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ScienceDirect
Procedia Computer Science 96 (2016) 305 – 314
Procedia Computer Science

20th International Conference on Knowledge Based and Intelligent Information and Engineering Systems

Development of Heartbeat Detection Kit For Biometric Authentication System

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Abstract

Automated security is one of the major concerns in modern time where secure and reliable authentication is in great demand. However, traditional authentication methods such as password and smart card are now outdated because they can be lost, stolen and shared. In this project, biometric system based on heartbeat signals which is also known as Electrocardiographic (ECG) signals is proposed. Heartbeat is chosen as modality due to an individual's ECG signals cannot be faked. Compared to fingerprint it can be fooled with fake fingers, face can be extracted using user's photo and voice can be imitated conveniently. As ECG signals are reflection of the mechanical movement of the heart, these features contain unique physiological information which make them a promising authentication technology. In this study, we develop a portable ECG detection kit for data acquisition. The prototype has successfully tested as a wearable bracelet heartbeat detection for personal system log in. For the software part, wavelet transform algorithm is used as feature extraction technique while for the classification process Support Vector Machine (SVM) is employed. Consequently, the whole system is then integrated on Intel Embedded N2600 Processor with Altera Cyclone IV FPGA Board (DE2-150) as biometric system. Experiment results showed that 2.0069% of EER performance has been achieved, thus this shows that the developed prototype can be a promising modality for biometric system.

Peer-review under responsibility of KES International

Keywords: detection kit; biometrics; heartbeat signal; ECG; wavelet transform.

1. Introduction

Electrocardiography is a transthoracic interpretation of electrical activity of heart over a period of time sensed by electrodes attached to the surface of the skin and recorded by an external device which attached on the body. The recording formed by this noninvasive procedure is termed an electrocardiogram (ECG), which used to measure the

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1877-0509
Peer-review under responsibility of KES International
doi:10.1016/j.procs.2016.08.143

heart's electrical conduction system. It picks up the electrical impulses produced by the polarization and depolarization of cardiac tissue and interprets into a waveform. The typical ECG waveform comprises of P wave, QRS complex and T wave as shown in Fig. 1. Therefore, the waveform is used to measure the rate and regularity of heartbeats as well as the position and size of the chambers, the existence of any damage to the heart and the effects of drugs. Most of the ECGs are performed for diagnosis of heart abnormalities or research.

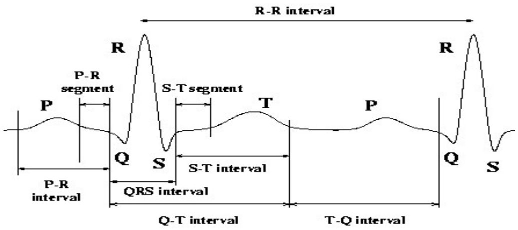

Fig. 1. Typical electrocardiogram (ECG) waveform.

The studies of ECG signals as a potential biometric trait have been reported by Biel et al.[1] and Kyoso and Uchiyama[2]. Over the past few years, the assessment of ECG signals as a prospective biometric modality has exposed promising results. Given the energetic and continuous nature of this information of source, ECG signals offer numerous advantages to the field of biometrics[3]. Since biometrics is the science of identifying a person using his/her physiological and/or behavioral characteristics, therefore biometric traits are difficult to counterfeit which results in higher accuracy compared to traditional authentication systems such as using passwords and ID cards. ECG is chosen as modality due to an individual's heartbeat cannot be faked. Compared to other biometrics such as fingerprint, it can be fooled with fake fingers, face which can be extracted using user's photo and voice can be imitated conveniently[3,4]. Thus, research on the use of internal features from body that is difficult to be spoofed like ECG is being focused by many researchers nowadays. Study on ECG to detect the heartbeat of the user for authentication system has also been done in Hegde et al. (2011)[5].

