated that the feature level fusion improves the recognition accuracy significantly. A modified GA was employed by [A+13] to maintain feature balance in the feature fusion of face and signature.

III. RESEARCH METHODOLOGY

The process flow of the bimodal system is shown in Figure 1. The process flow shows the training and testing phases. In the training phase, there are two biometric image databases which store the two biometric templates to be used in the recognition process. The next component is the preprocessing component where each of the traits is preprocessed to improve the image quality and at the same time, normalize the images for uniformity. The preprocessed image is then fed into the feature extraction component where discriminating features are extracted using DWT. The DWT coefficient from each image is then converted to feature vectors for fusion in the next component using CSA. The fused features are afterwards saved for comparison.

On the other hand, the testing phase involves the enrollment of the user where the desired biometric traits are acquired. The acquired traits were preprocessed independently. Features were extracted and fused as explained above. The fused feature vector is then compared with the fused feature vector in the training database by measuring the Euclidean distance between the two vectors in a component connecting the training and testing phase.

A. Data Acquisition

Majority of publicly available databases are captured in controlled environments and their images were tailored towards a specific need of an algorithm. However, the performances of biometric systems fluctuate when datasets used to benchmark the algorithms changes due to differences in the condition under which the images were captured. This necessitates the need for a database that was not captured under a controlled environment. Therefore, the images (faces, fingerprints and irises) used in this work were acquired from one hundred and fifty-four (154) randomly selected students and staff of Ladoke Akintola University of Technology (LAUTECH). This collection forms a rare nonchimeric multimodal dataset. The images were captured though in the software laboratory of the Department of Computer Science and Engineering but not under a controlled environment. The acquisition of faces and eye images was done with CMITECH iris camera while fingerprints were acquired using digital persona fingerprint scanner. There are 6 different images per biometric trait per subject. The facial images were all taken in frontal position with little variations in expression and illumination. However, there are variations in the distance between the subject and the camera.

