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IMAGE FUSION BASED MULTIMODAL BIOMETRIC RECOGONITION

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ABSTRACT

Multi focus image fusion in multimodal imaging for analysis is a process of fusing two or more images (i.e. iris & face scan images) to obtain a new one which contains a more accurate description of the individual source images. It is used to reduce the problems like blocking, ringing artifacts occurs because of DCT. The low frequency sub-band coefficients are fused by selecting coefficient having maximum spatial frequency. It indicates the overall active level of an image. The high frequency sub-band coefficients are fused by selecting coefficients having maximum code Finally, fused two different frequency sub-bands are inverse transformed to reconstruct fused image. after that Automatic defects detection in Multimodal images is very important in many diagnostic and therapeutic applications. Because of high quantity data in multimodal images and blurred boundaries, and classification is very hard. This work has introduced one automatic detection method to increase the accuracy and yield and decrease the diagnosis time. The goal is classifying the tissues to two classes of authorized and unauthorized using feed forward neural network.

Keywords: DCT, multimodal imaging, image fusion

1. INTRODUCTION

Many works in the literature have demonstrated that the drawbacks of the unimodal biometric systems are mainly genuine and imposters identification failure due to the intraclass variations and the interclass similarities, while the drawbacks associated with multimodal biometrics are increased complicity of the system with two or more sensors [2–6] and thus higher cost, as well as inconvenience of using several biometrics. So, identification of person with high accuracy and less complexity of the system is becoming critical in a number of security issues in our society. Iris and fingerprint biometrics are more simple, accurate, and reliable as compared to other available traits. These properties make their fusion particularly promising solution to the authentication problems today. Moreover, fusion of iris and fingerprint is more reliable than fusion of each one with another biometric like face .However, iris biometric has more features and stability and resistance to attacks than fingerprint biometric; despite this, the conventional fusion methods still use the same weight in fusion for each single biometric, and this is the reason for why their best error rates are far from perfect. False accept rate identifies the number of times an imposter is classified as a genuine user by the system and false reject rate pertains to misidentification of a genuine user as an imposter. Although ideally both FAR and FRR should be as close to zero as possible in real systems, however, this is not the case [8]. For an ideal authentication system, FAR and FRR indexes are equal to 0. To increase the related security level, system parameters are then fixed in order to achieve the FAR = 0% point and a corresponding FRR point

2. Related Works

Multimodal biometrics has been proposed by Ross and Jain in The concept of biometric multimo dalities fusion is introduced with different fusion strategies and various levels of fusion are also presented Fusion of iris and fingerprint has attracted a lot of attention and researchers have pres ented variety of approaches in the literature

In 2009 proposed a framework for multimodal biometric fusion based on utilization of a single matcher implementation for both modalities irisandfingerprint Virginia University's multimodal dat abase containing 400 images (4 enrolment images × 100 users) and the threshold is set to the equal error rate EER. The comparison is being made in terms of percentage improvement in EER rather than the EER values themselves. In 2010 introduced a technique for cryptographic key generation by fusing fingerprint and iris biometrics. The fingerprint extractor is minutia based while the iris extractor is based on canny edge detector and Hough transform. The minutiae points and texture properties were first extracted from fingerprint and iris images, respectively, and then they were fused at the feature level to obtain the multi biometric template and subsequently a 256-bit secure cryptographic key from the multi biometric template is generated.

In 2011, introduced a new framework for iris and fingerprint fusion at rank level; they conducted experimental tests using three implemented fusion methods: highest rank method, Brode count method, and logistic regression method. Their work achieved the best execution time required to match which is equal to 0.45 seconds for the highest rank method with optimal FAR and FRR equal, respectively to 0% and 0.25%.

3. STATE OF THE MULTIMODAL BIOMETRIC

In this section we summarize the main ideas and principles involved in the area of multimodal biometric recognition.

3.1. Multimodal Biometrics versus Multibiometrics.

As explained by most research papers in the field of biometric recognition the term "multimodal biometric" refers to multiple biometric traits used together at a specific level of fusion to recognize persons. The "multi biometrics" includes either the use of multiple algorithms, also called classifiers at enrolment or matching stages for the same biometric trait, or the use of multiple sensors of the same

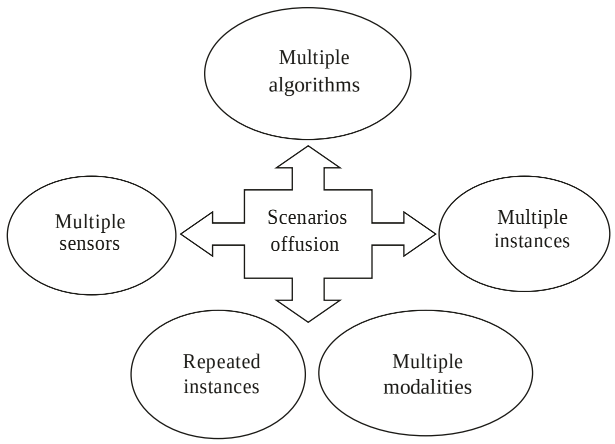

Figure 1: Fusion scenarios of multimodal systems.

biometric trait like using different instruments to capture the biometric details, or using multiple instances of the same biometric trait like the use of fingerprints of three fingers, or finally using repeated instances like repeated impressions of one finger.

