2014 IEEE International Conference on Acoustic, Speech and Signal Processing (ICASSP)

ON ESTABLISHING EVALUATION STANDARDS FOR ECG BIOMETRICS

Shahrzad Pouryayevali, Saeid Wahabi, Siddarth Hari, Dimitrios Hatzinakos

University of Toronto
The Edward S. Rogers Sr. Department of Electrical and Computer Engineering
10 Kings College Road, Toronto, ON, Canada, M5S 3G4
{shahrzad,swahabi,shari,dimitris}@ece.utoronto.ca

ABSTRACT

Electrocardiogram (ECG) biometrics are becoming increasingly popular. Numerous approaches to ECG processing have been proposed over the past years and the field has drawn significant attention from the biometrics community. However, less attention has been paid to developing a standard for ECG biometric testing for the evaluation of such algorithms. This paper proposes a set of standards for ECG signal recording and presents the UofT ECG Database (*UofTDB*) in order to evaluate the performance of various ECG biometric methods. Compared to existing databases, the UofTDB has three important characteristics namely, *large population size* (1012 individuals), *varying body postures*, *physical exercise* and *acquisition over a long period*. A promising equal error rate of under 5% is also reported.

***Index Terms*—** Biometrics (access control), Electrocardiogram, Electrocardiogram Database, Evaluation Performance

1. INTRODUCTION

Biometrics recognition systems are poised to replace traditional identification systems based on passwords, PIN numbers or tokens. Fingerprint, face and iris-based biometric systems are already deployed for securing passports and controlling access to high security environments, as well as for logging into electronic devices in the consumer market. As these biometric systems become widely deployed, there is an increasing risk from advancements in the methods and technologies for biometric falsification.

An important objective of the next generation of biometric modalities currently under research and development is to address the threats of circumvention, replay attacks and biometric obfuscation. Medical biometrics, in which internal physiological signals of the human body containing subject-specific information are used for recognizing users, offers inherent protection against such attacks. Examples of medical biometrics include the electrocardiogram (ECG), electroencephalogram (EEG), blood volume pressure (BVP), photoplethysmogram (PPG) and phonocardiogram (PCG). These signals have traditionally been used by physicians for disease diagnosis.

A number of research studies over the last few years have established the ECG signal as a biometric modality. There are two main approaches for feature extraction namely fiducial methods which use local characteristics of the heart-beats (e.g., temporal and amplitude distances between consecutive fiducial points), and non-fiducial methods which explore the waveform as a whole. A survey of these different methods can be found in [1].

An important property of ECG biometrics is that unlike the fingerprint or the iris, the ECG signal varies over time, and is affected by different factors such as exercise and stress. Additionally, the ECG signal can be acquired from multiple configurations of sensors on the body (e.g, from the chest, or from the fingertips) and is also affected by body position. While the importance of evaluating the robustness of different ECG-recognition algorithms to these variations is well understood, an important bottleneck is the lack of ECG databases that include these variations. In this paper, we present a new ECG database called UofTDB, which represents a first step towards addressing this gap.

The rest of the paper is organized as follows : in Section 2, we present a brief summary of existing ECG databases. Section 3 presents the details of the new UofTDB database. In Section 4, we present some initial results using the new database. Section 5 concludes the paper.

2. EXISTING ECG DATABASES

The ECG signal is time-series that reflects the electrophysiological properties of the heart but which is also affected by the various sympathetic and para-sympathetic processes of the autonomic nervous system (ANS) [18]. The latter contribute to the time-varying nature of the ECG signal. Furthermore, the ECG is affected by body posture [19] as well as variability of the heart rate due to physical activities such as exercise

This work was supported by the Natural Sciences and Engineering Research Council of Canada (NSERC)