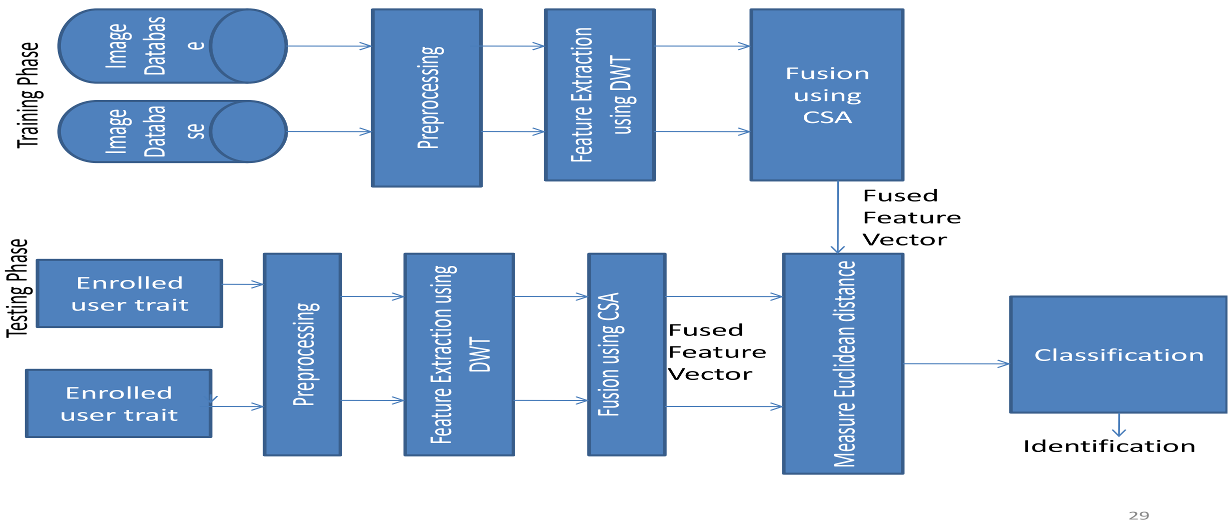


Figure 1: Process flow of a bimodal biometric system

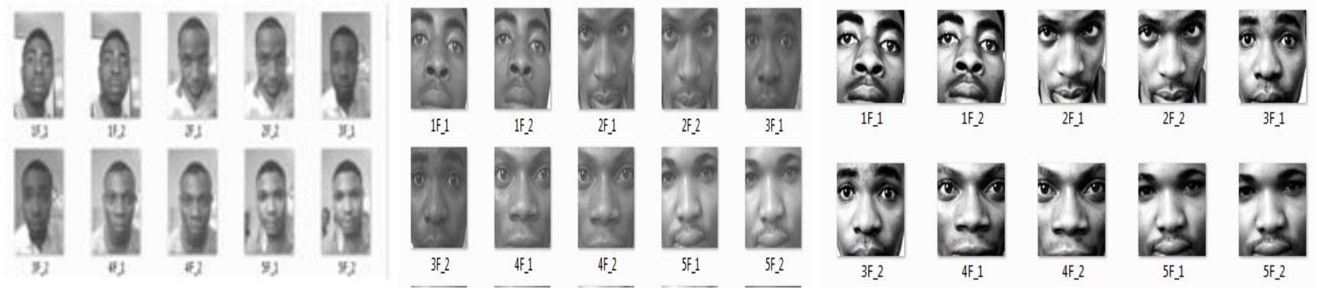
B. Image Preprocessing

The image preprocessing involves enhancement of the image. However, before preprocessing, all images were converted to JPEG format using Microsoft Picture Manager. This is done to compress the image so as to reduce the memory consumption during experiments. After conversion, each face image was 57.4Kb, iris was 41Kb and thumbprint was 34.6Kb but the image resolution still remains the same. After this, geometric normalization was done to convert the images to the same resolution since they have different resolution. For face images, the images were first automatically cropped from original size of 720x960 to a reduced size using the Adaboost algorithm. The cropping was done to retain only the face region with the extinction of areas such as ear and fore-head without distortion. The images were then resized to 100x100 pixels for uniformity. Meanwhile for iris and thumbprint images, they were only resized to 100x100 pixel level.

Second, photometric normalization was carried out on the entire image database to eliminate illumination effects, improve contrast, and enhance visual quality and to obtain a uniform histogram of the images. This was done by adopting histogram equalization which enhances the image contrast by transforming the values in an intensity image so that the histogram of the output image matches a specified histogram during normalization [Fal12].

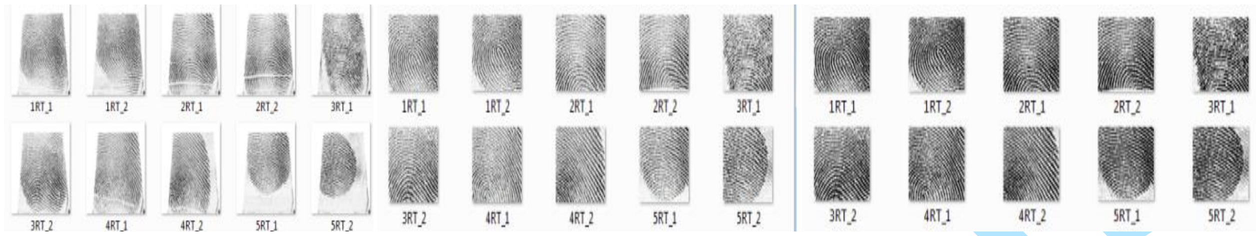
Iris Preprocessing

The preprocessing module for iris includes iris image localization, segmentation and enhancement. Localization involves locating the iris in an eye image while segmentation is the detection and exclusion of occluding eyelids, eyelashes or reflections. Is is also the process of decomposing the images into regions and objects by associating or labeling each pixel with the object that it corresponds to. Circular Hough transform approach was used to deduce the radius and center coordinates of the pupil and iris regions. Normally, irises from different people vary in size, even the irises from a single person, and this difference in size is due to illumination variation, pupil size and distance of the eye from the camera. To compensate for these different conditions and improve the precision of matching, Daugman’s rubber sheet model was used which projects the segmented disk into a rectangular region of fixed size. It unwraps the circular region of iris into a rectangular block of constant dimension.