In this project, the study and understanding about ECG signals are very important. At the core of heart, there are a set of myogenic cells whose main purpose is for the periodic self-stimulation capability, which eventually generates the cardiac cycle and rhythm. Nowadays, both the heart rhythm and cycle are familiar concepts, extensively studied in the healthcare domain. The cycle is categorized by the typical heartbeat waveform as shown in Fig. 1, while the rhythms is commonly known as the heart rate[6]. Besides that, it is also known that measurements of electrical potential at different locations on the body surface will generate different ECG vectors. Through the years, several authors have claimed the properties of the ECG in applications to biometric recognition[3,7,8]. In these researches, the focuses are mainly on sensing devices, feature extraction and recognition methods. There are several variations of the sensor devices have been reported. Most of the researches were dedicated on signals collected through "on-the-person" approaches, which include single- and multi-lead clinical-grade ECG acquisition devices. But currently, the researchers have pivoted towards "off-the-person" approaches, which involved a 2-electrode setup[9] and a 3-electrode setup[6]. Next, regarding the feature extraction, current approaches are categorized as fiducial, partially fiducial and non-fiducial. Fiducial method uses slope, latency and other measurements derived from anchor points within the signal to create feature vectors that are used as input to the recognizer[1]. Then, partially-fiducial method naturally uses the R-peak to achieve heartbeat waveform segmentation, assuming either the full waveform or a subset of it as input to the recognizer[10]. For non-fiducial method, it extracts information from the structure of the signals without the need of any reference points[9,11]. Consequently, for the recognition methods, authors have mostly discovered neural networks[12], statistical pattern recognition[13], wavelets[14,15] and support vector machines[16].

In this paper, we develop a heartbeat detection kit as data acquisition which can function for authentication system. The prototype has successfully been tested as a wearable bracelet heartbeat detection for personal system log in which consists of four main parts i.e. portable and wearable heartbeat detection kit, android platform application, Heart ID offline or online database server and Intel Atom N2600 embedded with Altera Cyclone IV FPGA board (DE2-150). The overall design of system architecture of this proposed system is shown as Fig. 2.

The rest of the paper is organized as follows: section 2 describes the methodology adopted in our system; section 3 summarized the experimental results and finally, section 4 provides the conclusion.

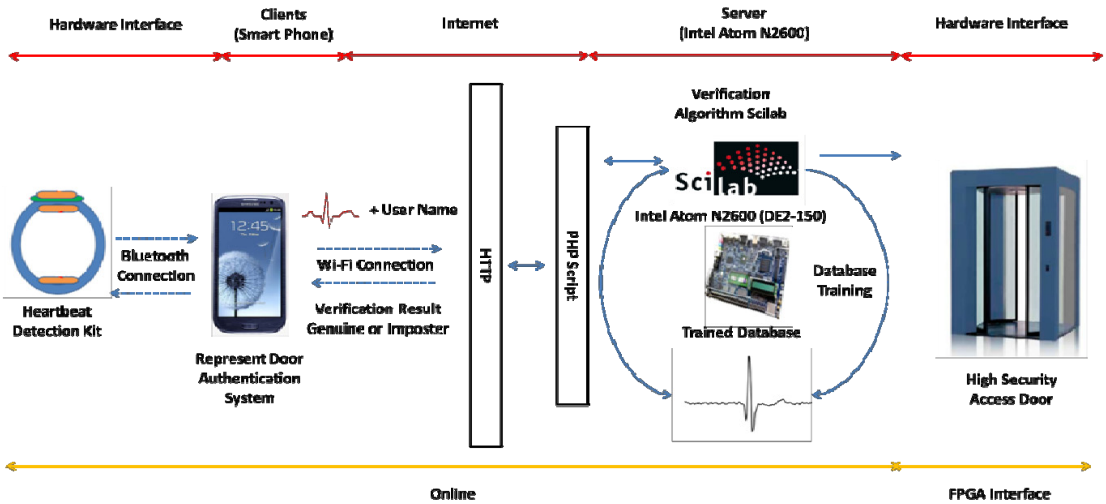

Fig. 2. Overall structure of heartbeat detection kit for biometric authentication system

2. Methodology

2.1. Design of portable and wearable heartbeat detection kit

Portable and wearable heartbeat detection kit is the most important part in our system. It takes the responsibility to detect the heartbeat signals of the user and send out the ECG signals to be processed through the Bluetooth module. In general, the heartbeat detection kit is formed by six main parts: instrument amplifier (IA), high-pass filter (HPF), 60Hz notch filter, low-pass filter (LPF), analog-to-digital converter (ADC) and signal transmitter. The block diagram of heartbeat detection kit is shown as Fig. 3.

