FEASIBILITY OF SINGLE-ARM SINGLE-LEAD ECG BIOMETRICS

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ABSTRACT

This work analyses the feasibility of electrocardiogram (ECG) biometrics using signals from a novel single arm single-lead acquisition methodology. These new signals are used and analysed in a biometric recognition system in verification mode for validation of a person's identity enrolled in a system database. The algorithm used for recognition in the proposed system is the Autocorrelation/Linear Discriminant Analysis (AC/LDA), which is combined with preprocessing stages tuned to the characteristics for ECG from the single arm. The signal is collected from 23 subjects in three scenarios and performance of the proposed scheme is evaluated. Considerably low Equal Error Rate of 4.34% is obtained using the described method, establishing the utility of these signals as viable candidates for ECG Biometrics.

***Index Terms*—** ECG, single arm, single lead, feasibility, AC/LDA, biometrics, equal error rate, verification

1. INTRODUCTION

Recognition of individuals using biometric signatures has been an area of major interest to researchers in the past decade as they have many advantages over traditional methods of recognition. Chief among them is that they posit a framework which uses the essence of the user to recognize her. This approach to recognition is closer to the actual person than indirect means such as a password, which is memorized by the user who wishes access to a system. Another advantage of using certain biological signals for biometrics is that they are almost universally present. Hence, modalities like fingerprint, face and iris have been successfully used in practical recognition systems for security. However, these aspects also raise concerns of various kinds of attacks which can compromise systems that use biometric security. An example is where one tries to impersonate the original signal. Also, privacy concerns are important in such systems because once a biological identity is stolen, it is usually hard to replace.

With these perspectives, the electrocardiogram (ECG) signal has been proposed as a modality for biometrics [1, 2]. An ECG is a trace of the electric activity of the heart obtained through a configuration of electrodes placed on the body at specific locations. It is a quasi-periodic signal with pulses corresponding to cycles of the body's cardiac functions. Biometric recognition using ECG consists of two broad approaches, namely the fiducial points dependent and the non-fiducial methods. Fiducials are specific points on the ECG heartbeat which can be used to extract features based on its temporal and amplitude characteristics. Approaches using fiducials are abundant in literature such as [1, 2, 3, 4, 5]. Notably, [1, 2, 5] report 100% identification accuracy using fiducial methods on modestly sized databases using conventional electrode configurations whereas [3] reports 99.6% and 88.2% identification accuracy using 2-lead fusion and 1-lead respectively. Non-fiducial methods used in [6, 7, 8, 9, 10] do not rely on specific points on the ECG curve but rather use statistical characteristics. For e.g., autocorrelation, which contains the same information as fiducials blended holistically is used in [6]. The method employed in our work uses a non-fiducial approach because of the poor quality and lack of clear fiducial points on the acquired single-arm ECG signal.

The existing methodology in all literature has as yet required sensors to be placed on either side of the body (e.g. fingers from both hands). This requirement becomes a major problem in user friendly applications as both sides of the body have to be in contact with the sensors. It is highly preferable instead to obtain ECG from only a single side of the body. This would pave the way for comfortable and user-friendly biometrics, applicable in devices such as a smartwatch. Placement criteria for the electrodes is key to obtaining a usable ECG signal and is based on both empirical observations and biological facts such as the axis of the heart and location of nodes. Recently, 1-lead ECG has been used in [11, 12, 13, 14], obtaining ECG from fingertips whereas in [3], both 1-lead and 2-lead signals obtained from Holter monitoring are used. To the best of our knowledge, this work is the first to use single-lead signals from only one side of the body, i.e. the left arm, for ECG biometrics.

In this paper, we propose a novel approach of using single-lead ECG signals from the upper left arm for biometrics. We call this the Single Arm ECG (SA-ECG). The SA-ECG signals were collected and the feasibility of this

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approach was analysed using the AC/LDA algorithm in three different case scenarios or posture-states of human beings. These results are compared with reported performances of recently proposed methods which also use 1-lead ECG signals such as Zhao *et al.* [11], Lourenco *et al.* [12] and Silva *et al.* [14], all of which use Fingertips ECG (henceforth called FT-ECG). As our work on SA-ECG is new in that there is no other SA-ECG database, we believe these works using single-lead signals provide reasonable preliminary comparisons for our system's performance.

