ECG Based User Authentication For Wearable Devices Using Short Time Fourier Transform

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***Abstract*—Electrocardiogram (ECG) is a promising biometric. There has been much research on ECG based user authentication and identification, but there have been few works to investigate ECG biometrics for stand-alone wearable ECG sensors, for quick response time using a single pulse ECG, and for small wearable devices that may have limited access to others' ECG information.**

Recently, ECG user authentication method using spectrogram yielded excellent detection performance. However, spectrogram only utilizes magnitude of short time Fourier transform (STFT) and phase information was overlooked for ECG features. In this paper, we address the issues of wearable ECG sensors, quick response time, and limited access to others' ECG information using a new STFT based method that uses phase information.

Our proposed method yielded 0.9% EER for ECG data set from wearable ECG sensors (15 subjects) and 2.2% EER (equal error rate) for public ECG-ID database (89 subjects).

***Keywords*—Biometric; ECG; phase information; short time Fourier transform; wearable device**

I. Introduction

Biometrics are promising alternatives for user authentication and identification [1]. Fingerprint and face are already used in many smart phones, tablet computers, and traveler identification systems with electronic passports. Electrocardiogram (ECG) is another candidate that can be used as a stand-alone biometric or as a part of multimodal biometrics [1], [2]. ECG characteristics such as P wave, QRS complex, and T wave are determined by atrial depolarization, ventricular depolarization, and ventricular repolarization of a heart [3] and their uniqueness depends on the structure and electrical conduction system of an individual heart.

Many previous research works investigated the possibility of using ECG signals as a biometric and yielded promising results for user authentication and identification [4]. In addition, ECG signals can also provide the proof of the liveness of users [5]. ECG signals have been used as a biometric by extracting fiducial features or non-fiducial features. Fiducial features of ECG such as amplitudes or onset time of PQRST features were estimated from raw ECG signals and these features were fed into classifiers such as linear discriminant analysis (LDA) [6], [7], [8]. Non-fiducial features of ECG signal have also been used for user identification such as principal component analysis (PCA), mutual nearest point distance, wavelet, and spectrogram [9], [10], [11], [12]. Sometimes, fiducial and non-fiducial features have been combined [13], [14]. A recent thorough comparative analysis of a wide range of methods is described in [15], [16].

Almost all previous research on ECG based user identification or authentication has investigated one-lead ECG signals from the chest with multiple ECG pulses for testing (potentially requiring at least a few seconds just for acquiring data to authenticate) and assuming that others' ECG information is available for a dimensionality reduction of features or to train classifiers such as support vector machine. However, in many small devices such as wearable smart watches, smart phones, or notebook computers, these assumptions may not hold. ECG data may have to be obtained from a finger tip or a wrist of a user using wearable ECG sensors. Users typically demand quick response times for user authentication, a constraint that requires testing be performed on a single ECG pulse. Moreover, such small systems may have very limited access to other users' ECG information. For example, regular users and potential intruders will not share their valuable ECG information since they may want to protect their own biometrics or to break into small systems with higher possibility.

In this paper, we address the issues of wearable ECG sensors, quick response time, and limited access to others' ECG information using a new short time Fourier transform (STFT) based method. Recent ECG user classification work by Odinaka *et al.* [12] used spectrogram, which is the magnitude of STFT, has yielded excellent detection performance [15]. However, phase contains signal structural information that may be important as ECG features. To our knowledge, the phase information of STFT has never been used for ECG-based authentication algorithms [15], [16]. We propose to use both magnitude and phase information of complex STFT of a single ECG pulse from a wristband type wearable ECG sensor and to use a simple detector using Euclidean distance that does not require other people's ECG information. Our proposed method can potentially be used for smart watch applications or other mobile devices that are connected to them wirelessly.

In Section II, we describe methods for preprocessing of ECG signals, extracting ECG features, and authenticating for small systems such as wearable devices. In Section III, we

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present experimental settings and simulation results with our preliminary ECG data set from wearable ECG sensors (15 subjects) in terms of various detection performance measures. We also evaluated our proposed method with larger public one-lead ECG database from regular ECG sensors (89 subjects).

II. METHODS

A. Pre-processing of ECG signals

A wearable ECG sensor with two electrodes (Nymi band, Nymi Inc., Canada) was used to acquire subject's ECG pulses. During data collection, one electrode is in contact with a finger on one hand and the other electrode touches the wrist of the other hand, as depicted in Fig. 1. An example of acquired ECG signals from the wearable ECG sensor is shown in the top figure of Fig. 2. Then, a bandpass Butterworth filter with order 14 (passband = [2Hz 40Hz]) was applied to ECG signals to reduce baseline wander and high frequency noise. The resulting ECG signals are shown in the bottom of Fig. 2. Note that no powerline interference was observed in these wearable ECG signals. The Pan-Tompkin algorithm was used to detect R-peaks as shown in the bottom of Fig. 2 with circle marks [17].