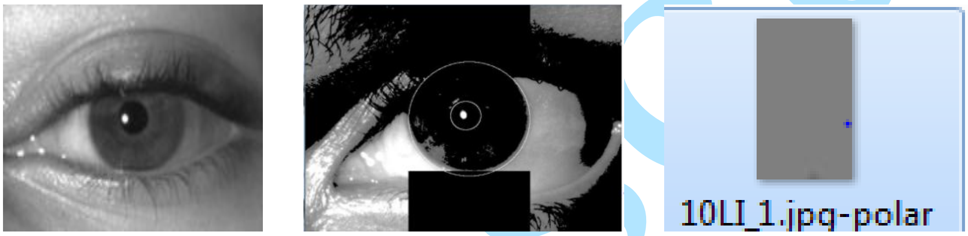
(a) (b) (c)

Figure 2: Sample Faces: (a) original faces; (b) Cropped and resized Faces; (c) Histogram Equalized Faces



(a) (b) (c)

Figure 3: Sample Fingerprint: (a) Original Thumbprint; (b) Cropped and resized Thumbprint; (c) Histogram Equalized Thumbprint



(a) (b) (c)

Figure 4: Sample iris image: (a) Original Eye image; (b) Eye image after Segmentation; (c) Normalized Iris image

C. Feature Extraction

Feature extraction is a special form of dimensionality reduction which contains more information about the original image. This stage describes the extraction of unique characteristics which can represent an image. The goal of feature extraction is to extract a set of features, which can maximize the recognition rate with the least number of elements. Discrete Wavelet Transform (DWT) was adopted for a transformation based feature extraction. A two level decomposition was performed on the preprocessed images. The DWT coefficient matrices extracted forms an efficient representation of the images in a lower dimension space. The output of DWT was converted to feature vector which serves as input to the fusion stage of the multimodal systems.

D. Feature level Fusion

Biometric fusion is the term used to describe the mechanism for integrating data from two or more traits. It refers to the consolidating of information or evidences presented by multiple biometric sources [JR04]. Feature level fusion can be done either at feature extraction stage or at feature selection stage [A+13, A+15]. 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. This paper presents an example of feature selection stage fusion using Clonal Selection Algorithm (CSA).

The CSA method is a member of wide category of Nature-Inspired methods for solving optimization problems. It is a special class of Artificial Immune System inspired from the clonal selection principle of AIS. Clonal selection in AIS is the selection of a set of artificial lymphocytes (ALCs) with the highest affinity with non-self pattern [DV02]. Similar to GA, CSA is a population based search algorithm where each individual is referred to as antibody and represents a candidate solution. But instead of crossover operator, it uses cloning operator to construct new generation of candidate solutions. A population of solution is randomly generated; the size of this population depends on the parameter setting of the algorithm. Each antibody's affinity towards the antigen is evaluated and highly fitted antibodies are then selected for cloning. The cloned antibodies are mutated to increase the diversity in the population, afterwards, their affinities are measured to evolve the next generation. The algorithm is given as follows:

Step 1: Initialize the antibody population.
Step2: Evaluate the affinity of all individuals.
Step 3: Select the best candidates from population
(a) Sort the antibodies by their affinity values
(b) Select the best antibodies.
Step 4: Clone the best antibodies.
Step 5: Mutate the clones and produce a new population.
Step 6: Evaluate the affinity of each antibody in the new
population.
Step 7: Repeat steps 3 through 6 until the stopping criteria is
met.

Affinity function

The affinity function is associated with each antibody and it represents the quality of the solution. The goal of multimodal system is to reduce inter-class similarities and increase intra-class similarities. Therefore, the affinity function used in this paper was adopted from the work of Aly, Onsi, Salama and Mahmoud [A+13]. The main objectives of the affinity function are:
(i) Maximize the between-class scatter (S_b) among the different classes.
(ii) Minimize the within-class scatter (S_w) in the same class.
(iii) Improve the recognition rate of the system.
Suppose there are C classes, y_i is the i^{th} vector, M_i the number of samples within class i, where i = 1, 2, …C. μ_i the mean vector of class I, and μ be the total mean vector of samples. The within-class scatter matrix is represented as:

$$S_w = \sum_{i=1}^{c} \sum_{j=1}^{M_i} (y_i - \mu_i)(y_i - \mu_i)^T \quad (1)$$

While the between-class matrix is given as:

$$S_b = \sum_{i=1}^{c} (\mu_i - \mu)(\mu_i - \mu)^T \quad (2)$$

Where $\mu = {}^{1}/_{c} \sum_{i=1}^{c} \mu_i$
Finally, the affinity function is computed by maximizing the between-class scatter matrix while minimizing the within-class scatter and is performed by:

$$\text{Affinity function} = \text{maximize} \quad \frac{\det(S_b)}{\det(S_w)} \quad (3)$$