Hannula *et al.* [15] showed that it was possible to get ECG from a single arm. Their work involved comparison of regular ECG measurement methods with their single-arm single-lead system. Also, their measured heart-rate correlated with the actual heart-rate. Later, Yang *et al.* [16] confirmed the existence of SA-ECG and also showed that it was better to use electrodes on the upper arm of the user. The user was assumed to be at rest to reduce EMG interference. It was also noted that SA-ECG was a very noisy compared to FT-ECG and other conventional ECG signals. Plessey Semiconductors [17] have also shown a method of SA-ECG acquisition using their EPIC sensors confirming the sensor location.

In these works, the signals were not studied for use in biometrics, which is the motivation for our work. Additionally, SA-ECG is extremely convenient to acquire with access only needed to a single location on the body. This is an important advantage in commercial biometric applications where comfort of use is key to success of new technology. Our work includes collection of SA-ECG signal in various scenarios and evaluation of verification performance for biometrics using a system described in the next section.

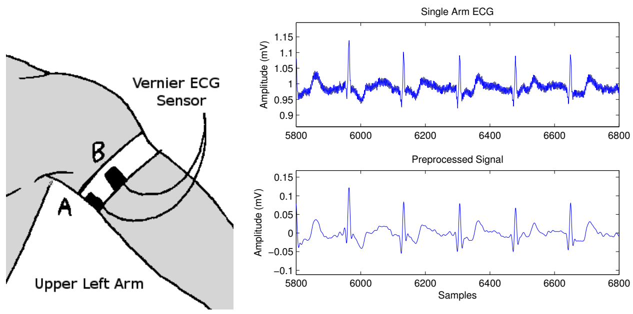
2. SYSTEM MODEL AND METHODOLOGY

For analysing the distinctiveness of SA-ECG from upper left arm among different individuals, the Autocorrelation/Linear Discriminant Analysis (AC/LDA) method is used followed by a classifier for comparison. Initially in the enrolling phase, SA-ECG signals are recorded from users and processed through various stages before using AC/LDA as described in detail in this section.

2.1. Experiment Process

For acquisition of ECG signals from the arm, we used a 1-lead Vernier ECG sensor with Kendall AgCl gel electrodes. Each recording was 120 seconds long with a sampling frequency of 200Hz. The SA-ECG was collected from the upper left arm as shown in Figure 1(a). The electrodes' location was empirically determined to get the best signal quality i.e. least noise and highest amplitude of the ECG signal. Note that though multiple such configurations exist at the upper left arm, the same electrode location was used for all subjects.

The data was collected in a single session scheduled at the Biometrics Security Lab at the University of Toronto through



(a) (b)

Fig. 1. (a) Electrode placement for SA-ECG acquisition: A and B are the two electrodes, (b) SA-ECG from a subject(top) and preprocessed signal(bottom)

the participation of 23 subjects. Appropriate ethics approval was obtained prior to the collection process. The volunteers were all in the age range of 18-30 years and had no history of heart-related disorders. ECG was collected in three cases/postures for each subject:

1. Sitting posture, subject at rest
2. Standing posture, subject at rest
3. Sitting posture, at rest, after 20 seconds of exercise

These three cases were chosen as they represent most possibilities of posture and state for human beings at rest. In this work, the three cases are analysed separately for biometric verification. Though the enrolment signal is 120s long, note that the actual procedure would require only a small duration signal equal to the window size chosen in Section 3.

2.2. Preprocessing, Segmentation and Outlier Detection

Since the SA-ECG is comparatively noisier than the FT-ECG or traditional lead ECG, the preprocessing stage becomes crucial. Apart from typical noise such as baseline wander and power-line interference, there is contact noise from the electrodes and EMG interference due to the biceps and triceps muscles. For these, we use a zero-phase butterworth band-pass filter whose passband and order are determined empirically depending on the signal characteristics (see Table 2). Figure 1(b) shows an example of this process.

Next, we segment the signal into overlapping windows. This is done blindly to the location of ECG heartbeats, making this method non-fiducial. However, the window duration is chosen long enough to contain several heartbeats. Then an outlier removal process removes the noisy windows which survived filtering. This is done using Euclidean distance by comparing the windows with the mean window using a variance dependent threshold. This stage gets rid of the windows which have sharp peaks and artefacts that are due to contact noise and movement. This is important as bad windows can produce anomalies that propagate to the learning phase of the system, i.e. the LDA.

2.3. Autocorrelation - Linear Discriminant Analysis

The AC/LDA method is a Non-Fiducial method successfully used in ECG biometrics that uses the autocorrelation of the ECG signals as a feature vector for classification (described in Agrafioti *et al.* [18]). It does so by projecting the AC feature vectors to a new space with lower dimensionality [19]:

1. *Normalized autocorrelation*: Each window is processed to calculate the normalized autocorrelation.
2. *Dimensionality Reduction*: Using the LDA Algorithm.
3. *Classification*: Using projections from the LDA, we compare the testing windows with those in the database.

