ECG BASED BIOMETRIC FOR DOUBLY SECURE AUTHENTICATION

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ABSTRACT

This paper presents a new ECG based biometric system that has a doubly secure characteristic when applied to authentication. In this system the parameters of the new underlying pulse active ratio (PAR) feature vector process are represented by a 4 digit security personal identification number (PIN). An authentication is achieved by firstly using the correct PIN and, secondly, by obtaining a positive ECG feature vector matches. The proposed method is validated by experiments on 113 subjects recorded over wide time duration. It is shown that the PAR parameters can be used to generate different set of features with similar high authentication performance in a doubly secure fashion.

1. INTRODUCTION

Skimming at automated teller machines (ATMs) has been a serious issue throughout the world. Criminals are now using a more advance devices which incorporate a micro camera for PIN captures and a skimming device to capture the ATM card data. The European ATM Crime Report published by EAST (the European ATM Security Team) shows a 24% increase in card skimming attacks at European ATMs equivalent to €144 million losses [1].

To counter this problem, biometric ATM has been introduced. Palm and finger vein biometrics are two available technologies incorporated with ATM which have been widely accepted in Japan and Brazil. In Europe, Poland is the first country to trial this technology [2]. Based on this technology, after the ATM card is inserted, hands or fingers are placed over a vein scanner which recognizes a unique data to authorise a transaction. Without entering PIN during the transaction process, capturing the PIN and ATM cards by the skimmers is no longer useful. In general consumers still refuse to accept this technology due to the risk of personal data infringements.

A physiological biometric normally cannot be changed. Hence, if it is compromised, it is possible that an authentication can be exposed to fraudulent transactions forever. Traditional physiological based biometric authentication systems such as Iris [3], fingerprint [4], palm [5] or finger vein [6] and ECG [7-11] provide just a single level of security which, if compromised, makes the biometric practically unusable for the lawful user.

In this paper, a novel biometric system based on ECG characteristic is proposed that addresses the above shortcomings. A new feature vector extraction method known as Pulse Active Ratio (PAR) is proposed which utilizes 4 parameters to generate a feature vector. This 4 digit number is also used as a PIN thus offering a doubly secure authentication system. The remainder of the paper is divided as follows. Section 2 describes traditional ECG based feature extraction methods. The fundamental concept of the new PAR process is presented in section 3. Simulation setup and results are presented in section 4. Section 5 discusses the application of the PAR algorithm for the doubly secure biometric authentication system. Section 6 concludes the paper.

2. ECG BASED FEATURE EXTRACTION

The feasibility of using ECG to identify individuals was reported by Biel et al [8] in 2001. By using 12 lead recordings configuration, ECG measurements were carried out on 20 subjects aged between 20 to 55 years old. The ECGs were then converted into 30 usable features which are normally used in the clinical analysis. A total of 360 features are extracted from all 12 leads ECG recordings. Their test shows that there are only small difference between using limb leads and the chest leads. It was concluded that only 1 lead is enough to identify a person. 30 features from lead 1 are then reduce to 12 by removing features which have relatively high correlation with the others.

Israel et al [10] described a more comprehensive study in using 15 ECG pulse temporal features for human identification. The ECG fiducial points are extracted in two steps. First, the peaks positions are located by finding the local maximum of each P, QRS and T waves. Then, the base positions are estimated through the location of the minimum radius of curvature. Normalizing using the period of pulse is carried out so that the features are invariant to heart rate changes. The original 15 features were then reduced to 12 features using Wilke's lambda [12] .Classification based on the majority voting is used in this work to assign individuals to the selected classes.

All the work described so far uses amplitude and temporal information by first detecting the fiducial points of the ECG complexes. Finding the boundary locations of the ECG complexes is more challenging compared to detecting the peak location of the ECG complexes especially in the presence of noise.

These problems have lead researchers such as Plataniotis et al [11] and Agrafioti et al [7], to consider non-fiducial point based features for ECG biometrics In these techniques, the lengths of each ECG for all individuals are the same containing multiple heartbeats in one recording. In [11] and [7] , windowed auto correlation process are performed on ECGs segment to generate features. This technique generates a high number of coefficients which are further processed using for example the Discrete Cosine Transform (DCT) to form a reduced feature vector dimension. This reduces the representation of the overall characteristic of the ECGs, which limits the identification performance in a large population group [9].

In this present work, new ECG based feature extraction is presented utilizing only 2 fiducial points of the ECG wave. The new scheme will be used to develop a 4 digit ECG biometric algorithm.

