Fingerprint-Sclera based Multimodal Biometric Authentication System using Hybrid Genetic Intelligent Technique for System on Chip Application

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Abstract—Multimodal biometrics is used to solve many problems associated with unimodal biometric authentication accuracy. The problem arises due to data acquisition noise, spoofing biometric identity and non-universality of biometric features. A significant improvement in accuracy is difficult to achieve in a unimodal biometric authentication system and the complexity reduction process is not suitable for low power VLSI implementation. Setting a portion of each modal in a biometric system is complex, the processing unit can be removed to process the application of VLSI chips. In addition, there is a need for a portable personal authentication conducted in this research to explore the multimodal biometric authentication in SOC system, in which the system is developed in an environment with limited resources. This paper proposes hybrid artificial intelligent tools such as genetic algorithm based Adaptive neuro fuzzy interference system for their powerful capabilities feature selection, learning and fuzzy expression to insure high quality of verification through multimodal biometrics fusion. As a first step, fingerprints and sclera are used as biometrics and the whole process is implemented in FPGA SOC and executed by the general purpose processor in which the strategy biometric information fusion applied to the matching score. Experimental investigation under different data conditions reveals the outstanding results over existing fusion techniques. The accuracy of the system is promising with a False Rejection Rate (FRR), False Acceptance Rate (FAR) and accuracy of 0.21, .12 & 99.3 respectively.

Keywords— System on chip; Multimodal Biometric; Adaptive Neuro Fuzzy System.

I. INTRODUCTION

Biometric authentication [7] is a technique to identify a person using one’s intrinsic physical and behavioral traits [1]. This method has become surprisingly popular in today’s security system [6]. The reason for this is because of the advantages of the biometrics replacing the possession-based (E.g., ID card) and knowledge-based (E.g., pass code) authentication method since the biometric identifiers cannot be misplaced, forgotten, guessed or easily copied. However, despite the advantages of biometric authentication [1], [9] method, the performance and reliability of the biometric authentication system needs rigorous work for improvement. It is generally enduring from enrollment problems due to non-universal biometric traits, vulnerable to biometric spoofing and insufficient accuracy due to noisy data acquisition [2].

A multimodal biometric authentication [7] is a relatively new approach to overcome these problems by combining information obtained from various sources [3-4]. The sources are (i) multiple sensors for same [9] biometric (optical and capacitive fingerprint sensors) (ii) multiple units of same biometrics (index and “middle fingerprints”) (iii) multiple snapshots of same biometrics (three templates of right index fingerprint) (iv) multiple representations and matching algorithm for same biometrics (“minutiae” and texture based matching algorithm for fingerprint) (v) multiple biometrics [8], [9] (fingerprint and face).
The advantages of multiple biometric authentication system [6] over unimodal biometric authentication system is it can overcome the non-universality, less affected by noise, provides stronger security environment and improve matching accuracy. This has received considerable amount of attention from researchers and has led to the rise of development of multiple biometrics authentication systems [6].

Multimodal biometric [3], [9] authentication system is often performed in an insecure environment that uses the central server for biometric templates storage. This can cause a critical biometric information leakage issue. Thus the implementation of multimodal biometric authentication system on an embedded system [6] can address this critical problem. This is because embedded system provides a medium of secure communication, secure information storage, and tamper resistance which protects from both physical and software attacks [4].

Fusion [10] of individual biometric traits in multimodal authentication system can be performed at various levels [3], [5]. They are fusion at feature level, fusion at matching score level and fusion at decision level. Fusion at level combines different biometric features into one joint feature. The joined feature is matched to the template in database which was stored during enrollment process. A score is calculated and appropriate authentication decision is made from the score. In fusion at matching score level, the features of each biometric trait are compared to the template in the database which was stored during enrollment process. Each biometric authentication subsystem calculates a matching score. These individual matching scores are combined into a final score. This final score is used to accept or reject an individual. Fusion at decision level refers to the decision from two multiple [3] unimodal biometric authentication systems which are combined into one fused decision.

In this paper, we propose fingerprint-sclera multimodal biometric authentication system at fusion matching score level a System-on-Chip (SOC) in Sparatan6 FPGA development board at 900MHz.

II. RELATED WORK

A number of research showing the advantages of multimodal biometrics have appeared in literature. Many researchers have shown that fusion of individual biometric traits in multimodal biometric authentication system is effective as it provides better accuracy than the unimodal biometric [7] authentication system.

