

Verification of Individuals from Accelerometer Measures of Cardiac Chest Movements

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Abstract: Biometric verification is gaining popularity particularly for personal security during internet and mobile device usage. A novel approach for verification of individuals is proposed to measure mechanical cardiovascular activity through an accelerometer sensor placed on the surface of the chest above the sternum. Time frequency analysis methods are employed to evaluate biometric performance. Accelerometer measurements were acquired on two different sessions from ten subjects after delays ranging from 1 to 2 weeks. For individual subject verification, Gaussian mixture models were built per each individual and a background model was created for the remaining impostors. A likelihood ratio test with background model was employed for testing. In this study we found preliminary evidence for the use of the cardiovascular signal measured with an accelerometer placed on the sternum as a biometric sensor to verify individuals. Verification testing using this approach obtained a mean EER rate of 0.06 for inter-session testing.

1 Introduction

Human authentication technologies are commanding more attention recently mainly due to the increased need for personal security in hand-held devices. Biometric systems are used to identify or verify the identity of a person based on biological, physiological or behavioral characteristics. Fingerprints, iris scans, face images are examples of primary physiological characteristics that have been proposed as biometrics [LWJ98][n99]. Gait and keystroke are two biometric signatures that have primarily behavioral characteristics [MR99][DHS06]. Any biometric measure should have universality, uniqueness (discriminability), permanence (stability), measurability, resistance to circumvention and acceptability properties. Circumvention is a type of biometric forgery where spoof signals are being used to gain access to a system [s02]. The heart signal can be more robust to circumvention attacks as it is hard to mimic a person's heart signature. In this paper we propose a new physiological biometric measurement that senses cardiac chest movements using an accelerometer. Our focus here is to assess the permanence and uniqueness traits of this biometric signal.

Conventional computer systems authenticate users only at the initial login stage. Continuous authentication has gained importance during recent years. In continuous authentication users are not only identified during initial login but are continuously monitored and verified for their identity. Keystroke biometrics and video of face are

some examples of a continuous authentication system [FR99][NUJ10]. Cardiac-based authentication can also be of use as a biometric signal for continuous authentication as the signal is present and can be readily measured continuously. Moreover, cardiac-based authentication has some advantages over other aforementioned biometric authentication systems as the heart is always beating whereas face may be obscured or users may stop typing.

Heart-based verification measurements can be summarized under three main techniques: The first group of techniques uses the mechanical activity of the heart, the second group of techniques measures the electrical activity of the heart and finally the third group of techniques measure the sound of the heart (phonocardiogram) for verification.

Mechanical activity of the heart in the literature is measured using displacement cardiograph techniques such as Ballistocardiogram (BCG) [Gu12], seismocardiogram (SCG) [Za90][Ca07], and finally Laser Doppler Vibrometry (LDV) [Ch10]. Sullivan et al developed a novel method to remotely sense mechanical activity related to the carotid pulse with Laser Doppler Vibrometry (LDV) [c09]. In SCG & BCG the minute movements caused by the beating heart are translated by a transducer into electric potential. In Guo et al's work BCG is recorded using a BCG chair [Gu12].

Most of the cardiac identification research to date focus on electrical measurements of the heart using an electrocardiogram (ECG). For example Kyoso et al has used ECG waveform features extracted from fiducial points of the ECG signal to identify subjects [KA01]. ECG verification and identification systems may require the use of electrodes to be attached to the surface of the body.

Beritelli et al examined the biometric characteristics of phonocardiogram (PCG) [BS07]. Phonocardiograph requires a high sampling rate. Using an accelerometer for measuring biometric cardiac signal has advantages in that accelerometers can be found cheaply and a single point of contact is needed for the measurement. LDV needs a large expensive laser which would not be appropriate for most applications.

Here we present a detailed examination of the accelerometer as a candidate biometric sensor measuring cardiorespiratory signal by measuring the chest movements over the sternum. The outline of the paper is as follows. First we describe the accelerometer data collection and signal properties. Next the application of time frequency analysis and feature selection is described. We then present how models are built for person verification. Finally results are reported and discussed.

