Implementation of the ECG Biometric Identification By using Arduino Microprocessor

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***Abstract*—This paper proposes the method of implementing the ECG biometrics for person identification system by using the Arduino Microprocessor. The Lead-I ECG data had been self-setup and collected, then the achieved ECG features are investigated on the Arduino Uno R3 microprocessor and e-health sensor board. After that, the simulation processes for the identification process are begun with the selection Single Beat ECG and analyzed by the Continuous Wavelet Transform (CWT). Then RMS value of total energy of the wavelet coefficients of each P, QRS, and T segment is calculated. Next, the Fisher Linear discriminant analysis (FLDA) is applied to all set of RMS value for dimension reduction. Lastly the normalized Euclidean distance is implemented as the classifier. The experimental results demonstrate that: our proposed method is achieved the accuracy of classification with 96%.**

Keywords—ECG Biometrics; Biometrics feature extraction; Person Identification.

I. INTRODUCTION

This recent year, Electrocardiogram (ECG) has been actively proposed as aliveness biometric for years. In realistic application, this type of biometrics is still needed to verify in some conditions related to the practical use. As we all know that the biometric provides higher security for identifying a person because of the biometric features are usually based on the anatomical, physiological and/or behavioral characteristics, which are significantly unique to individual. In addition, the biometric application for the disability people who have lost their hands, eyes, or voice is essential issues and challenge [1]. Currently there are mainly eight different biometrics that have been used as commercially which are including face, fingerprint, hand geometry, iris, retinal pattern, signature, voice-print, face thermo-grams and have actually been deployed for identification [2].

Currently, there are many researchers have been investigated and validated the characteristics of ECG signal as a new biometric such as: L. Biel et al. [3] who are the first to introduce the application of ECG as biometric, S. A. Israel et al. [4] are employed the features name: fidutial points detection by measure the temporal on the ECG features, and as well as the working group of Foteini Agrafioti and et al. [5, 6] are implemented both fidutial points (temporal and amplitude) and non-fidutial features. But there is very few publications reported about the variance of metric values on R- R interval that might be affected to the accuracy of identification system. Actually, this HRV might be caused by many factors including age, irregularities heartbeat [7], mental and emotional condition [8], and long-term variability condition [9, 10]. In this paper, the Lead-I ECG, which is measured from the Arduino Microprocessor and e-health board, is considered as the input ECG feature in our experiments.

II. RESEARCH METHODOLOGY

A. Methods to obtain/Record the ECG

Normally, The measurement between 2 leads situated on the right and left wrist, aV_R and aV_L respectively, and the lead situated on the left ankle aV_F, make up a triangle, known as "Einthoven's Triangle" [11] as shown in Figure1. The electrical information gathered between these leads is known as "bipolar". It is represented on the ECG as 3 "bipolar" leads. So, information between aV_R and aV_L is known as lead-I, between aV_R and aV_F is known as lead-II and between aV_L and aV_F is known as lead-III.

When realistic application is considered, the modification of Lead-I placement is applied with assign (+) electrode on right hand while the (-) and (N) electrode are combined on left hand.

The measurement is using Arduino Micro-processor and e-health board. The ECG lead is the standard modified limb leads I (ML-I), measure with Ag/Ag-Cl surface electrode, sampling rate at 300 samples per second. There are 6 volunteers are involved in the ECG signal recording to be representing for 6 IDs. In each record are random selected of

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10 sets of single heartbeats for Training process and another 50 sets of heartbeats for testing process.

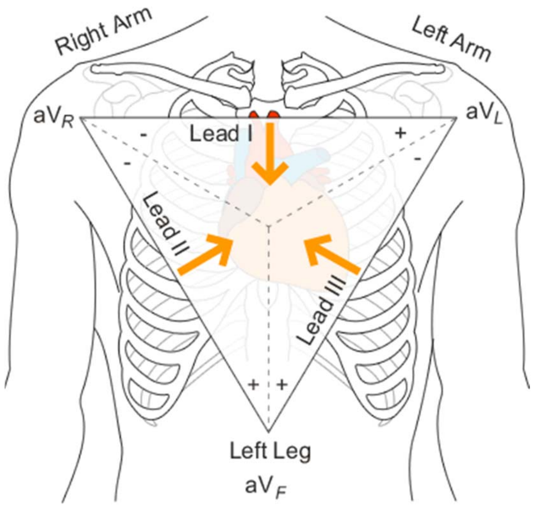

Fig. 1. ECG leads from Einthoven's Triangle [11]