3. PULSE ACTIVE RATIO (PAR) ALGORITHM FOR ECG BIOMETRIC

Figure 1shows the new Pulse Active Ratio (PAR) process for an ECG wave $y_{ECG}(t)$ of duration T_{ECG}. A triangular wave $y_{tri}(t)$ of a period T_{tri} with maximum amplitude of A_{tri} is used to modulate $y_{ECG}(t)$. This waveform is arranged to start at the peak of the P wave and end at the peak of the T wave as illustrated in Figure 1. The direct current (DC) off set of $y_{ECG}(t)$ is altered so that the minimum value of $y_{ECG}(t)$ is equal to zero. Furthermore, the peak to peak amplitude of $y_{ECG}(t)$ is the same value as its peak amplitude, A_{ECG}. Two constant parameters, the integer value modulation factor m_f and the modulation index m_i are introduced which are defined as:

$$m_f = \frac{T_{ECG}}{T_{tri}} \tag{1}$$

$$m_i = \frac{A_{tri}}{A_{ECG}} \tag{2}$$

These two parameters are used to relate the duration and amplitude between $y_{ECG}(t)$ and $y_{tri}(t)$ ensuring that there is an integer number of periods of the triangular waveform contained between the peaks of the P and T waves. Hence m_f represents the number of periodic triangular waves for $y_{tri}(t)$. In figure 1, m_f is chosen as 5.

Each period of this periodic triangular waveform intersects the underlying ECG signal. For each period, the location of the first intersection from the positive slope t_{+ve} and the location of the last intersection from the negative slope t_{-ve} are selected as the intersection points for that triangular wave period. Mathematically, this can be presented as follows:

$$t_{(2m-1)} = t_{+ve} \quad \text{for} \quad (m-1)T_{tri} \le t_{(2m-1)} \le \frac{(2m-1)}{2}T_{tri} \tag{3}$$

$$t_{2m} = t_{-ve} \quad \text{for} \quad \frac{(2m-1)}{2}T_{tri} \le t_{2m} \le mT_{tri} \tag{4}$$

$$T = \begin{bmatrix} t_{(2m-1)} & t_{2m} \end{bmatrix} \tag{5}$$

for $m = 1,2,3 \ldots m_f$

T corresponds to specific intersection location times as illustrated in Figure 1. Using rules (3) and (4) , a pulse waveform $o(t)$ is produced as shown in figure 1 where the odd index of the location variable $t_{(2m-1)}$ in (5) correspond to the transition to $O_{\max}$ from $O_{\min}$,and the even index of t_{2m} in (5) correspond to the transition to $O_{\min}$ from $O_{\max}$. Values for $O_{\max}$ and $O_{\min}$ are user specified. The vector T in (5) is now defined as the transition state vector for the ECG complex.

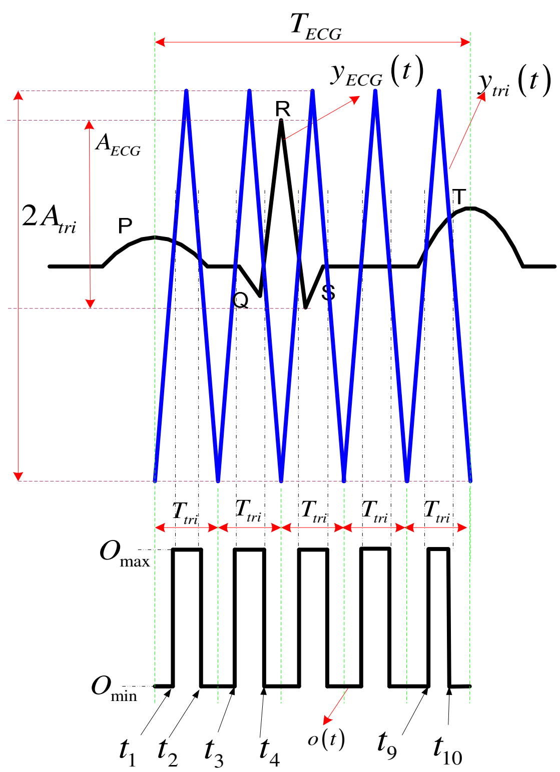

Figure 1 – PAR Pulse Generation

Mathematically the pulse active ratio (PAR) representation is defined as

$$X = x(m) = \frac{\int o(t)dt}{\int y_{tri}(t)dt} = \frac{\int_{(m-1)T_{tri}}^{mT_{tri}} o(t)dt}{1/2 \times T_{tri} \times 2A_{Tri}}$$

$$= \frac{1}{m_i A_{ECG}} \left\{ \frac{m_f}{T_{ECG}} \left[\left(t_{2m} - t_{2m-1} \right) \left(O_{\max} - O_{\min} \right) \right] + O_{\min} \right\} \quad (6)$$

for $m = 1, 2, \ldots m_f$

Equations (3), (4) and (5) guarantee that selecting a value for m_f will produce exactly a dimension of size m_f for the feature vector in (6).