2 Methods

2.1 Data Acquisition

Signals are recorded using a 3 axis MEMS accelerometer with a 256 Hz sampling rate. The accelerometer is coupled to the chest and placed on the center of the sternum. (See

Figure 1). In addition, a recording of the conventional ECG is obtained. Signal to noise ratio for ECG signal is approximately 17 dB. All data is digitized with a rate of 256 Hz and synchronized. Data is obtained during a continuous 4-min recording period, during which individuals were instructed to sit quietly and avoid voluntary movements. 10 individuals participated and subjects have an average of 304 heart beats per session. The ages of the individuals varies between 18 to 25 years. In order to assess the stability trait, these individuals are tested on two sessions (referred to as Sessions 1 and 2) with a one to two week interval in between the sessions.

Here the Richter vibrations are due to mechanical energy transmitted to the chest from various cardiac, respiratory, and other physiological sources. We focus here on the cardiac pulse sequence, which is referred to as accelerometer pulse signal.

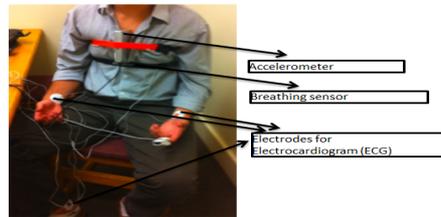


Figure 1: Experimental Setup

2.2 Signal Basics

ECG arises from the electrical activity in the heart whereas the accelerometer signal carries mechanical activity. In the heart cycle electrical activity precedes mechanical activity. This is reflected in Figure 2 where QRS wave in the ECG precedes the dominant accelerometer wave, likely the contraction of the ventricle. Figure displays a 12 second segment of the continuously recorded data drawn from a 4 minute recording.

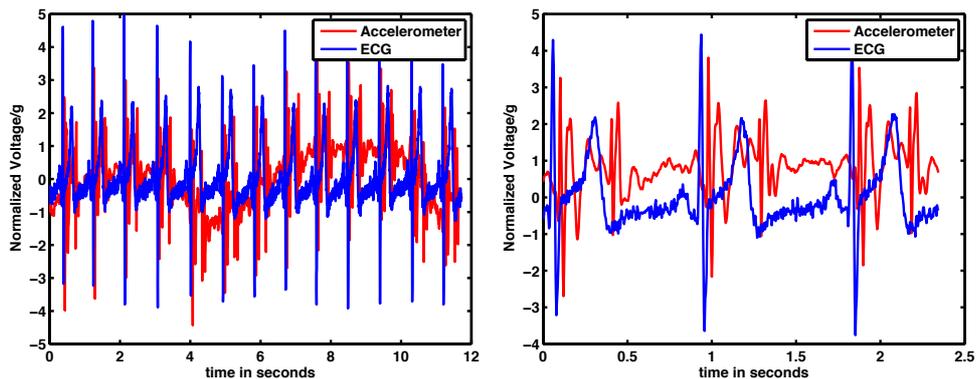


Figure 2: (a) ECG Signal (Blue) and Accelerometer Signal (Red) are displayed in time. (Right figure is zoomed version of the left figure). The Accelerometer Signal also carries the slow varying movements of the respiration signal.

2.3 Time Frequency Decomposition Based Analysis

In this experiment 900-ms windows were extracted for the analysis of each heart beat signal. The 900-ms epoch begins 300 milliseconds prior to the location of the detected ECG R peak point. Detection of R peak points can deteriorate under involuntary movements and on average 1 out of 300 beats were missed due to involuntary movements. Time frequency analysis based approach was used similar to techniques used in speech recognition and Laser Doppler Vibrometry [Ch10]. Time frequency analysis of accelerometer pulse signal was performed separately for the two peak regions (See Figure 3). The first peak region is from 270 to 470 milliseconds and the second peak region is 580 to 780 milliseconds. The accelerometer pulse signal around the peaks is normalized by subtracting the mean and dividing by the standard deviation of the signal patch. A Short Time Fourier Transform with a Hamming window of 96 milliseconds and a moving step size of 16 milliseconds is computed. The resultant spectrogram is a 7 (time) x 13 (frequency) matrix. Figure 3 displays the spectrograms of the accelerometer pulse signal obtained around the two peaks using these parameters. Later these two spectrogram matrices are combined into one matrix for feature selection.

