Utilizing ECG Waveform Features as New Biometric Authentication Method

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ABSTRACT

In this study, we are proposing a practical way for human identification based on a new biometric method. The new method is built on the use of the electrocardiogram (ECG) signal waveform features, which are produced from the process of acquiring electrical activities of the heart by using electrodes placed on the body. This process is launched over a period of time by using a recording device to read and store the ECG signal. On the contrary of other biometrics method like voice, fingerprint and iris scan, ECG signal cannot be copied or manipulated. The first operation for our system is to record a portion of 30 seconds out of whole ECG signal of a certain user in order to register it as user template in the system. Then the system will take 7 to 9 seconds in authenticating the template using template matching techniques. 44 subjects' raw ECG data were downloaded from Physionet website repository. We used a template matching technique for the authentication process and Linear SVM algorithm for the classification task. The accuracy rate was 97.2% for the authentication process and 98.6% for the classification task; with false acceptance rate 1.21%.

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1. INTRODUCTION

Recently, biometrics authentication has been widely researched and applied to enhance the security level of the current systems. The security level at a system is measured by the system immunity against intrusion and fake signature to identify the person during the authentication process [1]. Technically, some biometric methods have strong uniqueness such as scanning iris and retina. But they require expensive and special equipment to install them. Other biometric methods such as voice, face and fingerprint recognition have a strong uniqueness too. But even so; these features still easy to be obtained, since they are easy to be manipulated. Behavioral biometrics methods, like gait and handwriting analysis for instance, have a very weak uniqueness in comparison with the previous biometrics methods. ECG has been used to diagnose heart diseases and applied in other medical fields for a long time. Many recent studies confirm that it is possible to use ECG as one of the biometric features [2]. According to [3], [4], ECG is difficult to be cloned or manipulated because ECG signal is unique for each single person and not readily available to others. Moreover, it has a small computational and storage overhead as ECG is a one-dimensional signal; so, relative algorithms can be deployed in smart phones, smart watches and many new smart devices. For collecting ECG raw data, we need at least two locations in human body to place the electrodes [5].

It is pivotal to extract the ECG signal features that represent a vital information could be used to improve the authentication and classification performance. There are several techniques for extracting ECG signals features, which are classified into time, frequency and time–frequency extraction techniques. The extracted time domain features are the amplitude parameters (QRS, ST), duration parameters (QRS, QT, and PR) and heartbeat interval [2]. Time extraction technique do not provide good recognition; and that is due to the frequent changes in the amplitude and duration in the ECG Signal waves [3]. On the other hand, the frequency domain extraction technique do not provide interim information about the ECG signals waves. Applying suitable time–frequency technique can overcome this issue.

In the current biometric authentication using ECG signal waves related works, many researches had been performed; like in [1], the researchers have propused mobile biometric authentication algorithm based on ECG signal. They have conducted two experiment types; experiment using physionet ECG records and laboratory experiment. The first experiment type from their work is related directly to our work. So according to them, 73 records obtained from the Physionet database. The ECG time length for the obtained records scope between 30 mintutes to 24 hours. Their method had scord 1.29% false acceptance rate and 81.82% accuracy rate over 4 s of signal lenght.

In the work [6], they had a stratigy to extort frequency doiman features using Fourier transform method. They were seeking for certain features among the frequency doiman features; like slope, harmonic number, the magnitude gap and ratio of different frequency energy to total energy. For the classification process they had used correlation analysis and neural network were used in identification phase. They have scored low recognition rate, they believed the reason was in feature selection method; but from our research point of view we belive that the reason is in the feature extraction type due to insufficient information provede by this type of feature. They have scored 96.4% of accuracy rate with 3.61 false accept rate.

We have contributed to biometric authentication filed by increasing the accuracy rate level for authentication and classification phases; at the same time, we have reduced the false acceptance rate. We have scored a significant authentication accuracy rate by following certain proper steps; starting from preprocessing the raw ECG signal data, feature selection, segmentation and extraction technique. Also, we have used the best classification method in ECG signal case uinsg linear SVM classifier and at the same time we have used template matching technique for authentication process.