Table 1. Public and Private ECG Databases

Database/Researcher Name	Public/ Private	# of Subjects	# of Sessions	Sensor Positions	Conditions or Disorders
UofT Database(UTDB)	private	1012	up to 5	fingers	sit, stand, exercise, supine and tripod
Zhang and Wei [2]	private	520	-	limbs and chest	-
PTBDB [3]	public	290	up to 5	limbs and chest	healthy and cardiac disorders
Odinaka *et al.* [4]	private	269	3	lower rib cage	healthy and heart-related disorders
Shen *et al.* [5]	private	168	-	palms	sit
QTDB [3]	public	105	-	chest	exercise and variety of cardiac disorders
LTSTDB [3]	public	80	-	chest	-
EDB [3]	public	79	-	chest	myocardial ischemia
Wübbeler *et al.* [6]	private	74	2-20	limbs	resting in supine position
Jang *et al.* [7]	private	65	6	-	different stress levels
Chan *et al.* [8]	private	50	3	thumbs	-
Agrafioti & Hatzinakos [9]	private	52	up to 2	limbs and chest	-
MITDB [3]	public	47	-	chest	Arrhythmia
Irvine *et al.* [10]	private	43	-	neck and chest	different stress levels
Silva *et al.* [11] & Coutinho *et al.* [12]	private	26	-	chest	cognitive task
Yao and Wan [13]	private	20	up to 4	limbs	-
Biel *et al.*[14]	private	20	4-10	limbs and chest	resting
NSRDB [3]		18	1	-	no significant arrhythmias
Lourenco *et al.* [15]	private	16	1	fingers	-
Homer *et al.* [16]	private	12	12 or 18	-	-
Kim *et al.* [17]	private	10	-	arms	resting and exercise

[17, 20]. To date the investigation of the above-mentioned factors for the ECG, in a biometric recognition context, is very limited. This is primarily due to the lack of availability of a signal database that encompasses all this information simultaneously. It is important to note that the majority of the existing work in this area has focused on ECG biometric evaluation using signal readings that were acquired within the same experimental session or within the same day. In [1], the authors demonstrated the degradation of the ECG biometric accuracy using data that are recorded over multiple days.

Additionally, most of the early ECG databases have a small population size (couple of hundreds of subjects). Therefore, while earlier works demonstrated a proof of concept for ECG biometric systems, feasibility studies for large-scale deployments has, so far, been limited.

Table 1 lists the details of existing ECG databases. The largest private database is that of Zhang and Wei, which consists of 520 subjects [2]. The largest public database is the PTBDB (290 subjects) [3]. While, the database of Odinaka *et al.*[4] is smaller (269 subjects), this database is unique in that it includes recordings from multiple recording sessions spaced up to six months apart. The database of Irvine *et al.*[10] (43 subjects) contains recordings acquired after each subject performed tasks designed to elicit anxiety levels. The database of Kim *et al.*[17] (10 subjects) includes recording under both normal and elevated heart rate conditions. The PTBDB and Odinaka *et al.* databases also include some subjects with heart-related disorders.

3. UOFTDB ECG DATABASE

The rationale for the design of a new ECG biometric database was to create a benchmark that can be used for testing and which sufficiently covers factors that affect real-world ECG biometric systems. Central to the development of this database were the following factors: 1) Database size, 2) Signal evolution over time, 3) Body posture, 4) Physical stress and 5) Finger acquisition. We advocate that the above-mentioned factors sufficiently cover the real-world variability that is anticipated within healthy real-world users of the system.

The UofTDB includes ECG recordings from volunteers in multiple sessions, under exercise condition and different body postures. The main features of the new UofTDB ECG database are as follows:

- *Size*: The UofTDB includes recordings from 1012 healthy subjects (seated, single-session). The length of each recording varies from 2 to 5 minutes.
- *Evolution over time*: For specific volunteers, the ECG was recorded over five additional recording sessions which spanned over a *six-month interval*. These are recordings are available only from participants who agreed to participate in follow-up studies. Table 2 shows the number of subjects (out of 1012) that participated in these sessions. For instance, the UofTDB contains recordings from 6 sessions for 43 subjects.
- *Body posture*: The UofTDB includes ECG recordings in four different postures namely "sit", "stand", "supine" and "tripod". A graphical representation of these postures are shown in Figure 1. The number of subjects recorded in these different postures is presented in Table 2.
- *Exercise*: The UofTDB includes pre and post-exercise recordings for 71 subjects. Each subject in this set performed a few basic structural workouts such as jumping jacks and pushups for about 5 minutes. The average elevated heart rate was found to be 132 beats per minute.