This CSA based fusion technique combines the two feature vectors into a single feature without concatenation. Therefore, rather than adding up of dimensions from the two feature sets which results by concatenation, this technique combines them to reduce the feature space. The reduced vector is classified using Euclidean distance measure and Nearest neighbor classifier.
The bimodal systems presented in this paper was developed, trained and tested using MATLAB version 12 with a system specification of 1.80GHz processor, 500GB of HDD (hard disk drive), 4GB of RAM, and 64 bit operating system on window 7 platforms.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

Three bimodal biometric systems were developed in this work, they are Iris-Fingerprint (IR-FI), Face-Iris (FA-IR) and Face-Fingerprint (FA-FI) biometric systems. Features were extracted separately from each of the biometric traits and fusion of the features was done using CSA. The performance metrics employed for evaluation are Recognition Accuracy, Average training time and average recognition time. Each of the systems was trained with a total of eight hundred (800) images while four hundred (400) images were used for testing which implies that 60% of the dataset were used for training.. The summary of results obtained is shown in Table 1.

Table 1: Summary of Experimental Results

Biometric System	Recognition Accuracy (%)	Average Training Time (s)	Average Recognition Time (s)
IR-FI	89.50	5.35	3.81
FA-IR	89.63	10.08	4.91
FA-FI	88.25	8.39	4.07

The results of the experiments carried out are summarized as shown in Table 1. The second column of the table shows the recognition accuracy of the systems. Face-Iris bimodal system has the highest recognition accuracy of 89.63% when 60% of the dataset was used for training while the least accuracy was recorded with Face-Fingerprint bimodal system. This result implies that high

discriminating features contained in iris, when combined with features from other biometric traits will enhance the recognition accuracy of the system than face and fingerprint.
The results for the average training time indicate that Iris-Fingerprint (IR-FI) bimodal system has the least training time while the highest training time was recorded with the Face-Iris (FA-IR) system. This is an indication that face contains more features to be trained followed by iris. Similarly, the average recognition time follows the same trend.
Lastly, the accuracies of the systems are then compared with their unimodal counterparts under the same condition as reported in [A+18]. The comparison is given in Table 2.

Table 2: Comparison with unimodal systems

Biometric System	Recognition Accuracy (%)	Average Training Time (s)	Average Recognition Time (s)
Face	83.33	5.84	5.11
Iris	85.50	3.65	3.05
Fingerprint	82.75	1.27	1.28
IR-FI	89.50	5.35	3.81
FA-IR	89.63	10.08	4.91
FA-FI	88.25	8.39	4.07

From table 2, the accuracy of Face is 83.33%, Iris is 85.50% and 82.75% for fingerprint recognition system. The comparison with unimodal is done in order to see how important the implementation of multimodal biometric system as an alternative to overcome the limitations of unimodal systems. From the results, it is observed that all the bimodal systems have higher recognition accuracy compared to their respective unimodal counterparts. This implies that combining two or more modalities can improve the performance of a biometric system.

CONCLUSION

In this work, a parallel multimodal biometric system was proposed. The purpose of the research is to overcome the limitations in unimodal biometric system by combining face, iris and fingerprint at feature level. Thus, making it difficult for impostor to fool two different traits at the same time.DWT was used both to reduce the dimension of the images and at the same time extract discriminating features to represent the traits while the features were fused at the feature selection phase using CSA. Fusing at this stage helps in preventing information loss and also ensures that only the most significant information from the modalities are used for classification. The results obtained shows that multimodal biometrics are more efficient than unimodal ones. Future works may be geared towards investigating the effect of training dataset size on recognition accuracy of multimodal systems. Also feature level fusion of multiple instance of the same biometric trait may be researched to see whether the same system performance with multimodal may be achieved.

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