The normalized autocorrelation (AC) is calculated as:

$$\hat{R}_{xx}[m] = \frac{\sum_{i=0}^{N-|m|-1} x[i]x[i+m]}{\hat{R}_{xx}[0]} \tag{1}$$

where $x[i]$ is the window in question. N is the length of the window and m is the time lag with $m = 0, 1, \ldots, (M-1)$ where M is the total number of time lags. This is chosen to be low, i.e. $M << N$, as the useful discriminative information in the ECG AC is concentrated in the first few time lags [18].

2.4. Comparison Mechanism (k-NN Classifier)

After the AC feature vectors are projected to the new feature space using LDA, they are classified using a k-Nearest Neighbour classifier with Euclidean distance as the similarity metric. Here, k is chosen empirically optimizing for performance and we found it to be $k = 4$ for our system. After comparison with the windows in the enrolment database, we have either a False-Acceptance or a False-Rejection for cases of error. Their probabilities give the FAR and FRR measures which are used for performance analysis in Section 3.1.

3. EXPERIMENTAL RESULTS

The three cases as described in Section 2.1 are analysed in verification mode. The SA-ECG signals are noisier and of much lesser amplitude than FT-ECG signals of similar database size (23 subjects) used by Zhao *et al.* [11]. These two signals are compared in Figure 2(a,b) where the SA-ECG is from the 'sitting at rest' case. In Figure 2(a), note that the amplitude of SA-ECG is at (-8.45)dB compared to the FT-ECG. Lower quality of ECG signals result in worse verification performance. In (b), the amplitude spectrum of both signals is compared, revealing the gap in signal strength. Also, FT-ECG spans over a wider range of frequencies (0.5Hz to 40Hz) compared to the SA-ECG that has significant components in the 0.5Hz to 25Hz frequency range. Hence, the preprocessing stage for SA-ECG uses a passband which is suited to these characteristics.

Figure 2(c) shows the autocorrelation of windows of a single subject while 'standing' after preprocessing and outlier removal. Significant consistency in the AC curves of different windows belonging to the SA-ECG can be seen. This is encouraging as this translates to low variability for the feature vector within a single class in LDA. Note that the spread of AC curves of the windows from the median (dark) can be reduced by increasing the stringency of the outlier detection phase. However, this also reduces the number of windows surviving the outlier removal operation. We also know that the optimality of projection matrix from LDA is improved with more training data, i.e. more windows. Thus, a trade-off is in place and the stringency of outlier detection has to be tuned empirically based on the database to get best results.

Table 1. Mean $\pm$ deviation of number of outlier windows per subject in collected SA-ECG database

Case	Total Windows	Number of outlier windows
Sitting	58	7.94 ± 5.60
Standing	56	9.65 ± 7.87
After-exercise	58	10.5 ± 7.00

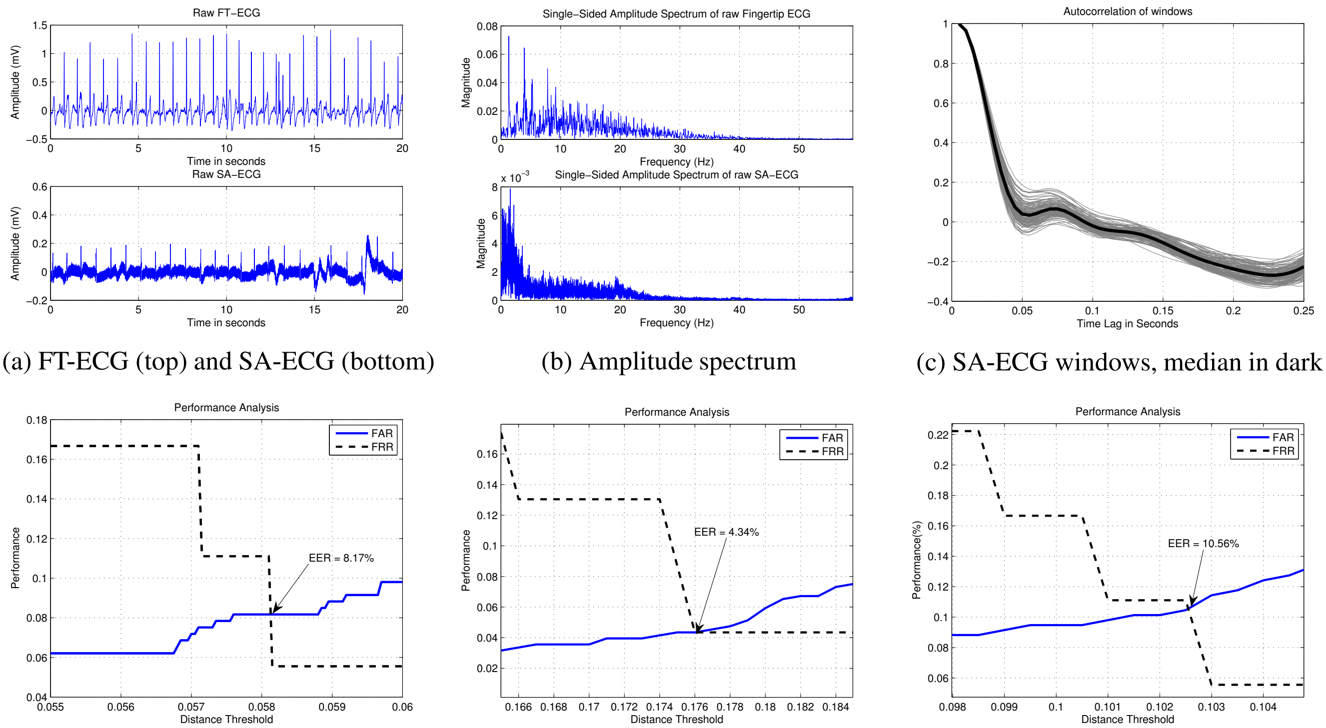
Table 2. EER and corresponding system parameters. Coloured cells indicate lowest EER for each case.