2. ECG SIGNAL PHYSIOLOGY

When the heart cells are in rest situation they considered as in polarized case which means that there is no electrical activity is taking place at the moment. Basically, the heart is depolarized when it is in systole state and repolarized when it is at diastole state. The depolarization case in normal ECG wave takes place from the beginning the P wave until the middle of ST segment as shown in Figure 1, while the repolarization case starts from the T wave [7], [8].

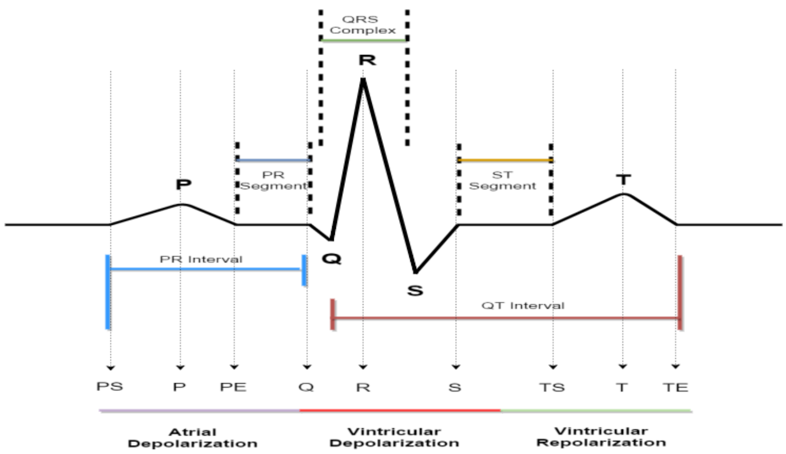

Figure 1. ECG signal physiology.

Broadly, ECG time–frequency features are classified as either waveform or characteristic based features. The simplest one to obtain among the features is characteristic based, because in order to start the extraction process ; it just require the ECG fiducial points information about one of ECG complex. In Figure 1 PS, P, PE, Q, R, S, TS, T,TE are the fiducial points of the given portion from the ECG signal. Fiducial points represent the correspondence points that intersect with the peaks and boundaries of P, QRS and T waves. In ideal ECG complex, there are six boundaries and three peaks (P, R, and T) as illustrated in Figure 1 [9].

The main features that aimed to be extracted are angle, slope, amplitude and duration (temporal). Discriminative characteristics must be selected from these features by applying extra processing over them [10]. The problem of extracting characteristic based features is when we use fiducial points that may cause difficulties in detecting the boundaries especially in the presence of noise.

On the other hand, Waveform based features processed by using the waveform process coefficient values such as autocorrelation, fourier coefficient, phase space reconstruction, and wavelet coefficient. It is worth mentioning that most of the ECG complexes are used in waveform technique for feature extraction. The technique has an advantage of not requiring detection of the fiducial points which may generate boundary detection difficulties in the presence of noise [11]. Therefore, inorder to avoid boundary detection difficulties issue, we have extorted waveform based feature out of the ECG signal.

3. RESEARCH METHOD

Our method structure is organized by a sequence of processing steps; starting with ECG preprocessing, ECG feature selection, Segmantaion, ECG feature extraction, Inter-Beat-Interval (IBI) preprocessing and IBI extraction.

The first step in ECG preprocessing, is that we should filter the ECG to maximize beat detection efficiency. High-pass filtering was used to remove the baseline wander, which is achieved by subtracting a low frequency trend line from the ECG [12]. This trend line was formed by applying a triangular (two-pass) moving average filter with a window size of 512 points and constent rate of 50 HZ to the ECG signal. On the other hand, Low-pass filtering is used to remove high frequency noise by using a triangular moving average filter with a window size of 3 points. Moving average filters provided a simple, valuable, and fast method to filter ECG [13], [14].We have applied feature selection phase by using *abs()* Matlab built-in function to apply the absolute value over the whole ECG signal data.