In (6), 4 variables namely m_f, m_i, $O_{\min}$ and $O_{\max}$ can be varied to represent a 4 digit security PIN as illustrated in figure 2. The modified algorithm and suggested range for the 4 variables required for the 4 digit ECG biometric will be discussed in the following section.

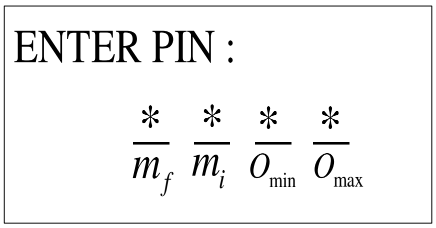

Figure 2 – Four digit biometric PIN

4. RESULTS

The ECGs used in this experiment are obtained from the Physikalisch-Technische Bundesanstalt (PTB) database [13]. The PTB database is selected in this study because the ECG recordings provided have an average time interval between any two recordings of the same subject of about 500 days (16.6 month) [14]. A total of 486 ECGs from 113 subjects are grouped into training (113 ECGs) and test database (373 ECGs). The training database contains one ECG from each subject, while the test database contains one or more ECGs from these 113 subjects. Both databases contain different ECG signals. As X in (6) is extracted from both databases, the similarity measurement process is conducted as indicated in figure 3.

To assess the performance of the PAR algorithm for the new ECG biometric system, the proposed feature extraction method is compared with methods used in [8] and [10]. PAR is set up as indicated in section 3 with m_f, m_i, $O_{\max}$ and $O_{\min}$ set to 14, 1.2, 1 and 0 respectively. The fiducial points used in [8] and [10] in this experiment are detected using ECGPUWAVE [15] .

Figure 3 shows the process used to generate the genuine and imposter matching score. A matching score is a measure of similarity between features derived from the training and test database. Each feature vector from the test database is compared to all feature vectors from the training database. Euclidean distances are used as a similarity measurement to generate the matching score. If the feature vectors from the test database and from the training database are from the same subject, the matching score is labeled as the genuine score. Otherwise, the matching score is labeled as an imposter score. The score vectors are input to the receiver operating characteristic (ROC) curve processing block.

The performance evaluation of the system is determined by comparing the value of the area under ROC (AUR) and the equivalent error rate (EER). AUR is a common quantitative measure for comparing ROC curves. Its value ranges between 0 and 1. EER is defined as the rate at which the false positive rate is equal to the false negative rate. A lower value of EER is desirable for practical systems. Figure 4 represents the ROC curves for PAR, Biel's [8] and Israel's [10] feature extraction methods.

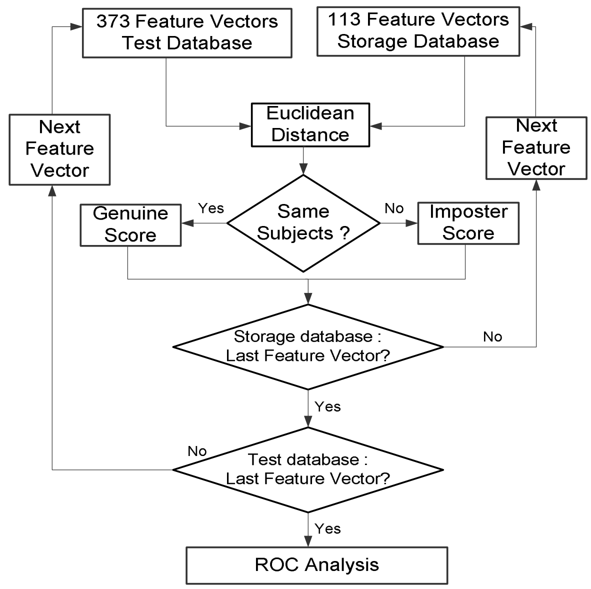

Figure 3 – Matching Score Process

From figure 4, PAR is seen to offer better performance with the max AUR equal to 0.835 compared to 0.786 for Biel's and 0.725 for Israel's method. PAR also produces the lowest EER of 0.252 compared 0.288 and 0.344 EER for Biel and Israel's methods respectively.