3.2. Fusion in Biometry. In order to join two or more biometric traits, a method called "fusion" is used. Fusion in biometry refers to the process of combining two or more

biometric modalities. In this section we presnt the different scenarios of fusion used by multimo dal biometric systems. It is worth noting that the multimodality does not involvethe use of multi ple biometric modalities in the strict sense of the term (such as combining iris and fingerprint), but its meaning is broader as defined in the following by the various scenarios of fusion (see Figure 1).

3.2.1. Level of Fusion. Five levels of fusion in multimodal systems were introduced in

the literature which are the following.

(1) Sensor Level. Multi sensorial biometric systems sample the same instance of a biometric trait with two or more distinctly different sensors. Processing of the multiple samples c an be done with one algorithm or combination of algorithms. Example face recognition application could use both a visible light camera and an infrared camera coupled with specific frequency.

(2) Feature Level. The feature level fusion is useful in classification. Different vectors are combined, obtained either with different sensors or by applying different feature extraction algorithms to the same raw data.

Decision Level. With this approach, each biometric subsystem completes autonomously the processes of feature extraction, matching, and recognition. Decision strategies are usually of Boolean functions, where the recognition

(1) Rank Level. Instead of using the entire template, partitions of the template are used. Ranks from template partitions are

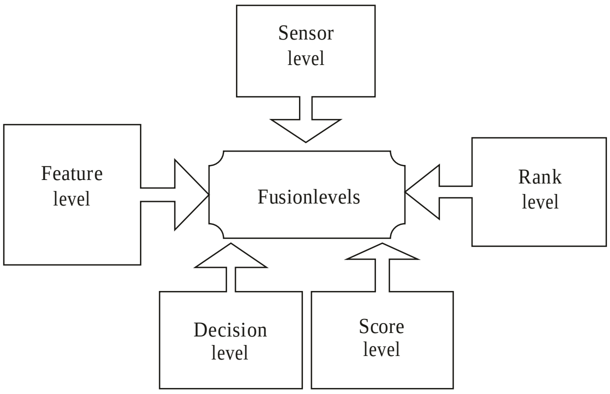

Figure 2: Fusions in Biometry.

consolidated to estimate the fusion rank for the classification.

Rank level fusion involves combining identification ranks obtained from multiple uni modal bio metrics. It consolidates a rank that is used for making final decision.

(1) Score Level. It refers to the combination of matching scores provided by the different sy stems. The score level fusion techniques are divided into two main sets: fixed rules (AND, OR, majority, maximum, minimum, sum, product and arithmetic rules) and trained rules (weighted sum, weighted product, fisher linear discriminate, quadratic discriminate, logistic regression, support vector machine, multilayer perceptrons, and Bayesian classifier).Figure 2 shows the five levels of biometric fusion.

3.2.2. Normalization. Score normalization brings both matching scores between 0 and 1 The normalization of both scores by the min-max rule are given by

$$\text{MSIris} - \text{minIris}$$

$$N_{Iris} = \quad maxIris - minIris$$

$$N_{Finger} = \frac{MSFinger - minFinger}{maxFinger - minFinger}$$

where MS_{Iris} and MS_{Finger} are the matching scores obtained from iris and fingerprint modalities, re spectively. min_{Iris} and max_{Iris} are the minimum and maximum scores for iris recognitionandmin_{Finger}andmax_{Finger} arethecorresponding values obtained from fingerprint trait. Other normalization algorit hms also exist, like score, TanH and Sigmoid which gave very good results. TanH method gave the best result but it involved a lot of parameters. *Z*-score and min-max are simple but they are insensitive to the presence of outliers [15].

4. The Research Methodology

Figure 3 shows the different stages included in our multimodal recognition system and the overal l system design shows the following.

(i) The level at which the biometric information of theiris and fingerprint are fused is indic ated (here two levels are used: the score level fusion is used for the

classical fusion and the decision level fusion is used for the fusion with fuzzy logic).

(ii) The fusion approach used is the approach by combining scores when the method of fusion is classic.

(iii) The other fusion approach used is fusion of decisions when the method of fusion is fuzzy.

(iv) The normalization of scores is required prior to the fusion only for the classical fusion (which is explained by the use of the approach by combining scores for both classical sum rule matching and matching by the linear weighted sum rule).