Right after the preprocessing comes the segmentation, ECG segments were processed for 30 seconds. This process starts by passing a moving window over the entire ECG data for 5 minutes [15]. Then, figures over ECG were collected for each window on time. According to the output, a list of functional ECG segments was created. The selection criteria for the applicable 5 minute segment have been achieved by the following:

a. Heart rate (HR) mean was more than 250 beats/min
b. The overall number of ectopic beats were less than 1% of total beats
c. The nonexistence of significant missing data, and the visual inspection of noise and ecotype.
d. Significant missing data was defined as having more than 150 consecutive missing data values or missing more than 150ms consecutively.
e. Segments with less than 150 consecutive missing data values were interpolated using cubic splie.

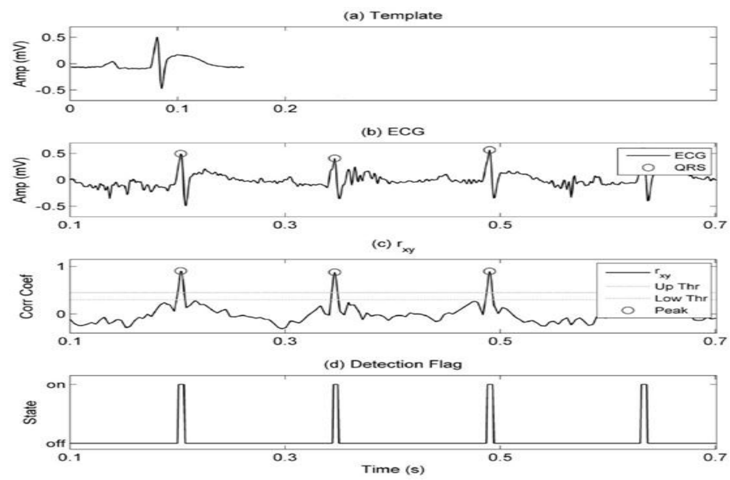

Figure 2. Template matching for QRS detection

As a result, the applicable 5 minute segment with the lowest HR was chosen for analysis.

For the ECG feature extraction, Correlation based template matching algorithm was used to locate QRS complexes [16]. However, two QRS types of templates were implemented to achieve template matching and they were created by averaging more than 20 QRS complexes [17]. The first type of template was the Global template; global in the sense that one template was suitable for all subjects as shown inFigure 2.

In IBI preprocessing and before initiating the correction process over the ectopic intervals, we should be acquainted with them. To achieve the proper detection techniques, we have used percentage, standard deviation and median filters. The median filter acts as an impulse rejection filter with threshold to delineate ectopic intervals [18,19]. A length of N with random variable x using a threshold of τ for median filter equation is given by the following equation:

$$D(n) = \frac{|x(n)-med(x)|}{1.483.med\{|x(n)-med(x)|\}} \quad (1)$$

If D (n) $\leq\tau$, then not ectopic; else ectopic

The correction process is established after detecting the ectopic interval by applying four correction techniques. The correction process is established after detecting the ectopic interval by applying four correction techniques [20]. The first one aims to eliminate any ectopic intervals could be found. The second technique is used to replace any ectopic interval with the mean value of w near the IBI intervals centered on the ectopic interval as shown in Equation (2). Median technique is related to the replacement of ectopic intervals with the median value of w neighboring the IBI intervals centered on the ectopic interval as shown in Equation (3). Finally, cubic spline replaces ectopic intervals by using cubic spline interpolation.

$$ibi'(n) = mean\{ibi(n+m): |m| \leq \frac{w-1}{2} \quad (2)$$

$$ibi'(n) = med\{ibi(n+m): |m| \leq \frac{w-1}{2} \quad (3)$$

There are multiple mechanisms of signal detrending (normalizing) to remove low frequency, some of these mechanisms are: linear detrending, polynomial detrending, wavelet detrending and wavelet packet detrending.