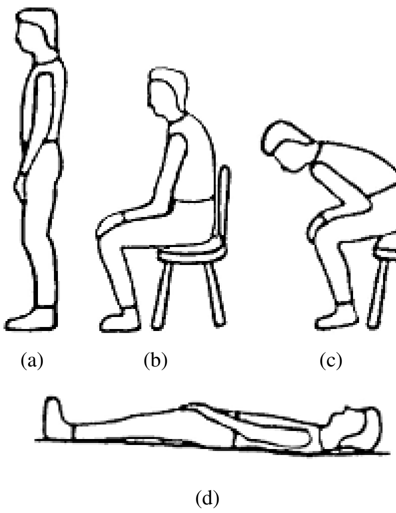

Fig. 1. (a) Stand, (b) sit, (c) tripod, and (d) supine

3.1. ECG Acquisition Protocol

All recordings in the UofTDB were performed in uncontrolled settings at different locations on the University of Toronto campus. The ECG signal was captured from the volunteers' fingertips according similar to a lead I configuration: the subjects held a pad with dry AgCL electrodes positioned such that the left thumb was placed on the positive electrode, the right thumb on negative electrode and the right index finger was placed on the reference electrode, as demonstrated in Figure 2. The Vernier EKG sensor and the Go!Link interface [1] were used for recording the ECG signals. The device was configured to 200Hz sampling frequency at a 12 bits per sample resolution.

All the subjects who attended the follow-up sessions were recorded in a seated position. A subset of them were also recorded in a resting state in three more postures (stand, supine, tripod) and exercise condition. In order to avoid the effect of fast heart rate in the resting state recordings, the exercise condition was collected in the end of the experimental protocol.

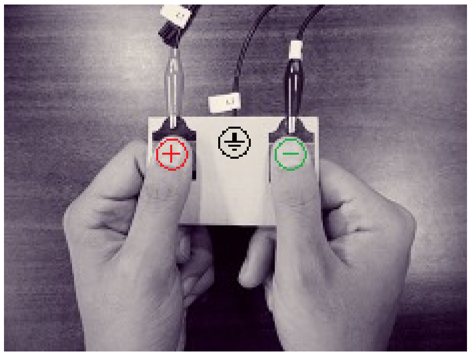

Fig. 2. Placement of electrodes according to lead I configuration.

4. INITIAL EXPERIMENTS

4.1. ECG Preprocessing

The raw ECG signals were filtered using a fourth-order bandpass Butterworth filter with cut-off frequencies 0.5 Hz and 40 Hz. Under 0.5 Hz the signal is corrupted by baseline wander, and over 40 Hz there is distortion due to muscle movement, power-line noise etc. [21]. The QRS detection algorithm described in [22] was employed to segment and align the heartbeats if needed. The individual heartbeats were truncated to a length of 700 msec with 200 msec before the R peak.

4.2. Testing scalability with increased population

We evaluated the performance of three ECG-recognition algorithms namely the AC/LDA proposed by Agrafioti *et al.* [23], the discrete wavelet transform method of Chan *et al.* [8] and the time-frequency content approach of Odinaka *et al.*

[1] www.vernier.com

Table 2. UofT ECG Database

	Number of Recording Sessions						Conditions				
	single	two	three	four	five	six	supine	tripod	exercise	sit	stand
Number of subjects	1020	72	65	54	47	43	63	63	71	1020	81
	Age Range: 18 - 52, Gender: 61% Female, 39% Male, ***Total number of subjects = 1020***										

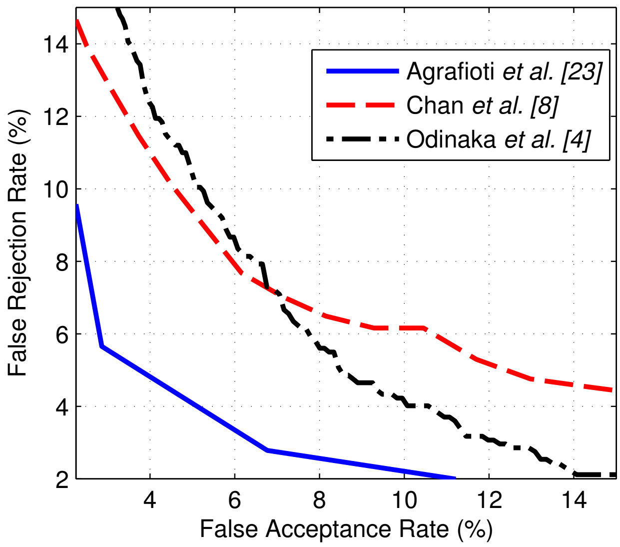

Fig. 3. Receiver operating characteristic (ROC) curve for the three methodologies.