Chaudhary and Nath [6] incorporate palm print, fingerprint, and [8] face biometrics at score level fusion [10] and proves that at the results of integrating the biometric trait did improve the accuracy of the combined biometric system. Nageshkumar et al. [7] shows incorporating palm print and face at matching score level makes the biometric system perform better. The same result applies to the work by Raghavendra et al. [8] which combines face, speech and palm print at the matching score level.

The implementation of multimodal biometric system in embedded system is reported by Wang J et al. [9] implements fingerprint and voiceprint multimodal biometric as embedded system. Fusion at matching score level was applied to fingerprint and voiceprint. The embedded multimodal system adopts ARM9-Core based S3C2440A microprocessor working at 400MHz and Microsoft Windows CE operating system. It has 128KB on-chip flash and 64KB of SDRAM. Work by Yoo et al. [10] describes implementation of face, iris and fingerprint biometrics as embedded system.

The VLSI system was made up of Spartan 6 processor clocked at 900MHz, 128MB SDRAM, Xilinx XC3S4000 onboard FPGA. However, no fusion strategy was applied in the embedded biometric system. Although there has been substantial amount of work on combining different biometrics for a variety of purposes but not much work has focused on the implementation of multimodal modal biometric system in resources-constrained embedded system for real-time performance as it is poses great challenge. Therefore it is least developed, more so with fingerprint-multimodal biometrics.
III. PROPOSED ARCHITECTURE

![Diagram of Proposed Multimodal Biometric System]

Figure: 1 Proposed Multimodal Biometric system

1. Fingerprint Module

For fingerprint subsystem, the minutiae-based verification system is used. The proposed System architecture of fingerprint module is shown in Figure 1. This module includes Shearlet transform for image preprocessing and feature extraction and ANFIS for fingerprint matching. ANFIS takes fingerprint image and locates all minutiae in the image and assigning each minutiae point its location, orientation, type and quality. Finger print module divided into image map generation, binarization, minutiae detection, removal of false minutiae such as islands, hooks, lakes and minutiae in poor quality image region, counting of ridges between a minutiae point and its nearest neighbor and minutiae quality assessment.

The minutiae points used are ridge ending and ridge bifurcation. Matching is a process where the extracted feature vector of the minutiae point is compared to a user template in a database. A matching score is generated based on the proximity of the matched feature vector. ANFIS matching algorithm computes a match score between the template and query fingerprint.

2. Sclera Recognition

Sclera of the eye is commonly known as "white" part. It is the outer covering and eye protection. It has four layers of clothing, i.e. episclera, stroma, endothelia and lamina fusca. The structure of the blood vessels of the sclera is unique to each person, and you can get the distance non-intrusive in visible wavelengths. The structure of blood vessels is visible and stable over time in the sclera. With increasing age, the set of elastic fibers deteriorates, dehydration and calcium salts and lipids sclera occurs, but no blood vessels accumulate deteriorate. Therefore, it is very suitable for human identification. The sclera recognition becomes worse because of the Sclera patterns. These Patterns are saturated and it has a non linear configuration. Also, it has a complex Structure to identify the appropriate users.

2.1 Estimation of Sclera Area

First, the pre-processing step includes, task to convert the input color image to gray scale image for easy computation. Then there are two classes in an input eye image, foreground (object) and background, which can be separated into two classes by...
intensity. The hue of the sclera area should have low hue (about bottom 1/3), low saturation (bottom 2/5), and high intensity (top 2/3). Therefore, the following heuristic is developed:

\[
\text{Result} \ (x, y) = \begin{cases} 
1 & \text{if } H(x, y) \leq t_h \text{ and } S(x, y) \leq t_s \text{ and } I(x, y) \leq t_i \\
0 & \text{else}
\end{cases}
\]

With the threshold calculated using:

\[
\begin{align*}
    t_h &= \text{arg}\{t | \min| \sum p_h(x) - T_h\} \\
    t_s &= \text{arg}\{t | \min| \sum p_s(x) - T_s\} \\
    t_i &= \text{arg}\{t | \min| \sum p_i(x) - T_i\}
\end{align*}
\]

Here

\[p_h(x)\] is the normalised histogram of the hue image, 
\[p_s(x)\] is the normalised histogram of the saturation image, 
\[p_i(x)\] is the normalised histogram of the intensity image and 
\[\text{Result} \ (x, y)\] is the binary sclera map.

### 2.2 Sclera Vessel Pattern Enhancement

Accordingly, sclerotic vascular patterns are often blurred and/or have very little contrast. Since vascular patterns may have multiple orientations, a bank directional Gabor filter is used for vascular pattern enhancement (shown in Figure 2).