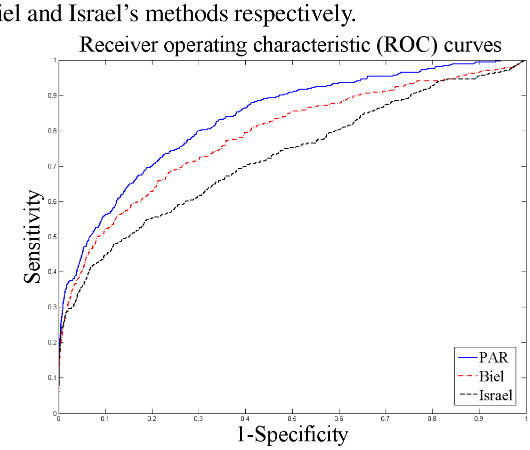

Figure 4 – ROC comparison curve

PAR is an easy feature extraction technique to setup, as it just requires detecting the approximation locations of the P wave and T wave rather than the actual precise location using

[8] and [10]. The exact locations of ECG fiducial points for the same subject are hard to determine as these locations vary with the heart rate.

The m_f, m_i, $O_{\max}$, and $O_{\min}$ values as in (6) are now varied to investigate their influence on the AUR and EER performances. Figure 5 illustrates the AUR performance for m_f ranging between 5 and 15 while m_i is set between 1 and 2. $O_{\max}$ and $O_{\min}$ are set to 1 and 0 respectively. It can be seen in figure 5, AUR varies only 3 % for the selected m_f and m_i ranges.

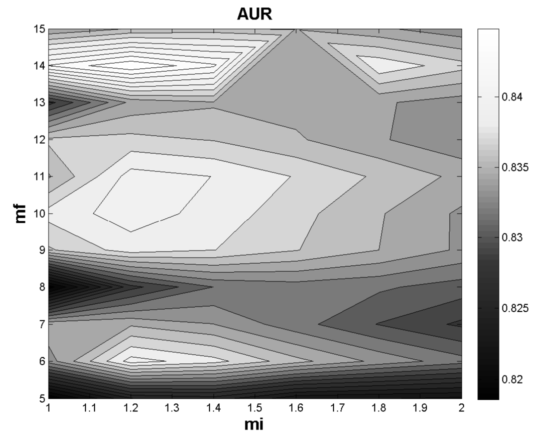

Figure 5 – AUR for different m_f and m_i

Figure 6 shows the EER performance for the selected m_f and m_i ranges. As can be seen from the figure, the EER varies around 3% for the m_f and m_i ranges.

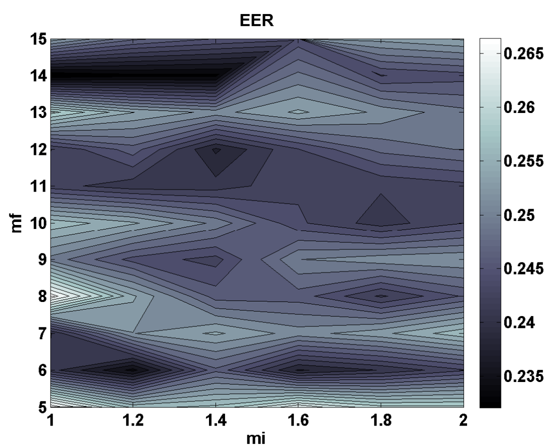

Figure 6 – EER for different m_f and m_i

The AUR and EER performance when varying $O_{\max}$ and $O_{\min}$ can be observed in figure 7 and 8. For these observations, $O_{\max}$ ranges between 1 and 100 while $O_{\min}$ varies between -10 and 10. For this simulation, m_f and m_i are set to 14 and 1.2 respectively. The AUR performance for the ranges of $O_{\max}$ and $O_{\min}$ is given in figure 7. By selecting the range of $O_{\max}$ greater than 70 and $O_{\min}$ between -10 to 0, the AUR difference is only 0.5%.