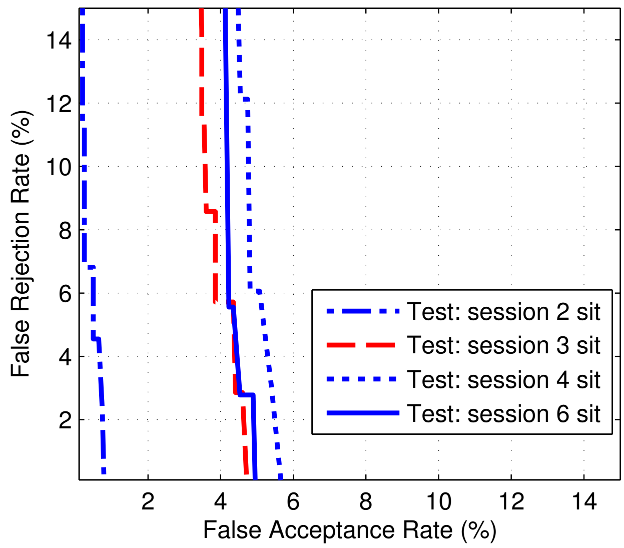

Fig. 4. Receiver operating characteristic (ROC) curve for AC/LDA methodology in the across-session analysis. Trained in session 2 in sit condition.

[4]. The performance of the three algorithms is evaluated in the verification mode of operation.

The AC/LDA method proposed by Agrafioti *et al.* [23] uses the autocorrelation (AC) of windowed ECG signals as the feature space, along with Linear Discriminant Analysis (LDA) method for classification. Chan *et al.* [8] use the detail coefficients of the discrete wavelet transform of PQRST complexes for the feature space and a proposed wavelet distance measure for classification. This method was evaluated with ECG signals captured from fingertips using dry electrodes which is similar to the UofTDB. Odinaka *et al.* [4] use the time-frequency content of the heartbeats as the feature space and propose a feature selection method for dimensionality reduction and performance enhancement.

A summary of the experimental results is shown in Figure 3. For most methods, the reported performance presents a significant drop from the previously reported results. This can be attributed to the increased population size as well as the noise that was present in signal acquisition in an uncontrolled environment. It should be noted that in this evaluation, no subjects of the database were discarded as outliers as the purpose of this work is to imitate real-world application settings.

4.3. Feature permanence over time

We evaluated the robustness of the AC/LDA algorithm to template degradation using the 47 subjects for whom recordings are available for four sessions in sit condition spread over a six month period. In this experiment, the AC/LDA was trained using the ECG signals acquired in the first session and then tested using the ECG recordings from subsequent sessions. The results are shown in Figure 4. From this figure, it is clear that there are factors that affect the biometric accuracy over time and thus emphasis should be hereon placed on establishing algorithms that are robust over such periods.

5. CONCLUDING REMARKS

This paper brings to the table the issue of establishing testing standards for ECG biometric systems. Factors that directly affect the ECG waveform and impact the biometric accuracy are identified and a new testing database is presented as a benchmark for algorithmic evaluation. The UofTDB database covers conditions such as exercise and mental variability as well as morphology evolution over a period of six months.

6. REFERENCES

[1] I. Odinaka, P.-H. Lai, A. D. Kaplan, J. A. O'Sullivan, E. J. Sirevaag, and J. W. Rohrbaugh, "ECG biometric recognition: A comparative analysis," *IEEE Trans. Inf. Forensics Security*, vol. 7, no. 6, pp. 1812–1824, 2012.

[2] Z. Zhang and D. Wei, "A new ECG identification method using Bayes' teorem," in *Proc. IEEE Region 10 Conf.*, 2006, pp. 1–4.

[3] A. L. *et al.* Goldberger, "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals," *Circulation*, vol. 101, no. 23, pp. e215–e220, 2000.

[4] I. Odinaka, P.-H. Lai, A. D. Kaplan, J. A. O'Sullivan, E. J. Sirevaag, S. D. Kristjansson, A. K. Sheffield, and J. W. Rohrbaugh, "ECG biometrics: A robust short-time frequency analysis," in *Proc. 2010 IEEE Int. Workshop on Information Forensics and Security*, 2010, pp. 1–6.

[5] T.-W. D. Shen, W. J. Tompkins, and Y. H. Hu, "Implementation of a one-lead ECG human identification system on a normal population," *J. Eng. Comput. Innovations*, vol. 2, pp. 1221, 2011.