(v) Fusion by fuzzy logic does not require normalization of scores and only decisions are used by the fuzzy inference system.

(vi) Three matching algorithms are used: the classical sumrule matching, the weighted sum rule matching, and our proposed matching with fuzzy logic.

5. System Implementation

The programming language used to implement our system is MATLAB 7.10.0(R2010a). MATLAB as well as its interactive environment is a high-level language that allows the execution of tasks requiring high computing power and whose implementation will be much easier and faster than with traditional programming language s such as C, C++. It has Toolbox" which proposes a set of algorithms and graphical reference tools for the processing, analysis, visualization, and image processing algorith m development. Our application is implemented on a laptop (HP630) Intel CORE I3 CUP M370 with 2 Giga byte of RAM and 320 Giga byte hard drive disk HDD and has a 2.40 GHz speed. The minimum required material characteristics for the application are 512 Mega byte of RAM and 80 Giga byte hard drive. To perform tests with our application, we use four databases which ar e as follows.

(i) CASIA-Iris V1, CASIA V1, contains 756 images from 108 eyes. For each eye, 7 images are captured in two sessions with a homemade iris camera, where three samples are collected in the first session and four in the second session. All images are stored a s BMP format with resolution 320* 280.

(ii) CASIA-Iris V2contains 2400 images from 120 eyes. For each eye, 10 images are captured using two different instruments (OKI and. All images are stored in BM P format with resolution 640 * 480. CASIA-Iris V2 contains blurry images with different illuminations and wearing glasses is authorized. The database is available for free on demand.

(iii) FVC 2004 contains four sets DB1 A, DB2 A, DB3 A, and DB4 A. Each of these databases contains 800 fingerprints equivalent of one hundred (100) individuals each having eight (08) impressions. FVC 2004 database is characterized by different fingerprint image qualities. The database is purchase d upon request.

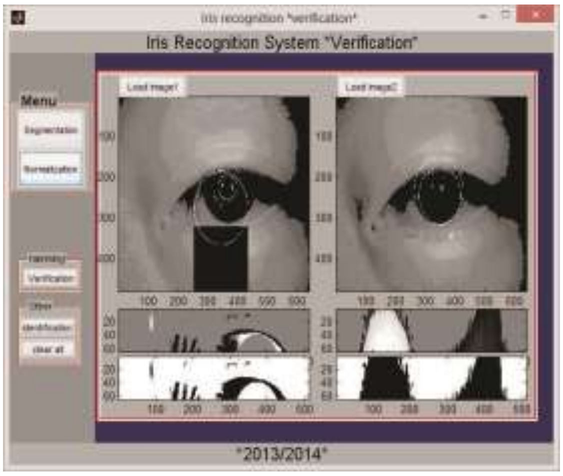

Figure 3: Multimodal Recognition System

6. Experimental Results

The application is divided mainly into three modules.

6.1. Iris Recognition Module. Both verification and identification processes are implemented. Figu res below present the graphical user interfaces GUIs allowing the user to load an iris image fro m a database and to do segmentation, feature extraction, and either verification (see Figure 7) (the user has to upload another iris image) or identification (see Figure 8) (the system searches similar code in database).

6.2. Fingerprint Recognition Module. Like the iris recognition module, both verification and ident ification processes are implemented. Figure 9 shows the GUI allowing the user to load two fingerprint images and then visualize the result s of each step of the fingerprint recognition algorithm (binarisation, region of interest and the orientation field localisation, the process of image thinni ng also called skeletonization, the extraction of minutia, the elimination of false minutia, and fin ally the matching by the Euclidian distance).

Figure 4. Identification process in the iris monomodal recognition system.

Figure 5: GUI of the verification process in the fingerprint mono modal recognition system.

The identification process in the fingerprint mono modal recognition system consists of matc hing the generated code from the input image with all codes stored in databases; if the identific ation failed, the user is asked either to add or not the non identified image to a chosen databas e (see Figure 5).

6.3. Combined Iris and Fingerprint Recognition Module. Three matching algorithms are impleme nted; first is the matching using the fusion of iris and fingerprint by the sum rule, second is th e matching of both modalities by the weighted sum rule, and the final is the matching using th e fusion by the fuzzy logic if-then rules and the fuzzy inference system.

Figure 3 shows the GUI allowing the user to see the verification result of iris and fingerprint combin ed biometric traits.

Figure 4 presents the graphical user interface of the recognition module based on the fusion by the w eighted sum rule and the score normalization is done prior to fusion using the min-max rule and then the fusion is done; in our experimentation we set 0 to 0.8 for the iris modality and 1-α=0.2 for the fingerprint modality.