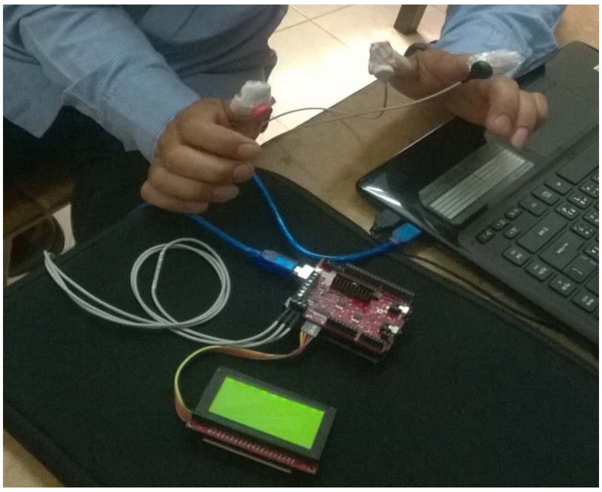

Fig. 2. The process of measures Lead-I ECG

Fig. 2 shown the process of measures the ECG Lead-I from left and right hands.

To conduct the experiments, The Lead-I ECG type is self-

The process of record Lead-I ECG signal is operated in 2 steps, The first ECG measurement is started to record the Training-ECG signal for 2 minutes and the volunteer relax break for 5 minute, then the second ECG measurement is started to record the Testing-ECG signal for another 2 minutes. Fig. 3 shows the Lead-I ECG obtained from Arduino Microprocessor and e-health board.

B. *Methods of ECG identification*

The overall process of identification is shown on the Fig. 3. The training process is mainly consisting of ECG signal Preprocessing, ECG feature extraction uses single beat selection and CWT.

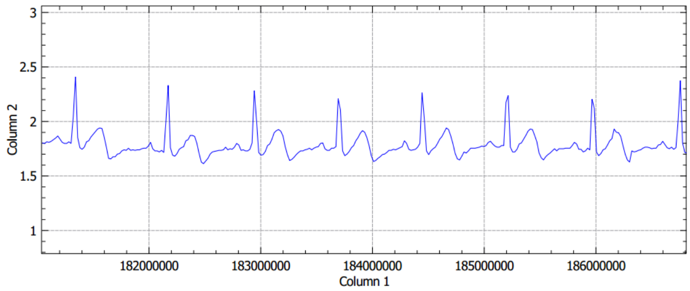

Fig. 3. Lead-I ECG signal

In the last part of training process, each class of ECG features ID are reduced dimensions by the Fisher's Linear Discriminant Analysis (FLDA). After that, each of the feature vectors is projected on to the new basis corresponding to the first 90% largest components generated by the Eigen values. Then, the center of feature vectors of each class is manually defined and trained. During the testing process, the unknown data sets are passed through the ECG features extraction step. Then, the projection of the same components in FLDA feature space achieved in the training process is performed. After that, the distance between the unknown feature vectors and the center of trained feature vectors of each class are calculated and classified into their nearest class. The testing process by the Fisher's Linear Discriminant Analysis combine with Euclidean distance to classify the unknown ECGs is described in Figure 3.