In the IBI extraction step, the data contain beat-to-beat intervals that were basically elicited from the ECG signals. Commonly, we rely on R-wave to find the temporal locations of beats as it is often the easiest wave to distinguish. Moreover, R waves typically have the largest amplitudes in comparison with surrounding P, Q, S, and T waveforms [21].

The following equation clarifies how to calculate time series IBI of an ECG segment containing N beats, where beat (n) is the time location of the nth beat:

$$IBI(n) = beat(n+1) - beat(n): 1 \leq n \leq N-1 \quad (4)$$

The system model consists of a series of process start from recording a portion of 30 second from the raw signal for the first time, Pre-process the raw signal, Extort the feature out of it then in the authentication process the system will apply template matching technique as shown in Figure 3. After the system will successfully recognized the user; the Linear SVM classifier will classify the users according to authorization level associated with all granted privileges to each level such as “admin” or “regular user” level. The system will display the user name, age, gender, ECG signal, spectrum, QRS complex, heart beat based on signal and heart beat based on spectrum [22-24].

We have used LIBLINEAR [25], [26] over 8 subjects’ ECG records for training set and 36 subjects’ ECG records for testing set. We have applied linear SVM according to [27] recomandation; after they have done a comparsion in their work between the linear and non-linear SVM performance. The subject can provide the ECG signal to our system in many ways, one of the ways is by touching the mobile and bracelet electrodes with the fingertips for first-time enrollment and template creation or by just toching the bracelet that contains two electrodes that located in the upper side and under the bracelet like in Nymi band case. The other way is by doing the ECG recording in clinic or hospital but it is not convineant one because it is not practical due to some limitiations like it will not be avialabe all of the time to apply it.

We used the following equation to assess accuracy rate (AR) over the classification and authentication phases of our experiment:

$$AR = \frac{s_{Correct}}{s_{Total}} \quad (5)$$

Where $S_{Correct}$ variable represent the number of the samples that have tested correctly during the classification and authentication phases. The S_{Total} variable represent the total number of 44 subjects' test samples.

For the purpose of evaluating the authentication phase of our experiment, we have used the following equations where Equation (6) is to obtain false accept rate (FAR):

$$\text{FAR}=\frac{FPS}{ANS}\times 100\% \tag{6}$$

In fact, in equation number 6; FPS represent the number of false positive samples and ANS represent the number of actual negative samples.

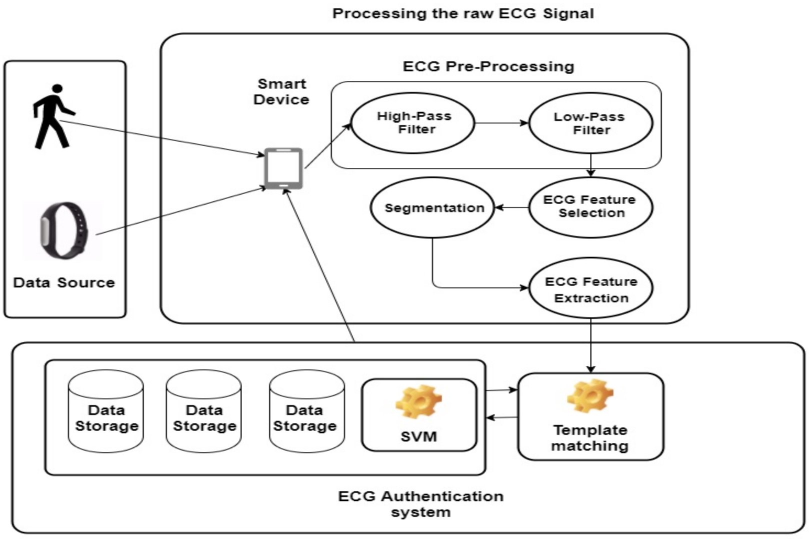

Figure 3. ECG Authentication System Technical Approach

4. RESULTS AND ANALYSIS

We have tested 44 subjects' ECG raw records with the extensions (*.mat, *.txt, *.dat); 22 of the subjects' samples were authorized inside our system as 11 males and 11 femeles as shown in Figure 3 while the other 22 as 11 males and 11 femeles are not authorized users as shown in Figure 4. The accuracy rate was 97.2% for the authentication process and 98.6% for the classification task over all the segments of the whole signal.