![Figure: 2 Sclera based Biometric system](image)

\[
\begin{align*}
\text{Result} \ (x, y) &= \begin{cases} 
1 & \text{if } H(x, y) \leq t_h \text{ and } S(x, y) \leq t_s \text{ and } I(x, y) \leq t_i \\
0 & \text{else}
\end{cases} \\
\end{align*}
\]

Where \((x_0, y_0)\) is the center frequency of the filter, 
\(S\) is the variance of the Gaussian and \(\theta\) is the angle of the sinusoidal modulation.

\[
I_p(x, y, \theta, s) = I(x, y) \times G(x, y, \theta, s)
\]

\(I(x, y)\) is the original intensity image

\(G(x, y, \theta, s)\) is the Gabor filter

\(I_p(x, y, \theta, s)\) is the Gabor-filter image at orientation \(\theta\) and scale \(s\).
\[ F(x, y) = \sqrt{\sum_{s \in S} \sum_{\theta} I_F(x, y, \theta, s)^2} \]

\[ B(x, y) = \begin{cases} 1 & F(x, y) > th_b \\ 0 & \text{else} \end{cases} \]

\[ th_b = \text{arg}\left\{ \text{min} \right\} \sum_{x=1}^{t} p_{\text{edge}}(x) - T_p \]

\( F(x, y) \) is the vessel boosted image

\( B(x, y) \) is the binary vessel mask image and

\( p(x) \) is the normalised histogram of the non-zero elements of \( F(x, y) \).

2.3 Sclera Vein Feature Extraction

In the sclera, there may be several layers of veins. The movement of these layers can cause scleral blood vessels show different patterns. But, in the same layers, blood vessels keep many forms. When the number of branches is more than three branches, the vessels may come from different layers of the sclera and the deformed modal with the eye movement. Y-shaped branches are observed to be a stable characteristic and can be used as a function of the sclera descriptor. To detect the shape of branches in the original modal, we look for the nearest set of neighbours in all line segments in a regular distance. Then classify the angles between these neighbours. If there are two types of angle values in the segment of full line, this set can be derived as a Y-shaped structure and angles of the line segments is recorded as a new feature in the sclera.

To tolerate errors in calculating the center of the pupil at the stage of segmentation, we also recorded the center position \((x, y)\) of Y-shaped branches as auxiliary parameters. So in our rotation vector, displacement and scale invariant function is defined as \( Y (\phi_1, \phi_2, \phi_3, x, y) \). The Y-shaped descriptor is generated with reference to the center of the iris. Therefore, it is automatically aligned with the center of the iris. It is a descriptor rotational- and Scale-invariant.

2.4 Sclera Vein Matching

The featured vector for all images that are in the databases are pre-computed and stored during the enrollment stage. In the verification stage, Ye and Ya are the Y shape descriptors of test template \( T_t \) and target template \( T_o \) respectively. \( d_{\theta} \) is the Euclidian distance of angle element of descriptors vector defined. \( D_{ij} \) is the Euclidian distance of two descriptor centers and is the matched descriptor pair number and their centers distance respectively. \( t_b \) is a distance threshold and \( t \) is the threshold to restrict the searching area. We set to 30 and to 675 in our experiment. Here

\[ d_{\theta}(y_{tei}, y_{tai}) = \sqrt{(\theta_{i0} - \theta_{j0})^2 + (\theta_{i1} - \theta_{j1})^2 + (\theta_{i2} - \theta_{j2})^2} \]

\[ d_{xy}(y_{tei}, y_{tai}) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \]

To match two sclera templates, search the areas nearby to all the Y shape branches. Here, is a factor to fuse the matching score which was set to 30 in our study \( d \) is the total numbers of features in template \( N_i \) and \( N_j \) separately. The decision is regulated by the threshold value \( t \). When the sclera’s matching score is lower than \( t \), the sclera will be discarded. The matching score is calculated by

\[ \text{matching score} = \frac{2 \sum n_i - a \sum d_i}{\max(N_{te}, N_{ta})} \]

The metrics used for evaluation are False Acceptance rate (FAR) and False Rejection Rate (FRR).
3. Fusion Matching Module

Fusion at matching score level consists of two steps: normalization and fusion. Normalization converts the matching scores obtained from different biometric authentication system to a comparable range of values. Fingerprint and sclera authentication system deploys different matching algorithms from each other. Thus the matching scores at the output of each individual matcher are represented in different ways.