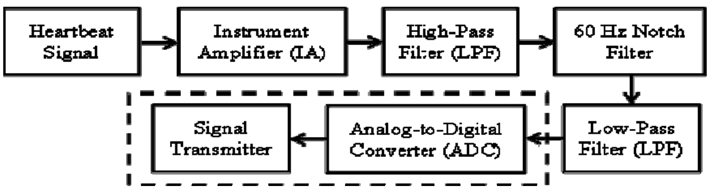

Fig. 3. Block diagram of heartbeat detection kit.

In order to design a portable and wearable heartbeat detection kit, flexibility of the device is our main concern. So, in this study, the device is designed as a wearable bracelet to be used by user for system log in. Thus, we decided to use three electrodes to detect the ECG signals in our kit instead of twelve electrodes which are normally used in standard clinical 12 lead ECG devices. The placement positions of the electrodes are set as shown in Fig. 4. By placing a finger on the topside electrode while the user's wrist is in contact with another two electrodes, an electrical circuit is completed, thus ECG signals are able to be detected by the device. Since the ECG signal's voltage is normally just a few millivolts or less, thus, it needs to pass through the following amplifier stage in order to amplify and pre-process the signal before it can be executed to the back-end system.

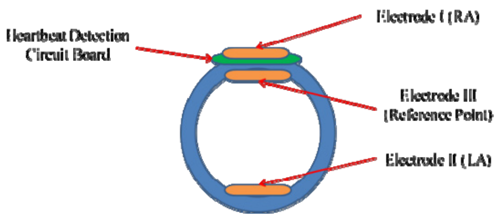

Fig. 4. Wearable and portable heartbeat detection kit.

2.1.1. Instrumentation amplifier

In order to obtain a high common-node rejection ratio (CMRR), an instrumentation amplifier is chosen as the preamplifier in the analog front-end system. In this project, an instrumentation amplifier with chip INA-128 was used. It provides a high CMRR (at least 120dB), high precision, low power consumption and low quiescent current. Besides that, the gain of this amplifier can be adjusted to an appropriated level in order to fit the operation condition of the chip.

2.1.2. High-pass filter, 60Hz notch filter and low-pass filter

After the instrumentation amplifier (IA), a high-pass filter with an active RC circuit is used to decrease the low-frequency noise under 0.05Hz. The next stage is a notch filter with a Twin-T notch structure; it keeps the circuits against the 60Hz electrical noise. Then, an active RC low-pass filter is used to cut down the high-frequency that above 150Hz, thus the desired heartbeat signal from 0.05Hz to 150Hz is obtained.

2.1.3. Analog-to-digital converter and signal transmitter

To apply digital signal processing (DSP) at the back-end of the system, the analog signal from the low-pass filter is converted into digital signal by analog-to-digital converter (ADC). Referred to Fig. 3, there is a dotted block which consists of analog-to-digital converter and signal transmitter. In this case, both of these are done by an Atmel AVR microcontroller, ATmega328 and a Bluetooth module, HC-06. This is due to the microcontroller consists of 10-bit resolution ADC; therefore external ADC is not needed here. Besides, it consists of 32kB flash memory which allowed us to write a C program to interface with any hardware through the input / output (I/O) pins. Thus, we integrated the Bluetooth module, HC-06 with the microcontroller to form as a signal transmitter by writing a C program to control the follow. The program flow of the signal transmitter is shown as Fig. 5.

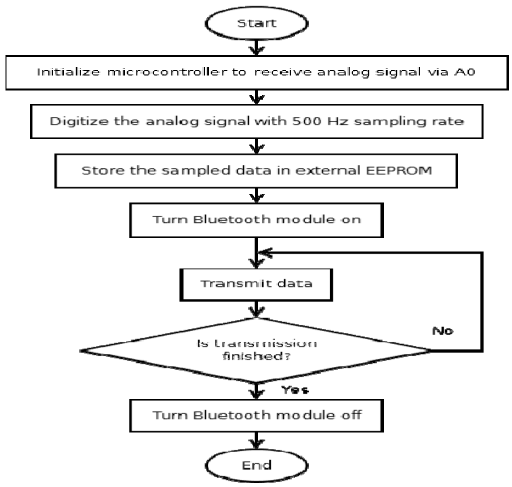

Fig. 5. Program flow in the microcontroller.