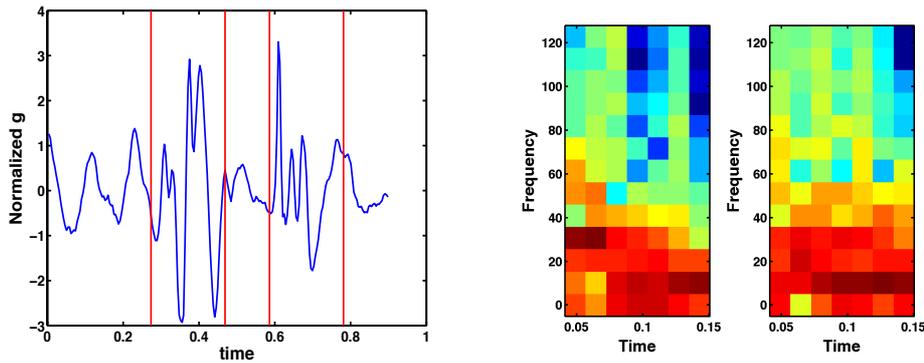


Figure 3: Spectrograms around the two peaks of the signal is displayed above.

2.4 Selection of Important Spectral Bins / Statistical Model for Spectrogram with Informative Components Extraction

Chen et al developed an approach for identification of individuals from the vibration on the carotid artery measured using a Laser Doppler Vibrometry (LDV) [Ch10]. In their approach relative entropy of the spectrogram bins is estimated to select bins that carry significant information in identifying individuals. Freedman et al proved that the Fourier coefficients for stationary or asymptotically stationary random processes are independent complex Gaussian random variables [f80]. Chen et al used this theorem and stated that the magnitude of the Fourier coefficients is exponentially distributed [Ch10]. Chen et al calculates the relative entropy as in equation 1 where $X_{i,n}(l)$ is the training data in the l 'th time frequency bin of the n 'th spectrogram for the i 'th individual. $M_o(l)$ is the l 'th component of the background model, and N is the number of training spectrograms.

$$J_i(l) = \frac{1}{N} \sum_{n=1}^N \frac{X_{in}(l)}{M_o(l)} - \ln \frac{X_{in}(l)}{M_o(l)} - 1 \quad (1)$$

Here we employ Chen's approach for selecting significant spectrogram bins for verification using equation 1. The Relative Entropy for each bin is estimated with the assumption that the spectrogram bins are exponentially distributed. In equation 1, $M_o(l)$ is estimated by calculating the overall mean spectrogram of the first session subjects excluding the individual test subject. The top 50 highest entropy bins of an individual were selected as features for use in verification.

2.4 Person Verification

Background models have been used in biometric verification and in particular speaker detection [MR99]. Reynolds et al. used a single speaker-independent background model trained to represent speaker independent distribution of features for speaker detection. Their system used a likelihood ratio test for verification [MR99]. In this paper we employ likelihood ratio test for verification of individuals where the numerator denotes the probability of the signal patch coming from the hypothesized individual (individual model) and the denominator denotes the probability of it coming from the background model. Both models are built using Gaussian Mixture Model (GMM) distributions with diagonal covariance matrices.

Given a set of training vectors, GMM maximum likelihood model parameters are estimated using the iterative expectation-maximization (EM) algorithm. Individual subject model is trained from the 1st session of the individual subject data. The background model is trained using 1st session data of all the subjects excluding the hypothesized subject (from a set of 9 subjects). Background GMM model for each individual is trained with 10, 20, 30, 40 mixtures and the model with the minimum Akaike Information criterion (AIC) is selected and stored. Similarly individual GMM models are trained with 1,2,3 and 4 mixtures and the model with the minimum AIC is selected. Testing is performed on the 2nd session data using individual equal error rate thresholds (See Table 1). The EER threshold selection method and the results are reported in the next section.