Figure 5 presents the graphical user interface allowing the user to verify the similarity between two in dividuals by opening the fingerprint and iris images belonging to each

Figure 6. GUI of the identification process in the finger print mono modal recognition system.

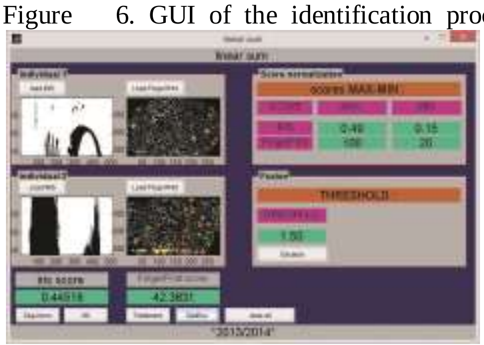

Figure 7. GUI the matching using the fusion by the sum rule.

Figure 8. GUI showing the matching using the fusion by the weighted sum rule.

Figure 9. GUI showing the matching using the fusion by the fuzzy inference system.

individual, doing feature extraction, and matching operations between the two irises and the two fingerprints, output the matching distances and the decisions of both modalities and then plot the fuzzy membership function for each decision and finally calculate the decision of the combined modalities and plot its fuzzy membership function.

7. Performance Evaluation and Comparison

In order to test our proposed schemes for mono modal and multimodal biometric recognition systems and proceed with their evaluation and comparison, the following experiments are conducted

Experiment 1. Both verification and identification processes are implemented within a mono modal iris recognition system. We use the public code for the verification and we extend it to perform the identification. The feature extractor employed for Iris modality is based An Iris code comprising bit streams called Iris generated. The hamming distance based matcher provides the matching score. The experiment uses CASIA-V1 iris database.

Experiment 2. Both verification and identification processes are implemented within a mono modal iris recognition system.
For the verification and we extend it to perform the identification. The experiment uses CASIA-V2 iris database.

Experiment 3. Both verification and identification processes are implemented within a mono modal fingerprint recognition system and we propose a minutia based fingerprint recognition system using the algorithm to localize the region of interest and the orientation field, and the algorithm for the extraction of minutiae and post treatment. Matching is based on Euclidian distance. The experiment uses FVC2004 fingerprint database.

Experiment 4. Only verification process is implemented within a multimodal biometric recognition system of combined iris and fingerprint using the sum rule based matching. The experiment uses an equi valent number of images from CASIA Iris-V2 and FVC2004 fingerprint databases (5 from each modality * 50 subjects).

Experiment 5. Only verification process is implemented within a multimodal biometric recognition system of combined iris and fingerprint using the weighted sum rule based matching. The experiment uses an equivalent number of images from CASIA Iris-V2 and FVC2004 fingerprint databases (5 from each modality * 50 subjects).

Experiment 6. Only verification process is implemented within a multimodal biometric recognition system of combined iris and fingerprint using our proposed fuzzy logic based matching. The experiment uses an equivalent number

8. Conclusion

The objective of this research is the introduction of a novel matching approach for multimodal biometric recognition based on fuzzy logic. The biometric traits used in our work are iris and fingerprint.

In this paper a novel combination of iris and fingerprint biometrics is presented in order to achieve best compromise between a zero FAR and its corresponding FRR; in our approach, iris trait has more weight in fusion with fingerprint and the system decision is made to have more intermediate values between bad and good recognition and the weight is simply an appreciation we assign to the matching distance for each single biometric set by fuzzy membership function; the fuzzy inference system mimics our human thinking and this is mainly the reason we get enhanced results. The contribution of this research is threefold, first designing and implementing mono modal systems for the biometric recognition of iris and fingerprint, second designing and implementing a multimodal biometric system of combined iris and fingerprint using the previous mono modal systems with three different matching algorithms, two classical matching algorithms and our proposed one based on fuzzy logic, and third carrying out exhaustive and intensive tests on the iris and fingerprint databases using the proposed recognition schemes to conclude at the end the best one. At last, a comparison of the achieved results with similar works in the current literature is given and our experimental results are the best in terms of matching time, error rates, and accuracy.

The normalization of scores is required prior to the fusion only for the classical fusion. Fusion by fuzzy logic does not require normalization of scores; only decisions are used by the fuzzy inference system. Three matching algorithms are used: the classical sum rule matching, the weighted sum rule matching, and our proposed matching with fuzzy logic. These fusion methods act on two different levels, namely,

(i) the score fusion level: in which we implemented the method of the classical linear sum rule of iris and fingerprint scores and method of the weighted linear sum which give weight to iris and fingerprint sores,

(ii) the decision fusion level: where we have designed and implemented a fuzzy matching technique after converting iris and fingerprint scores to fuzzy sets (this conversion is called the fuzzy inference system produced fuzzy results (bad recognition, or very bad, or medium, or good, or very good or excellent).

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