2.2. Android platform application

In this proposed project, we developed an Android platform application which functions as a security login in system. This application receives the serial data from the heartbeat detection kit through Bluetooth connection. Then, the incoming data as *.dat file is saved when sign in or sign up function in the application is triggered. After that, the *.dat file is sent to the Heart ID database server through Wi-Fi. At the same time, the database will trigger the back-end system which is the Intel platform board to perform the embedding, features extraction and pattern matching processes. Once the processes are done, the verification result will be sent to the android application GUI.

2.3. Embedding process, features extraction and pattern matching process

In this part, the software written in Scilab which, consists of segmentation, features extraction and pattern matching algorithms is developed in the Intel platform board. The algorithm is able to segment the signal into arrays of independent pulses for the recognition purpose. Subsequently, signal pre-processing is applied to reduce noises. After that, the wavelet transform algorithm is used to extract the features of the pulses and stored into the database. These features are the training sets for Support Vector Machine (SVM) model. Finally, the SVM is used as heartbeat classifier. The overall process which runs on the Intel platform board is shown as Fig. 6.

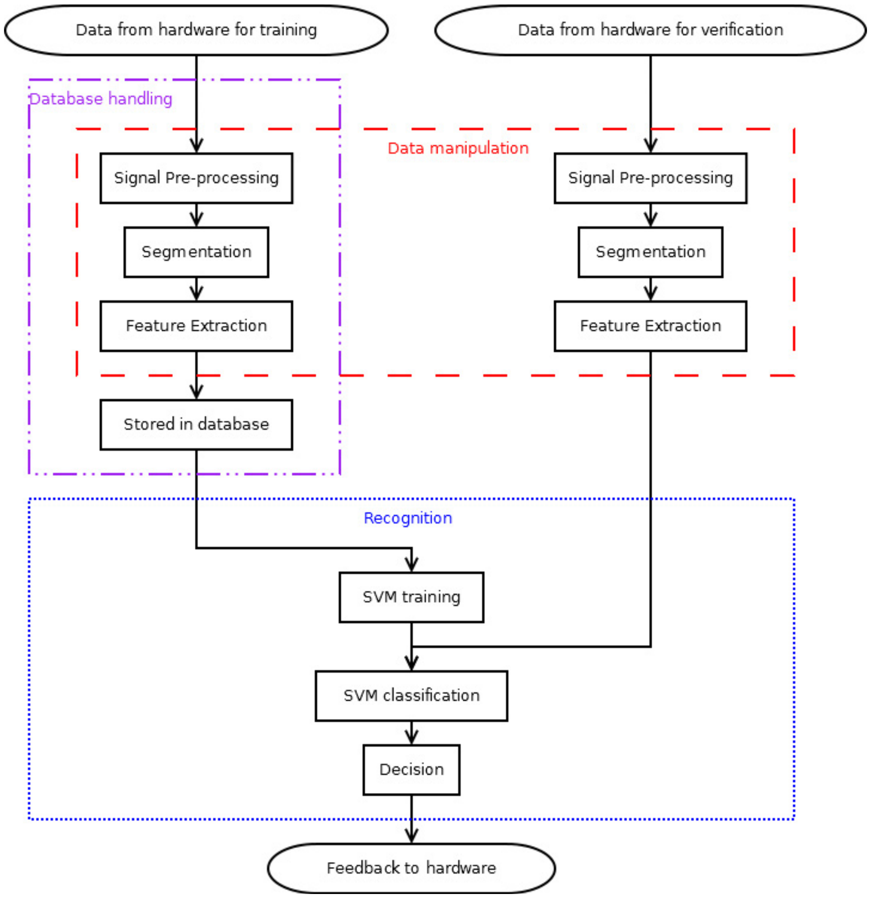

Fig. 6. Overall algorithms on the Intel platform board.

2.3.1. Data Acquisition

The built heartbeat detection kit is used to collect the ECG signals from the users of the system. In this study, a total of 50 subjects were enrolled for the experiment. The subjects consists of 37 males and 13 females, with subject age ranging between 20 and 30 years old. None of the participants has any health problem. The positive and ground electrodes are placed on left hand and negative electrode is placed on right hand. In the enrolment session, the subjects were asked to sit for 4 minutes in a resting position. Each individual provides the recording of ECG signals for about 40 seconds. For the testing data, the recording of 10 seconds is done, 3 weeks after the enrolment. During the data acquisition process, the ECG signal is sampled at 500Hz and stored in the android platform phone. Then, it will be sent to the back-end system to perform signal pre-processing.