![Figure: 3 Performance metrics](image)

Figure 3 shows the Matching results of fingerprint authentication system are represented in proximities. The matching results of sclera authentication system are represented in distances. Moreover, the fingerprint and sclera authentication systems have different numerical range from one another. Furthermore, genuine and imposter matching scores of fingerprint and sclera authentication system does not follow the same statistical distribution. Therefore, the scores have to be normalized in order to represent it in same domain and same numerical range. Fingerprint and sclera scores are normalized using Min-Max normalization. It is the simplest normalization technique that achieves the common numerical range of the scores [0, 1] while retaining the shape of original distribution. As with most normalization technique, there are two cases relating to the character of the scores: (i) distance scores (ii) proximity scores. Let X denotes the set of raw matching scores from specific matcher. The normalized score of x is denoted by x'.

Given the max(X) and min(X) are maximum and minimum scores respectively. The normalized score are calculated as below.

For proximity based score:

\[ x' = (x - \text{min}(X)) / (\text{max}(X) - \text{min}(X)) \]

For distance based score:

\[ x' = (\text{max}(X) - x) / (\text{max}(X) - \text{min}(X)) \]

The normalized fingerprint and sclera scores are combined at matching score level using simple sum technique to generate final matching score as follows:

\[ \text{final fingerprint Sclera MS} = MS_f + MS_s \]

4. Feature Selection Module

The genetic algorithm (GA) is almost powerful search based optimization tool, which represents the problem solution as chromosomes. The GA is used to produce population solution by applying genetic operator such as crossover, reproduction, and mutation. The methodology is as follows:
Step 1: Initialization of search space population of randomly produced Chromosome

Step 2: The objective cost function (fitness) assign score to all chromosomes.

Step 3: Selection of member called parental chromosomes based on fitness value.

Step 4: Crossover parental chromosomes and mutation of Parents → children.

Step 5: The generation of the new children and selected members of the current population. Go to step 2.

Genetic algorithms are divided into optimization techniques, for feature selection process which are able to find the global optimum function. This algorithm can be used for modeling or control of the linear or nonlinear system for Simple Adaptive Neuro Fuzzy interference system (ANFIS).

When neural networks are used, the desired settings on the chromosomes can be connections of the neural network, the weights, and biases or the both. In the case of fuzzy logic, the wanted parameters are parameters of membership functions, base of rules or the both. In modeling of a system, the optimized function is the cost function:

$$K = \sum_{i=1}^{N} |e_i| = \sum_{i=1}^{N} |t_i - tm|$$

where \(t\) is output from the system, \(tm\) output from the modal of system, \(e\) is modal error and \(N\) is number of patterns.

In control of a system, the optimized function is the cost function

$$K = \sum_{i=1}^{N} e_i = \sum_{i=1}^{N} S_1 - S_i$$

Where \(s\) is reference variable, \(t\) is controlled output, \(e\) is control error and \(N\) is number of patterns.

In the both of cases, the minimum of fitness is searching. Fitness is represented by the cost function or in the case of control, by the modified cost function, which can be penalized for example by derivation of process output \(y\), or by measure or derivation of control action \(u\).

5. Database Training

For the training of databases images \(t1, t2,\) and \(t3\) the reference points are \(p1(x, y)\), \(p2(x, y)\), and \(p3(x, y)\) which represent the radius of the scalera fundus images. Then, these datasets are arranged as as follows.

1) Let \(p1(x, y)\) be the point where \(b\) and \(t3\) are to be aligned.

2) Then \(t2\), subtract \((p1(x, y), p2(x, y))\) to extract the shift values (hrv, vrv) in the horizontal and vertical axis.

3) Use a circular shift where \(t2\) is shifted in both horizontal and vertical directions directions as \(t2(x + hrv, y + vrv)\).

4) Repeat t
6. Decision Module

The score level of fusion process decision is based on the use of genetic algorithm based adaptive neuro-fuzzy inference system (GA-ANFIS). The final score of mapping is compared to a threshold value for distinguishing the authentic person or impostor.

IV. EXPERIMENTAL RESULTS

Experiments were carried out to evaluate the performance of the systems in term of accuracy and speed. The database consists of 50 fingerprint images and 50 sclera images. They are composed of 10 fingerprint and sclera images of same finger and same eye from 6 different users.

Figure: 4 Feature Selection based on fused data

Figure: 5 TS-Rule viewer of Multimodal Biometric system

Figure 5 shows the receiver operational characteristic (ROC) curve of multimodal system, fingerprint system and sclera system. As shown in Figure 4, the multimodal system of fingerprint and sclera outperforms unimodal fingerprint and sclera system. This part of the study investigates the efficiency of the proposed method of fusion and decision scheme in enhancing the reliability of multimodal fusion when the biometric datasets are free from degradation.
The datasets considered for the fingerprint and sclera modalities in this investigation are extracted from the XM2VTS and TIMIT databases respectively [Zafeiriou, 2006; Alsaade, 2005]. Using these biometric datasets, a total number of 140 client tests and 19460 non-client tests is used from the development data. While the total number of client and non-client tests used in investigating the performance for the proposed schemes is 140 and 19460 respectively.