B. ECG Features: Short Time Fourier Transform

Many ECG features have been investigated for user authentication or identification. Fiducial ECG features such as amplitudes or time points of P wave, QRS complex and T wave (see the top figure of Fig. 3 for more information on PQRST of ECG pulse) were initially used [6], [7], [8] and later non-fiducial ECG features were also used such as principal components, ECG pulse itself, wavelet, or spectrogram [9], [10], [11], [12].

Among them, ECG user authentication using log-normal spectrogram yielded high performance [12], [15]. Spectrogram is the magnitude squared of the short time Fourier transform (STFT) as follows:

$$|X(m, w)|^2. \tag{1}$$

where for given ECG signal $x[n]$ and a window function $w[n]$, the discrete time STFT of $x[n]$ is

$$X(m, w) = \sum_n x[n]w[n-m]\exp(-jwn). \tag{2}$$

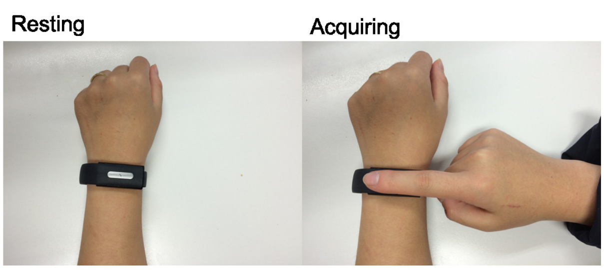

Fig. 1. An example of ECG acquisition from wearable ECG sensors. One electrode is touching a wrist while the other electrode is touching a fingertip when the data is acquired.

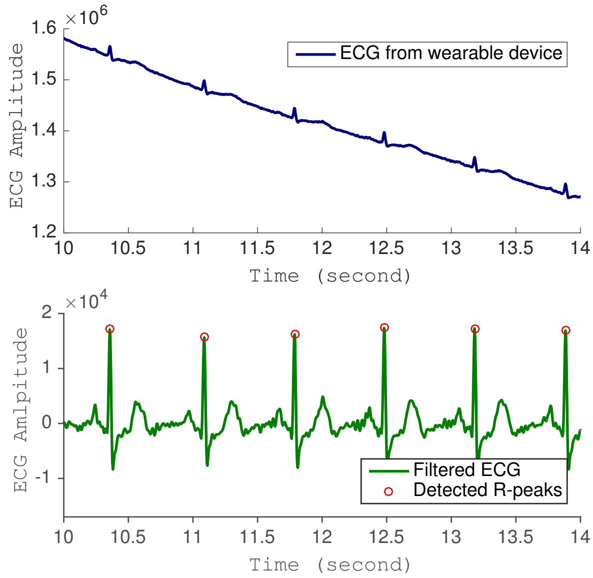

Fig. 2. ECG signal from wearable device (no unit for ECG amplitude) and bandpass filtered ECG signal for the same signal with detected R-peaks using Pan-Tompkin algorithm.

A usual choice for the window function $w[n]$ is a Hamming window. Evaluating $X(m, w)$ for many (m, w) points can provide high resolution information with increased computation time. We chose 0.2 second width of window function support for $w[n]$ and 0.02 second increment for m ($m = 250$Hz $\times 0.02$ second $= 5$). Optimizing these parameters can potentially improve detection performance.

The spectrogram in (1) can provide excellent spatio-temporal information on ECG pulses for user identification as investigated in [12]. However, phase information also contains important information that characterizes the contents of signals [18]. Therefore, we propose to use both magnitude and phase information of STFT in (2) for ECG based user authentication task. Fig. 3 shows an example of magnitude image (middle figure) and phase image (bottom figure).

C. User Authentication for Small Systems

Odinaka *et al.* achieved excellent performance using two important methods: 1) feature selection using relative entropy and 2) log-likelihood ratio test (which is known to be optimal by Neyman-Pearson lemma). However, these require knowledge of a normal model or ECG information of all subjects. For many small systems such as wearable devices, others' ECG information may not be accessible. Therefore, we propose to use a simple Euclidean distance as follows:

$$\begin{array}{ll} ||X_t(m, w) - X(m, w)||^2 < \tau & : \mathcal{H}_1 \\ ||X_t(m, w) - X(m, w)||^2 \geq \tau & : \mathcal{H}_0 \end{array} \tag{3}$$

where X_t is a complex STFT of an enrolled ECG pulse of a user (ECG template) and X is a complex STFT of an input ECG pulse to authenticate. For fixed threshold τ, $\mathcal{H}_1$ is a hypothesis that incoming user is the enrolled user and $\mathcal{H}_0$ is a null hypothesis that incoming user is not.