2.3.2. Wavelet Decomposition

Wavelet transform splits the input signal into a few signals. These signals are the representations of the original signal which corresponding to different frequency ranges. Each of these signals are providing a particular frequency ranges that exists at that particular time interval. Therefore, these signals express the original signal neither in fully time domain nor in fully frequency domain but somewhere in between[14,15]. The Continuous Wavelet Transform (CWT) is define in equation (1).

$$X_{\psi}(a,b) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty} x(t)\psi^{*}(\frac{t-b}{a})dt \qquad (1)$$

where x is the original signal in time domain, X is the wavelet transformation of x, a is scale, b is translation and ψ is the mother wavelet. High scale will have more information on low frequency components. It has less detail on the signal but span a longer time which gives a global view on the signal. On the other hand, low scale will have more detail on high frequency components. It has a detail view which last for a short period of time.

The discretization of CWT is Discrete Wavelet Transform (DWT). It produces two sets of coefficients i.e. approximation coefficients cA_1, and detail coefficients $cD1$. These vectors are obtained by convolving x with the low-pass filter for approximation, and with the high-pass filter for detail and undergo down sampling process. The approximation coefficients cA_1 is split into two parts again using the same method by replacing x with cA_1, and producing cA_2 and cD_2, and so on for the desired number of levels of decomposition.

2.3.3. Signal Pre-Processing (wavelet de-noising process)

The raw ECG signal is needed to go through the de-noised process before the segmentation takes places because the raw signals are often contaminated with noises. In this study, we use wavelet de-noised process to ensure the peak (QRS complex) can be observed clearly as the noises are suppressed as shown in Fig. 7. The wavelet de-noising can be divided into three steps, namely as decomposition, adjustment of wavelet coefficient and signal reconstruction[14]. For example, 'db10' (10^{th} order Daubechies) wavelet is used to decompose the signal into 4^{th} scale wavelet transform. The raw signal S is decomposed into 5 parts shown as:

$$S = a_4 + d_4 + d_3 + d_2 + d_1 \qquad (2)$$

The parameters, a_4 represents the approximate component of the signal while parameters, d_1 to d_4 represent the detail component of the signal in the levels respectively. Since lower scale detail contains higher frequency component of the signal, therefore by lowering the coefficient of the lower scale detail can reduce the high frequency noise. Consequently, the thresholding process is executed in this system. This involves the replacing the coefficient values that are less than the threshold value with zeroes. After thresholding, the signal is reconstructed.

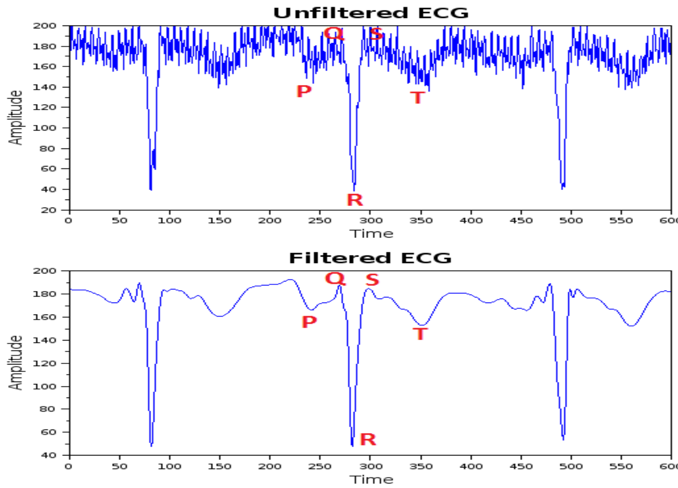

Fig. 7. Comparison between noisy signal and de-noised signal.