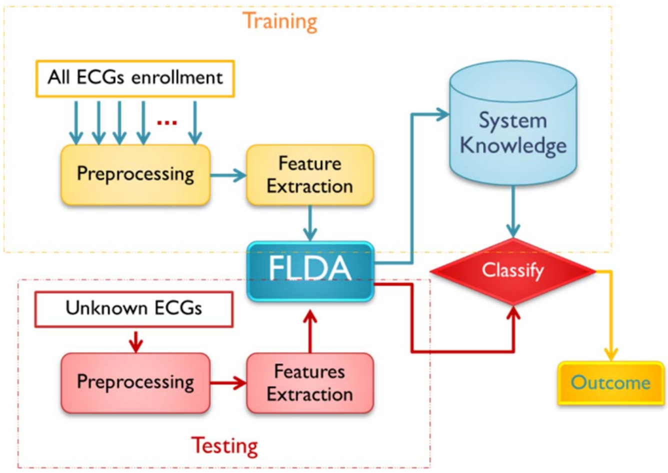

Fig. 3. Block diagram of the Lead-I ECG Identification System

C. *Feature extraction by CWT*

The proposed of feature generation process consists of two steps; Extract by wavelet and Forming into feature vector. First, The continuous wavelet transform (CWT) is a decompose operation of a signal with different window width, which is called the scale or resolution of observation. The wavelet transform of a continuous time signal, $s(t)$, is defined as:

$$\mathrm{CWT}(b,a) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} s(t)\,\Psi^*\left(\frac{t-b}{a}\right)dt\ldots\ldots\ldots(1)$$

Where $\Psi^*(t)$ is the complex conjugate of the analyzing wavelet function $\Psi(t)$

'a' is the dilation parameter of the wavelet.

'b' is the location / shifting parameter of the wavelet.

Second step the feature that representing of Lead-I ECG is forming into a feature vector. The CWT feature is then divided into 3 parts (P area, QRS area, and T area); At P, QRS, and T each area contain 7 blocks of the RMS value of the sum energy along the length of location b at scale a = 4 – 16, step-up by 2; because of the scale a =1 - 3 have very low energy or near zero, so the energy at this scale will not calculate. Finally 7 coefficients from each part (P, QRS, and T) are horizontally concatenated to form a 21 coefficients feature vector, as shown in Fig. 4.

D. Fisher's Linear Discriminate (FLD)

FLD is a widely used method for feature dimension reduction. Fisher's idea utilizes a set of M feature basis vectors $\{\Psi_m\}_{m=1}^{M}$ in such a way that the ratio of between-class and within-class scatters of the training sample set is maximized. The maximization is equivalent to the following eigenvalue problem.

$$\Psi = \arg\max_{\Psi} \frac{|\Psi^T S_b \Psi|}{|\Psi^T S_w \Psi|},$$
$$\Psi = \{\Psi_1, \dots \dots \dots \Psi_M\} \dots\dots\dots\dots\dots\dots\text{(2)}$$

Where S_b and S_w are between-class and within-class scatter matrices respectively.

For an input heartbeat Z, its FLD-based feature representation can be obtained simply by a linear projection in equation (3).

$$y = \psi^T Z \dots\dots\dots\dots\dots\dots\dots\dots\text{(3)}$$

E. Euclidean Distance

The normalized Euclidean distance function $D(y, \mu)$ measures the distance between FLD feature vectors y and the center of each class μ in FLD feature space is defined as:

$$D(y, \mu) = \frac{1}{V}\sqrt{(y-\mu)^T(y-\mu)} \dots\dots\dots\dots\text{(4)}$$

Where V is the dimension of the feature vectors, which is the number of CWT coefficients. After obtaining the distance between the unknown subject and all trained vectors, the classifier applies to the majority of the shortest distances between the trained vectors of the cluster.

III. RESULTS AND DISCUSSIONS

The experiment in this paper is aims to observe the accuracy of the classifier when we the system is training with the 10 beat and testing with another 50 beat of Lead-I ECG. This experiment is used 6 difference data sets measure by Arduino Uno R3, ATmega328 chipset, system clock 16 MHz, Memory 32 KB, RAM 2 KB and e-health board. The results of our experiments demonstrate that, the features of 6 ECG data are well classified into their own class as shown in the Fig. 5. The performance of the proposed method is described in the table 1.

The factors to evaluate the system performance of our proposed methods are considered in the following issues: (i) Time to acquire the ECG is very short, because our system has an advantage of analyzes ECG by beat, so time to acquire the ECG is approximately 1second or less. (ii) Learning ability of the system is quite high; our proposed identification system required the number of train subjects as small as only 10 subjects while our system still maintains the high accuracy of classification.