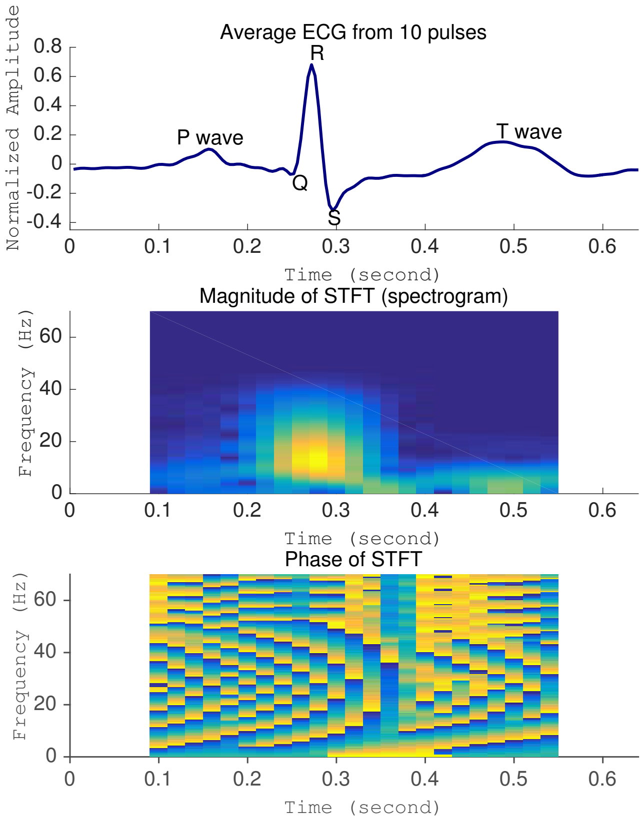

Fig. 3. Average ECG from 10 pulses (or ECG template, top) with ECG features (P wave, QRS complex, T wave) and its spectrogram (or short time Fourier transform) with magnitude (middle) and angle (or phase, bottom) using 0.2 second window and 0.02 second increment.

III. Results

A. Experiment Settings

Two 2-minute length ECG pulse trains were acquired using wearable ECG sensors for 15 subjects (10 male, 5 female) on the same day. An ECG pulse train was sampled at 250 Hz. Then, the Pan-Tompkin algorithm was used to detect R-peaks of a bandpass filtered ECG signal and then each ECG pulse was selected with the length of 0.64 seconds or 160 samples (-67, +92 samples from each R-peak) covering all PQRST segment. Ten ECG pulses were selected for analysis from each of the two sessions recorded for each participant. The selected pulses had the minimum Euclidean distance to the per subject, per session mean in order to remove outliers due to, for example, instabilities in finger or wrist contact with the ECG electrodes. For each subject, two-fold cross validation was performed using two ten-pulse sets from two records, respectively. The 10 pulses in the training set were averaged to generate a template that each individual pulse from the testing set was matched against.

Our proposed method was also evaluated with larger, public ECG data set (ECG-ID, PhysioNet) containing 89 subjects [19], [20]. Two records per subject that were collected on the same day were chosen in this study. This data was acquired using one-lead chest ECG sensor with 500 Hz sampling rate and pre-processed with a baseline drift filtering using wavelet decomposition, a power-line noise filtering using adaptive bandstop filter (50 Hz), a high-frequency noise filtering using Butterworth low-pass filter, and a smoothing with the support size of 5 [20].

Complex STFT was obtained using a 0.2 second length Hamming window with step size of 0.02 second. MATLAB was used for all implementations (The Mathworks, Inc., Natick, MA, USA).

B. Results of Two Studies

Our proposed method with complex STFT was applied to our ECG data set from wearable sensors (15 subjects) and compared with other methods (ECG signal itself using Euclidean distance, Spectrogram using magnitude information only of STFT). Fig. 4 shows that the receiver operating characteristic (ROC) curve of our proposed method yielded better ROC curve than spectrogram based method, but comparable ROC curve to ECG signal based method. At around false alarm rate of 1%, our proposed method yielded the best detection probability (see Table I) among all other methods, but in some lower (at around 0.5%) or some higher (at around 3%), simple ECG signal based method yielded better detection power than all other methods. Table I shows that our proposed method yielded better EER and detection power at the false alarm rate of 1% than other previous methods. It seems that more ECG data from wearable sensors will be required for more robust results.