2.3.4. Segmentation

In this study, partially-fiducial method is used for segmentation. Since R-peak has the highest amplitude, therefore it is obvious to be captured and used as separation point for the segmentation[15]. The raw ECG signal is decomposed using ‘db6’ up to 4^{th} level. The signal is reconstructed back using 4^{th} detail, d_4. That suppresses all the coefficients to 0 except d_4. P wave and T wave are suppressed so that R peak becomes more visible. Then, the signal is subtracted with its own mean value. Next, the signal is divided by its maximum absolute value to normalize the signal. The amplitude of the signal can easily be referred as its percentage. Thus, the location of peaks in the signals are obtained with the minimum peak distance of 200 (equivalent to 0.4 second) and with minimum peak height of 50% of the highest peak. These locations are assumed to be the location of R peaks. With the location of R peaks, the heartbeat is assumed lying in between the portion of data which is location of R peak minus 79 and location of R peak plus 110. These ranges are chosen as it yields the best recognition result for the developed system as shown in

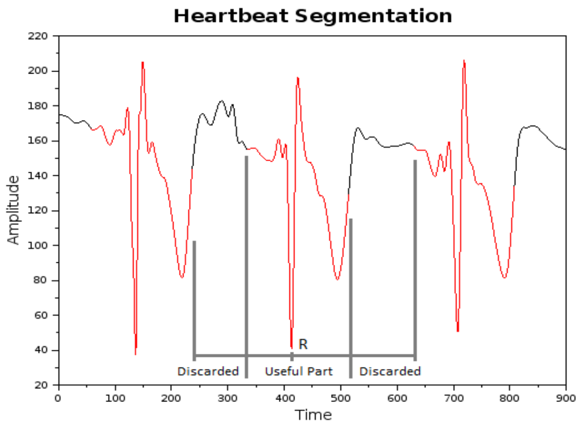

Fig. 8.

Fig. 8. Range of segmented signal

2.3.5. Feature Extraction

The heartbeat signals contain useful features, redundant features and leftover noises. It is important to pick only the features that are unique, significant and least corrupted by noise. For this purpose, wavelet transformation is used to decompose the ECG pulses into their corresponding wavelet coefficients and select a handful of points as their features. So, after the segmentation process, each heartbeat pulse S(x) is subtracted by its own mean (Eq. 3) to get W(x) shown as Eq. 4. This is to eliminate the baseline wandering effect.

$$m = \frac{\sum_{i=1}^{n} s(i)}{n} \tag{3}$$

$$W(x) = S(x) - m \tag{4}$$

where W(x) is then wavelet decomposed up to 3th scale using 'sym3' (3rd order symlet).

$$W = a_3 + d_3 + d_2 + d_1 \tag{5}$$

The coefficients of the approximate, a_3 and the coefficient of the 3rd and 2nd details, d_3 and d_2 are taken as the feature of the heartbeat.

2.3.6. Pattern matching

The type of SVM classifier used is C-Support Vector Classifier (C-SVC). C is the classifier's regulation parameter.

The kernel function used is radial basis function (RBF). The SVM training parameters needs to be chosen carefully in order to train the machine to generalize while not over trained. The LIBSVM library provides a useful tool which uses cross-validation (CV) to estimate the training parameters. For each of the parameter setting, LIBSVM obtains a CV accuracy. The function returns the values of parameters that have the best CV accuracy. Using this tool, the biometric system models the ECG features using the best parameter. The training produces models which associates to the features. They are stored in database to be used during verification.

The verification feature sets are verified using the model from training. LIBSVM provides a function to predict and label the verification set. The labels are predicted based on a decision values which are proportional to how close the verification set is to the model. In this project, both decision values and the predicted labels are considered in making the final decision.

2.3.7. System performance evaluation

The biometric system accuracy is evaluated by using receiver operating characteristics (ROC) plot. This plot indicates the biometric system "false rejection rate" (FRR) and "false acceptance rate" (FAR) as its characteristics. The false rejection rate is the frequency which samples from the same class (genuine) are erroneously assessed to be from different class (imposter). On the other hands, the false acceptance rate is the frequency which biometric samples from different class (imposter) are erroneously assessed to be from the same class (genuine). Subsequently, to access the sensitivity of the biometric system, 'genuine acceptance rate' (GAR) is used as another characteristic for the biometric system which measures the percentage of authorized individuals admitted by the system. Equal error rate (EER) is also used to measure the performance of a biometric system. EER take the value at which the FAR is equal to FRR. Lower the EER, the better performance of the biometric system in term of accuracy.