![Image of Multimodal ANFIS Fingerprint-Sclera classification](image1)

**Figure: 6 Multimodal ANFIS Fingerprint-Sclera classification**

![Image of ANFIS measurements based on root mean square values.](image2)

**Figure: 7 ANFIS measurements based on root mean square values.**

The ANFIS structure is generated automatically with the following properties. Both range normalized biometrics scores are defined by five membership functions ranging from "very low" to "very high" of the form bell function uniformly distributed over the range (0, 1) as shown Figure 6.

<table>
<thead>
<tr>
<th>Biometric Modal</th>
<th>FRR(%)</th>
<th>FAR(%)</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Finger print</td>
<td>1.2</td>
<td>.17</td>
<td>97.4</td>
</tr>
<tr>
<td>Sclera</td>
<td>2.1</td>
<td>.14</td>
<td>95.2</td>
</tr>
<tr>
<td>Multimodal [fingerprint+sclera]</td>
<td>.21</td>
<td>.12</td>
<td>99.3</td>
</tr>
</tbody>
</table>

**TABLE I. PERFORMANCE EVALUATION**
Table 1 shows the results for the system accuracy in term of False Rejection Rate (FRR) for both unimodal fingerprint and Sclera system and fingerprint-sclera multimodal system. As shown in the Table 1 fingerprint-sclera multimodal has lowest FRR of 0.21%. The Multimodal ANFIS Finger print-sclera measurements based on root mean square values (RMSE) as shown in Figure 7. The accuracy of sclera authentication system in is reported as 1.0037%. Accuracy obtained in this experiment varies because sclera samples are not the same. The sclera samples used in this experiment were affected by noise during data acquisition which causes the FRR of sclera system to increase.

**Firmware Architecture**

The multimodal Fingerprint-sclera based Biometric system Architecture having both software and hardware elements commonly known Firmware. The hardware platform having reconfigurable low power Floating point arithmetic operation. Real time execution of multimodal biometric algorithm consumes less power and higher computational speed, which implemented in Field programmable Gate Array (FPGA).

<table>
<thead>
<tr>
<th>Biometric Modal</th>
<th>Execution Time</th>
<th>EER(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Finger print</td>
<td>1.8</td>
<td>4.53</td>
</tr>
<tr>
<td>Sclera</td>
<td>1</td>
<td>1.68</td>
</tr>
<tr>
<td>Multimodal [fingerprint+sclera]</td>
<td>.8</td>
<td>1.2</td>
</tr>
</tbody>
</table>

The FPGA increase execution speed of the biometric algorithm and also improve the performance through parallel processing. The multimodal biometric authentication system is implemented fully as XILINX FPGA software and was executed on the Spartan 6 clocked at 900 MHz. Table 2 shows the execution time of each image based on equal error rate (EER). Figure 8 shows the performance of fingerprint, sclera and multimodals.

![Performance analysis of fingerprint, sclera and Multimodal methods.](image)

V. **CONCLUSION**

This paper has presented a new fusion scheme that relies on genetic algorithm based Adaptive Neuro Fuzzy Interference System (ANFIS) techniques. In order to investigate the effectiveness of the proposed approach, it was compared to well-known unimodal Biometric systems. The experimental investigations have been carried out under three different data conditions. As
expected in the three cases of data condition (for all modalities), the results have shown that the use of GA-ANFIS scheme leads to the highest accuracy. This is due to the characteristics of the proposed GA-ANFIS hybrid system such that ANFIS takes into account the statistical distribution of the modalities (in terms of fuzziness) and hence uses the best-fit fuzzy rules to generate the proper output (decision).

The 'learning' capabilities of such system make this possible in combination with the power of expression of fuzzy rule and inference. However, the effectiveness of neuro-fuzzy techniques relies strongly on the parameter settings of the ANFIS structure and training conditions.

Efforts will focus on using GA-Based hybrid intelligent systems. Search and optimization capabilities of Genetic algorithms will certainly help automate the process of generating the best-fit settings for an Adaptive fuzzy inference system for fusion-decision purposes based on the results, it can be concluded that fingerprint-sclera multimodal system targeted for SOC FPGA has been fully developed. The accuracy of the system is promising with an FRR of 0.21%. Work is in progress to embed the image acquisition modules of fingerprint and sclera to FPGA development board and to create a fully embedded multimodal biometric system. Work also in progress to accelerate the Image Map Generation block in hardware so that it can be in real time.

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