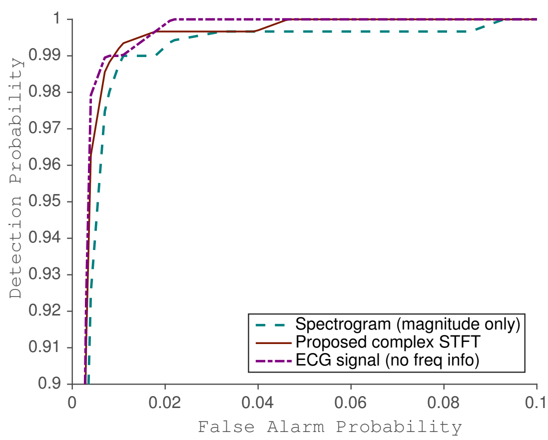

Fig. 4. ROC curves of spectrogram based method, proposed method using complex STFT, and ECG signal based method using Euclidean distance for wearable ECG data set (15 subjects). Our proposed method using complex STFT yielded better ROC curve than spectrogram based method, but comparable ROC curve to plain ECG signal based method.

TABLE I. Performance Summary for ECG database from wearable sensors (15 subjects). P_D* is a detection probability at false alarm $= 1\%$.

Method	**AUC**	**EER (%)**	P_D*
ECG signal (no frequency info)	0.9992	1.0	0.9900
Spectrogram (magnitude only)	0.9986	1.1	0.9873
Proposed complex STFT	0.9991	0.9	0.9920

Our proposed method with complex STFT was also applied to the public ECG-ID database (89 subjects) and similar tendency was observed with our wearable ECG sensor study. A ROC curve shows that our proposed complex STFT method yielded better ROC curve than other two methods in Fig. 5.

Table II also shows consistent results: our proposed method yielded better AUC (area under the curve), EER (equal error rate), and the detection probability at the false alarm $= 1\%$.

Note that EER results of our proposed method (EER $=$ 0.9% for ECG dataset from wearable sensors, EER $= 2.2\%$ for public ECG-ID database) was higher than the result of [12] (EER $= 0.37\%$) for different ECG data sets that were collected on the same day, respectively. Direct comparison may not be possible due to different ECG data sets used, but our Euclidean distance based simple user authentication may not be as effective as relative entropy based feature selection and likelihood ratio test that were used in [12]. However, the method in [12] requires all ECG information for all users, while our proposed method does not, which may be more suitable for small systems such as wearable devices.

IV. Conclusion

We proposed a new ECG based user authentication method using complex STFT and simple Euclidean distance for wearable devices that have wearable ECG sensors in the wrist and that may not have access to others' ECG information. Our proposed method yielded better detection performance than spectrogram based authentication method in terms of EER. It also yielded better performance than ECG pulse based method for ECG-ID database and comparable results for ECG dataset from wearable sensors in terms of ROC curve, AUC and detection power at the false alarm rate of 1%.

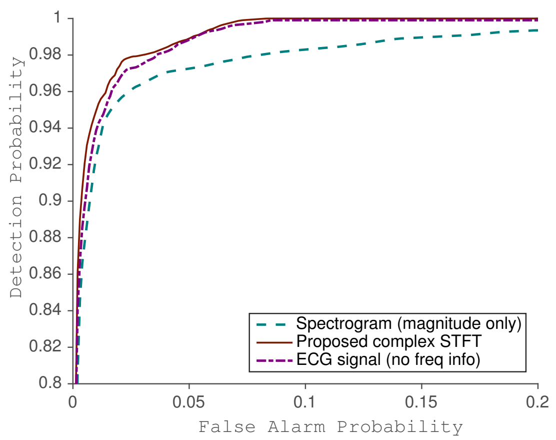

Fig. 5. ROC curves of spectrogram based method, proposed method using complex STFT, and ECG signal based method using Euclidean distance for ECG-ID database (89 subjects). Our proposed method yielded better ROC curve than other two methods.

TABLE II. Performance Summary for ECG-ID database (89 subjects). P_D* is a detection probability at false alarm $= 1\%$.

Method	AUC	EER (%)	P_D*
ECG signal (no frequency info)	0.9971	2.7	0.9388
Spectrogram (magnitude only)	0.9943	3.3	0.9244
Proposed complex STFT	0.9978	2.2	0.9496

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