3. Results

In this project, the system performances are evaluated on each part of the developed systems for easier troubleshooting. Fig. 9 and 10 represent two plots of the output signals collected from the front-end system. The first plot is the output from the Android platform phone where the signal is stored in *.dat file after the process of digitalizing and filtering. The second plot is the output signal from the heartbeat detection kit which viewed directly from the LabView oscilloscope. By referring to the Fig. 10, it is found that the heartbeat waveform is found to be a bit noisy compared to the typical ECG waveform shown in Fig. 1. This is due to different placement position of the electrodes where the reference point electrode is put very near to the two electrodes (positive and negative) which produces different form of ECG vector as explained in Section 2. Since our heartbeat detection kit is designed to be portable and wearable, then the reference point is not suitable to be put further as normally being placed on the left leg. However, when the *.dat file is received by the Intel Atom N2600 Board, it undergoes the wavelet de-nosing filtering. By referring to the Fig.7, the noisy signal in the *.dat file has been de-noised and later the QRS complex of the ECG signal becomes more obvious to be interpreted by the system.

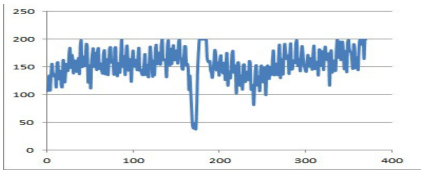

Fig.9. Output signal which is stored in the *.dat file in Android phone

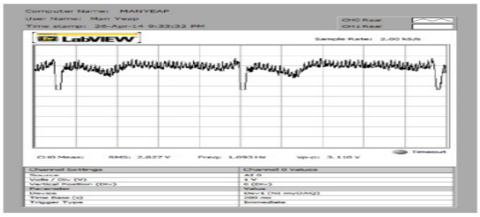

Fig.10. Output signal from the output of heartbeat detection kit

Subsequently, Fig. 11 shows the segmentation result by the developed algorithm. It is observed that the segmentation algorithm is able to separate the continuous ECG signal correctly with more than 90% accuracy. Finally, the classification performance based on different prototypes is evaluated. Prototype 1 (baseline prototype) has minimal requirements that needed for the heartbeat biometric system. Prototype 2 is an improved version on the feature extraction part by optimizing the used of mother wavelets i.e. ‘symlet’, ‘daubechies’ and ‘coiflet’ for wavelet decomposition. Prototype 3 optimizing the use of wavelet de-noising methods i.e. ‘heursure’, ‘rigrsure’, ‘sqtwolog’ and ‘minimaxi’. Finally, prototype 4 optimizing the parameters used in SVM modelling. Fig.12 shows the performance of the FAR against the GAR. The performance comparison based on ERR is also shown in Table 1. Prototype 1, 2 and 3 shows steady improvement while Prototype 4 are significantly superior to all its predecessors. Prototype 1 only made it to 75% GAR at 1% FAR while Prototype 2 has 78% GAR and Prototype 3 has 85% GAR at the same FAR. Prototype 4 has its GAR at 97% at 1% FAR.

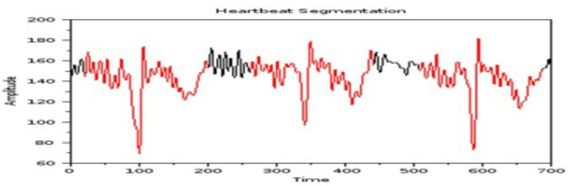

Fig.11. Three examples of segmented signal (red color).

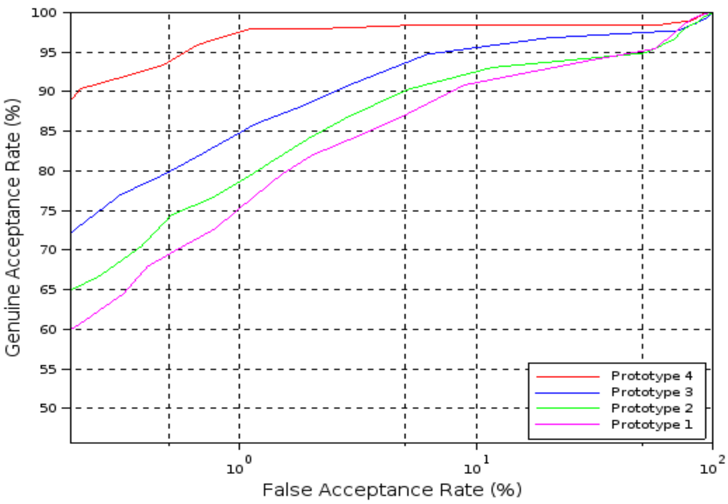

Figure 12: System performances based on different prototypes testing.