3 Results

False acceptance and false rejection rates (FAR & FRR) are employed as a performance measure. The FAR and FRR is computed using a preselected threshold where the threshold is determined from the first session of the data as follows. For each individual subject the first session data is randomly partitioned into two where first half of the data is used in building models and the rest of the data is used for selecting the threshold as displayed in Table 1 (left table). Each subject's individual and background models are built with the first half of the data. The second half of the data is used in testing the models and determining the value of the equal error rate thresholds which are stored for

the inter-session performance estimation. Table 1 right displays the inter-session training and testing for an individual using the stored thresholds.

EER threshold determination for an individual	Inter-Session training and testing for an individual
Impostor Model Training Half of randomly selected first session data 9 subjects x ~300 instances/2 ~ 1350 training instances	Impostor Model Training 9 subject's combined first session data 9 x ~300 ~ 2700 instances
Individual Model Training Half of randomly selected first session data 1 subject x ~300 instances /2 ~ 150 training instances	Individual Model Training First session of the subject data ~ 300 instances
EER threshold determination Rest of first session data ~150 authentic instances, ~1350 impostor instances	Testing Second session of the data ~2700 impostor instances, ~300 authentic instances

Table 1: Data partitioning for EER threshold determination for an individual is displayed on the left. Right table displays partitioning of the data for intersession training and testing for an individual.

Subject #	FAR	FRR	FAR sum 5	FRR sum 5	FAR sum 10	FRR sum 10
Subject 1	0.04	0.03	0.01	0.04	0.01	0.07
Subject 2	0.00	0.08	0.00	0.00	0.00	0.00
Subject 3	0.03	0.01	0.00	0.01	0.00	0.02
Subject 4	0.15	0.15	0.07	0.01	0.05	0.00
Subject 5	0.02	0.53	0.02	0.62	0.00	0.67
Subject 6	0.27	0.22	0.16	0.11	0.13	0.10
Subject 7	0.24	0.04	0.16	0.07	0.13	0.04
Subject 8	0.02	0.29	0.00	0.24	0.00	0.24
Subject 9	0.29	0.03	0.29	0.03	0.28	0.01
Subject 10	0.32	0.16	0.26	0.09	0.25	0.08
Mean	0.14	0.15	0.09	0.12	0.08	0.13
Std. Dev.	0.12	0.15	0.11	0.18	0.10	0.19

Table 2: Inter-Session FAR and FRR single beat and sum FAR and FRR rates using 5 and 10 heart beats are displayed

The results for the intra-session comparisons are not shown here to conserve space. Average inter-session FAR and FRR performance numbers for single beats and using the sum over 5 and 10 heart beats are reported in Table 2. A mean of 0.14 FAR and a mean of 0.15 FRR was achieved for inter-session person verification with a single heart beat. Moreover when the sum over 10 heart beats is employed our error rates decreased to a mean of 0.08 FAR and 0.13 FRR. Summation over more than 10 heart beats did not lead to a significant increase in performance.

Figure 4 displays the equal error rates for each individual by using single beat EER and 10 heart beat EER measures. The mean EER for 10 heart beats obtained a rate 0.06. This suggests a preliminary evidence for uniqueness in the heart signal measured with the accelerometer placed on the sternum using frequency spectrogram measures.