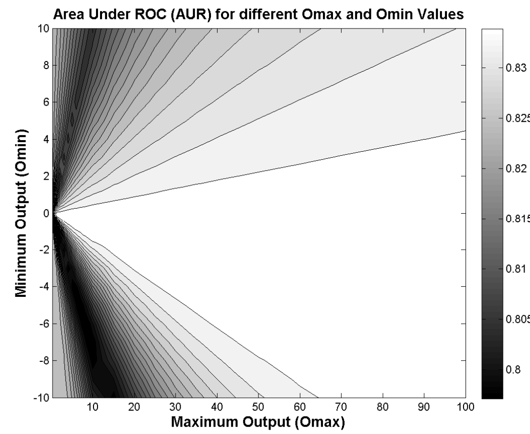

Figure 7 – AUR for different $O_{\max}$ and $O_{\min}$

Figure 8 shows the EER performance for different values of $O_{\max}$ and $O_{\min}$.

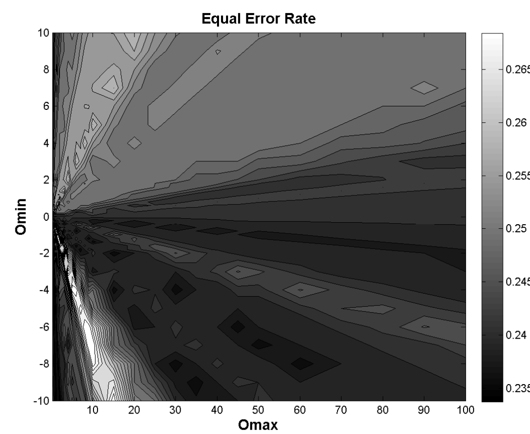

Figure 8 – EER for different $O_{\max}$ and $O_{\min}$

By selecting the range of $O_{\max}$ and $O_{\min}$ greater than 70 and between -10 to 0 respectively, the EER profile varies around 1 %.

5. PAR BASED DOUBLY SECURE AUTHENTICATION

In the previous section, it was shown that PAR gives superior biometric performance compared to [8] and [10]. For the given set of ECGs data, by changing the 4 parameters within specific bounds, the AUR and EER performance only varies up to 3% . The possible values of PAR parameters that provide good authentication performance facilitates the use of a wide range of PIN values. As indicated in section 3 the PAR ECG biometric system requires 4 digits of the PIN to generate the ECG biometric features. From the simulation results in section 4, the proposed range of the 4 variables for similar authentication performance is shown in the Table I.

Table I. Suggested ranges of PAR variables

PAR Variables	Ranges
m_f	5 to 15
m_i	1 to 2
$O_{\max}$	70 to 100
$O_{\min}$	-10 to 0

In figure 2, only 4 digit ranges between 0 and 9 are used as the PIN. In order to link the PIN with the ranges of PAR parameter values shown in Table I, the following PAR parameter selection process is proposed:

$$m_f = \left(1^{st} \text{ PIN digit}\right) + 6 \tag{7}$$

$$m_i = 1 + \left(2nd \text{ PIN digit}\right)/10 \tag{8}$$

$$O_{\max} = 70 + \left(2 \times 3^{rd} \text{ PIN digit}\right) \tag{9}$$

$$O_{\min} = 0 - \left(4^{th} \text{ PIN digit+1}\right) \tag{10}$$

The value of each feature is different when different combinations of PIN are presented. The first PIN digit is the most important digit to counter skimming. It represents the dimension of the feature vectors. For example, if m_f equals to 6, there should be 6 feature vectors from the ECG for comparison.

If the feature vectors stored have a different length compared to the submitted one, the system can automatically terminate the authentication process and hence decline the user. This reflects the first level of the security system where the submitted PIN must match the PIN stored. In case where the user PIN is acquired fraudulently, the authentication still fails as the generated feature vectors from the PIN and user ECGs will be different. This reflects the secondary level of the security system, which requires the ECG from the same subject to be presented for authentication.

If the ECG signal and the user PIN are compromised then the PAR ECG based biometric remains useable by simply changing the user PIN and registering this change in the system. This is a significant advantage over other non-flexible ECG based systems [3-8] and other biometric systems such as iris and fingerprint.

6. CONCLUSION

A doubly secure ECG based biometric system using a new pulse active ratio (PAR) was presented. It was shown that the first level of security for a biometric system is the 4 digit PIN that represents the 4 PAR parameters. Feature vector of the ECG wave generated by the PAR algorithm becomes the secondary level of security. Throughout experiments using the ECG dataset, it was shown that the proposed PIN range of the PAR ECG based biometric system generates a similar good performance.

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