Table 1. EER performance based on different prototypes testing

Prototype test	1	2	3	4
EER (%)	9.0154	8.1597	5.6906	2.0069

4. Conclusion

This paper presents an authentication system to perform biometrics recognition by using heartbeat signals/ECG signals. The method used is based on ECG wavelet coefficient matrices. The ECG signals are acquired from a portable and wearable heartbeat detection kit which is developed in this project as data acquisition tool to collect the signals for the back-end system. The back-end system is operated by Intel Atom N2600 processor which perform the human identity recognition by executing the developed software consisting signal de-noising, segmentation, wavelet feature extraction and SVM pattern matching. A promising results are observed with the EER of 2.0069% is achieved. Improvement on the techniques used from the front-end to the back-end system are continuously being done for the more robust system.

Acknowledgements

This works was supported by Universiti Sains Malaysia under Fundamental Research Grant Scheme (FRGS): 203/PELECT/6071266.

References

1. Biel L, Pettersson O, Philipson L, Wide P. (). ECG analysis: a new approach in human identification. *IEEE Transactions on Instrumentation and Measurement* 2001; **50**:3, 808-812.
2. Kyoso M, Uchiyama, A. Development of an ECG identification system. In: *Engineering in Medicine and Biology Society, 2001. Proceedings of the 23rd Annual International Conference of the IEEE* 2001; **4**, 3721-3723.
3. Silva H. ECG biometrics : principles and applications state-of-the-art. *Proc. 6th BIOSIGNALS Conf* 2013.
4. Lourenço A, Silva H, Fred A. Unveiling the biometric potential of Finger-Based ECG signals. *Computational intelligence and neuroscience* 2011; **5**, 1–8.
5. Hegde C, Prabhu HR, Sagar DS, Shenoy PD, Venugopal KR, Patnaik LM. Heartbeat biometrics for human authentication. *Signal, Image and Video Processing* 2011; 5:4, 485-493.
6. Malmivuo J, Plonsey R. *Bioelectromagnetism: principles and applications of bioelectric and biomagnetic fields*. Oxford University Press; 1995.
7. Odinaka I, Lai PH, Kaplan AD, O'Sullivan JA, Sirevaag EJ, Rohrbaugh JW. ECG biometric recognition: A comparative analysis. *IEEE Transactions on Information Forensics and Security* 2012; **7**:6, 1812-1824.
8. Agrafioti F, Hatzinakos D, Gao J. Heart biometrics:Theory, methods and applications. INTECH Open Access Publisher; 2011.
9. Chan AD, Hamdy MM, Badre A, Badee V. Wavelet distance measure for person identification using electrocardiograms. *IEEE Transactions on Instrumentation and Measurement* 2008; 57:2, 248-253.
10. Wang Y, Agrafioti F, Hatzinakos D, Plataniotis KN. Analysis of human electrocardiogram for biometric recognition. *EURASIP journal on Advances in Signal Processing 2008*; **19**.
11. Shen TW, Tompkins WJ, Hu YH. One-lead ECG for identity verification. In: *Proceedings of the 24th Annual Conference and the Annual Fall Meeting of the Biomedical Engineering Society EMBS/BMES* 2002; **1**, 62-63.
12. Boumbarov O, Velchev Y, Sokolov, S. ECG personal identification in subspaces using radial basis neural networks. In: *IEEE International Workshop on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications* 2009; 446-451.
13. Wang Y, Plataniotis KN, Hatzinakos D. Integrating analytic and appearance attributes for human identification from ECG signals. In: *Biometric Consortium Conference, 2006 Biometrics Symposium: Special Session on Researc*h 2006; 1-6.
14. Yao J, Wan Y. A wavelet method for biometric identification using wearable ECG sensors. In: *5th International Summer School and Symposium on Medical Devices and Biosensors* 2008; 297-300.
15. Martínez JP, Almeida R, Olmos S, Rocha AP, Laguna P. A wavelet-based ECG delineator: evaluation on standard databases. *IEEE Transactions on Biomedical Engineering* 2004; **51**:4, 570-581.
16. Lourenço A, Silva H, Fred A. ECG-based biometrics: A real time classification approach. In: *IEEE International Workshop on Machine Learning for Signal Processing (MLSP)* 2012; pp. 1-6.