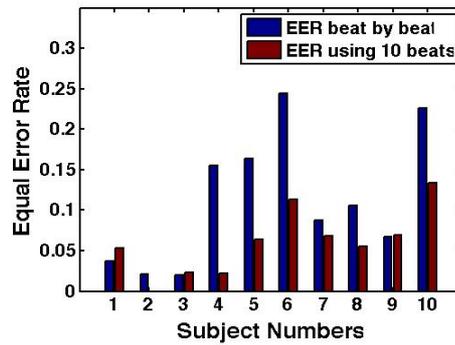


Figure 4: Equal error rate performance results are displayed for single beat and 10 heart beat results

4 Conclusion

Using an accelerometer for measuring biometric cardiac signal has advantages in that accelerometers can be found cheaply and a single point of contact is needed. Moreover, accelerometer data is computationally inexpensive in comparison to methods that require a high sampling rate such as phonocardiogram. Cardiac measurements using an accelerometer does not require an expensive setup as opposed to Laser Doppler Vibrometry. Our studies confirm that the accelerometer is promising as a biometric sensor to measure cardiac pulse signal and has verification strength for individuals. More subjects are needed to evaluate this approach in larger populations. The signal may be affected by factors such as physical exercise and mental stress, hence, we plan future experiments to investigate this.

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References

- [BS07] Beritelli, Francesco, and Salvatore Serrano. "Biometric identification based on frequency analysis of cardiac sounds." *Information Forensics and Security, IEEE Transactions on* 2.3 (2007): 596-604.
- [Ca07] Castiglioni, Paolo, et al. "Wearable seismocardiography." *Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE. IEEE, 2007.*
- [Ch10] Chen, Mei, et al. "Laser doppler vibrometry measures of physiological function: evaluation of biometric capabilities." *Information Forensics and Security, IEEE Transactions on* 5.3 (2010): 449-460.
- [c09] Chen, Mei, et al. "Biometrics with physical exercise using laser doppler vibrometry measurements of the carotid pulse." *Biometrics, Identity and Security (BIdS), 2009 International Conference on. IEEE, 2009.*
- [DNR77] Dempster, Arthur P., Nan M. Laird, and Donald B. Rubin. "Maximum likelihood from incomplete data via the EM algorithm." *Journal of the Royal Statistical Society. Series B (Methodological)* (1977): 1-38.
- [DHS06] Gafurov, Davrondzhon, Kirsi Helkala, and Torkjel Søndrol. "Biometric gait authentication using accelerometer sensor." *Journal of computers* 1.7 (2006): 51-59.
- [f80] Freedman, David. "The empirical distribution of Fourier coefficients." *The Annals of Statistics* 8.6 (1980): 1244-1251.
- [FR99] Monrose, Fabian, and Aviel D. Rubin. "Keystroke dynamics as a biometric for authentication." *Future Generation Computer Systems* 16.4 (2000): 351-359.
- [Gu12] Guo, Hong, et al. "Ballistocardiogram-based person identification using correlation analysis." *World Congress on Medical Physics and Biomedical Engineering May 26-31, 2012, Beijing, China. Springer Berlin Heidelberg, 2013*
- [KA01] Kyoso, Masaki, and Akihiko Uchiyama. "Development of an ECG identification system." *Engineering in Medicine and Biology Society, 2001. Proceedings of the 23rd Annual International Conference of the IEEE. Vol. 4. IEEE, 2001.*
- [LWJ98] Hong, Lin, Yifei Wan, and Anil Jain. "Fingerprint image enhancement: algorithm and performance evaluation." *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 20.8 (1998): 777-789.
- [n99] Negin, Michael, et al. "An iris biometric system for public and personal use." *Computer* 33.2 (2000): 70-75.
- [NUJ10] Niinuma, K.; Unsang Park; Jain, A.K., "Soft Biometric Traits for Continuous User Authentication," *Information Forensics and Security, IEEE Transactions on*, vol.5, no.4, pp.771,780, Dec. 2010
- [RQD99] Reynolds, Douglas A., Thomas F. Quatieri, and Robert B. Dunn. "Speaker verification using adapted Gaussian mixture models." *Digital signal processing* 10.1 (2000): 19-41.
- [s02] Schuckers, Stephanie, et al. "Issues for liveness detection in biometrics." *Proceedings of Biometric Consortium Conference. IEEE, New York. 2002.*
- [Za90] Zanetti, J. "Seismocardiography: A new technique for recording cardiac vibrations. Concept, method, and initial observations." *Journal of cardiovascular technology* 9.2 (1990): 111-118.