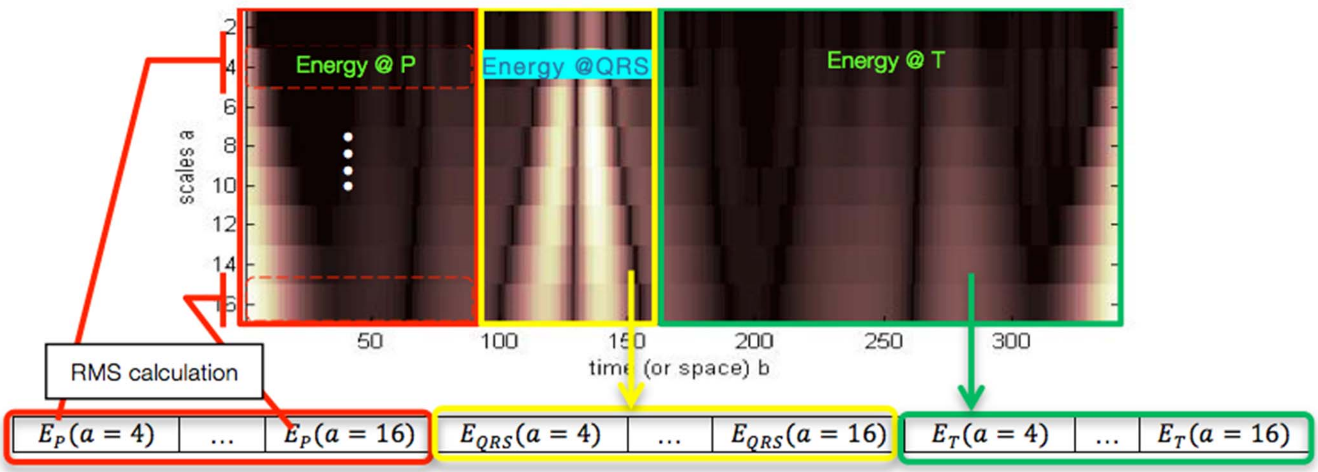

Fig. 4. Process of generate 21 RMS coefficients of features vector for a Lead-I ECG

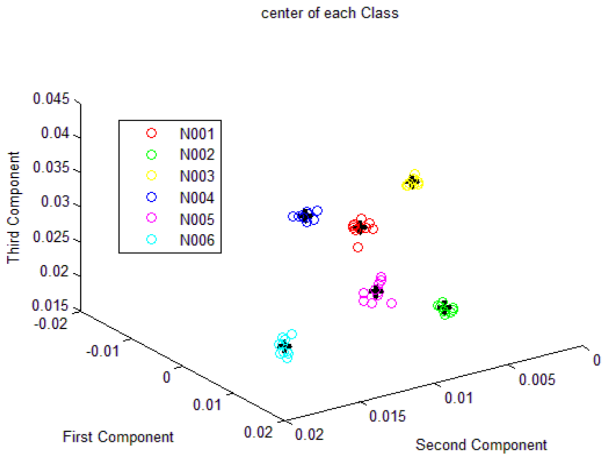

Fig. 5 the scattering plot of ECG data of 6 users are plot in the feature space

TABLE 1. Results the classifying when training with 10 ECG subjects.

Database	Correct classify	% of Accuracy
N001	46/50	92%
N002	45/50	90%
N003	50/50	100%
N004	50/50	100%
N005	47/50	94%
N006	50/50	100%
Total Accuracy is 96%		

IV. CONCLUSIONS

In this paper, proposed a analysis of using new biometric feature called "Lead-I Single Beat Electrocardiogram", which is obtained from the Arduino Microprocessor and e-health board. Then this type of ECG is introduced over the CWT analysis. Then the Fisher's Linear Discriminant Analysis (FLDA) and the normalized Euclidean distance were used to reduce the dimensions of the feature vector and classify the ECG beat respectively. The main point of this research work is study the possibility of using Lead-I ECG in person Identification. As the results of the experiment show that the proposed our method is achieved the accuracy of 96% and it is possible to implement the ECG beats as a biometric for identification system. However, in the future of development of application of ECG for person identification in the embedded system or mobile are very interested and challenged, since there are many process is required to minimize the complexity.

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