[6] G. Wubbeler, M. Stavridis, D. Kreiseler, R.-D. Bousseljot, and C. Elster, "Verification of humans using the electrocardiogram," *Pattern Recognit. Lett.*, vol. 28, pp. 1172 – 1175, 2007.

[7] D. Jang, S. Wendelken, and J. M. Irvine, "Robust human identification using ECG: eigenpulse revisited," in *Proc. SPIE*, 2010, vol. 7667.

[8] A. D. C. Chan, M.M. Hamdy, A. Badre, and V. Badee, "Wavelet distance measure for person identification using electrocardiograms," *IEEE Trans. Instrum. Meas.*, vol. 57, no. 2, pp. 248–253, 2008.

[9] F. Agrafioti and D. Hatzinakos, "Signal validation for cardiac biometrics," in *Proc. 2010 IEEE Int. Conf. Acoustics Speech and Signal Processing (ICASSP)*, 2010, pp. 1734–1737.

[10] J. M. Irvine, S. A. Israel, W. T. Scruggs, and W. J. Worek, "Eigenpulse: Robust human identification from cardiovascular function," *Pattern Recognit.*, vol. 41, pp. 3427 – 3435, 2008.

[11] H. Silva, H. Gamboa, and A. Fred, "One lead ECG based personal identification with feature subspace ensembles," in *Proc. 5th Int. Conf. Machine Learning and Data Mining in Pattern Recognition*, 2007, pp. 770–783.

[12] D. P. Coutinho, A. L. N. Fred, and M. A. T. Figueiredo, "One-lead ECG-based personal identification using Ziv-Merhav cross parsing," in *Proc. 2010 20th Int. Conf. Pattern Recognition (ICPR)*, 2010, pp. 3858–3861.

[13] J. Yao and Y. Wan, "A wavelet method for biometric identification using wearable ECG sensors," in *Proc. 5th Int. Summer School and Symp. Medical Devices and Biosensors*, 2008, pp. 297–300.

[14] L. Biel, O. Pettersson, L. Philipson, and P. Wide, "ECG analysis: a new approach in human identification," *IEEE Trans. Instrum. Meas.*, vol. 50, no. 3, pp. 808–812, 2001.

[15] A. Lourenço, H. Silva, and A. Fred, "Unveiling the biometric potential of finger-based ECG signals," *Computat. Intell. Neurosci.*, vol. 2011, no. 720971, pp. 5:1–5:8, 2011.

[16] M. Homer, J. M. Irvine, and S. Wendelken, "A model-based approach to human identification using ECG," in *Proc. SPIE*, 2009, vol. 7306.

[17] K.-S. Kim, T.-H. Yoon, Lee J.-W., D.-J. Kim, and H.-S. Koo, "A robust human identification by normalized time-domain features of electrocardiogram," in *Proc. 2005 IEEE Eng. Medicine and Biology 27th Ann. Conf., Shangai, China*, 2005, pp. 1114–1117.

[18] F. Agrafioti, D. Hatzinakos, and A. K. Anderson, "ECG pattern analysis for emotion detection," *IEEE Trans. on Affect. Comput.*, vol. 3, no. 1, pp. 102–115, 2012.

[19] M. G. Adams and B. J. Drew, "Body position effects on the ECG: Implication for ischemia monitoring," *J. Electrocardiol.*, vol. 30, no. 4, pp. 285–291, 1997.

[20] M. Chen, J. A. O'Sullivan, A. D. Kaplan, P.-H. Lai, E. J. Sirevaag, and J. W. Rohrbaugh, "Biometrics with physical exercise using laser doppler vibrometry measurements of the carotid pulse," in *Proc. 1st IEEE Int. Conf. Biometrics, Identity and Security*, 2009, pp. 1–6.

[21] L. Sörnmo and P. Laguna, *Bioelectrical Signal Processing in Cardiac and Neurological Applications*, Elsevier Academic Press, June 2005.

[22] J. Pan and W. J. Tompkins, "A real-time QRS detection algorithm," *IEEE Trans. Biomed. Eng.*, vol. BME-32, no. 3, pp. 230–236, 1985.

[23] F. Agrafioti and D. Hatzinakos, "ECG based recognition using second order statistics," in *Proc. Communication Networks and Services Research Conf. 2008*, 2008, pp. 82–87.