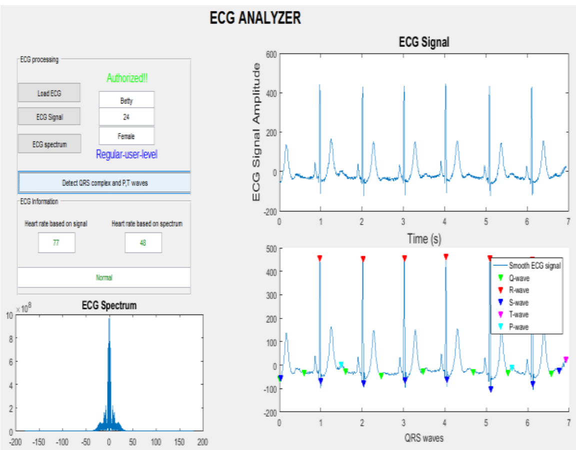

Figure 4. ECG Authentication System result for authorized user

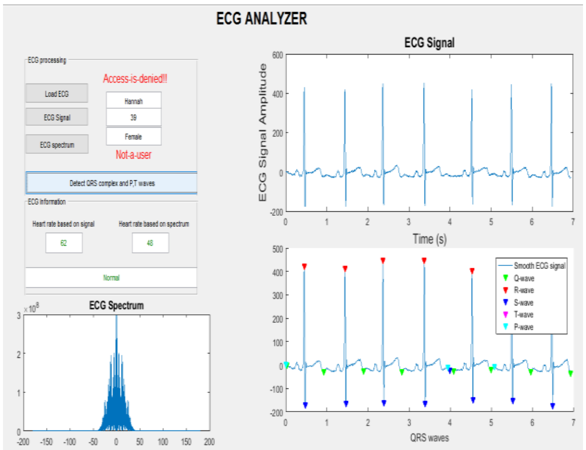

Figure 5. ECG Authentication System result for unauthorized user

In time, when we applied the SVM classifer over a portion of the signal which technicily one segment out of the signal, we found that the classification accuracy average was 95.8% and with authentication accuracy average of 96.9%. Regarding segment processing case, the accuracy is nearly the same to the processing of the whole signal case; but the time required for authentication was faster in the segmantion situation. To over come this issue, we have processed the whole signal as a series of segments; so we gain the high accuracy rate along with speed in performance.

We have done a compersion between our method and previous related wroks in term of number of subjects, false accepted rate and accuracy matters like in Table 1. It is obvious that we have increased the authentication accuracy rate and decreased the false acceptance rate.

Table 1. Authentication Result of Mothods

Recerch	No. Subjects	Year	FAR	Accuracy
W. Yarong et al. [6]	15	2015	3.61%	96.4%
J. S. Arteaga-Falconi et al. [1]	73	2016	1.29%	84.93%
Our propoused method	44	2017	1.21%	97.2%

5. CONCLUSION

Our design paves the way towards a comprehensive secure system that is using a new feature which is ECG signal analysis as one of the biometric methods. By using ECG signal waveform features as biometric authentication we have concluded that these features cannot be copied or manipulated. Therefore, systems immunity against intrusion and fake signature to identify the person during the authentication process will be impervious.

We have increased the accuracy rate and reduced the false accept rate significantly, comparing with previoues related work like in [1, 6] cases. By reducing the false accepted rate, the authentication accuracy will be steadily increased. We have successfully reached a high accuracy level in authentication and classification wise of ECG raw signal. We are looking forward to deploy my system effectively in many life aspects like health monitoring; not just regarding systems security matters.

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