Filter Passband	Window Size 4 sec	Window Size 5 sec	Case
$[0.5, 15]$ Hz	16.67%	8.17%	Sitting
$[2.0, 15]$ Hz	11.34%	11.11%	
$[0.5, 15]$ Hz	13.04%	14.63%	Standing
$[2.0, 15]$ Hz	4.34%	10.38%	
$[0.5, 15]$ Hz	10.56%	14.98%	After-exercise
$[2.0, 15]$ Hz	22.22%	16.67%	

3.1. Performance Analysis

For the performance analysis, SA-ECG is obtained from 23 subjects, each 120 seconds long. Empirically, we found that a preprocessing stage with passbands in Table 2 using a butterworth filter of order 4 led to best performance. We adopt a 2-fold cross validation strategy by using $60s$ of each signal for training the AC/LDA and the rest as testing data for verification. The signal is segmented into overlapping windows having a $2s$ overlap. Then they are passed through an outlier detection stage as described in Section 2.2. Table 1 characterizes the number of outlier windows caught, for each case, at best performance. For the window ACs, M is chosen to be 50 which corresponds to 250ms.

The performance analysis was done using the Equal Error Rate (EER) as the performance metric, i.e. the error at which the FAR is equal to FRR. The results and system parameters used are shown in Table 2 with best EERs highlighted. In Figure 2, the FAR-FRR results are shown for the three different cases. Of particular interest is the EER for 'standing' case (shown in Figure 2(e)), which is obtained to be 4.34% using the AC/LDA - extremely promising for SA-ECG biometrics. Also, SA-ECG from the 'sitting posture without exercise' case (shown in Figure 2(d)) has slightly higher but still considerably low EER of 8.17%. Both of these are lower than



(a) FT-ECG (top) and SA-ECG (bottom) (b) Amplitude spectrum (c) SA-ECG windows, median in dark

(d) Sitting SA-ECG (e) Standing SA-ECG (f) After exercise sitting SA-ECG

Fig. 2. Signal Characteristics of SA-ECG signals and performance of system in various cases

the 8.68% and 13.0% obtained for FT-ECG in [11, 12], but higher than [14]. For the 'sitting posture after-exercise' case in Figure 2(e), we obtain an EER of 10.56%. These verification performances are encouraging mainly because they correspond to low quality SA-ECG compared to better quality FT-ECG signals. Thus, comparisons with [11, 12, 14] are valid because they essentially use the same signals with better quality and similar database sizes (except [14], who use a bigger database). Hence, we observe promising results using the AC/LDA for low quality SA-ECG signals in biometric verification mode.

Note that the ECG signals used in this performance evaluation were pre-screened for quality. There were 3 recordings each in 'sitting' and 'after-exercise' SA-ECG which had very poor SA-ECG with considerable noise and were discarded while evaluating the system performance. Without this pre-screening, it was observed that we still obtained an EER of 4.34% for the 'standing' case whereas the 'sitting' and 'after-exercise' cases worsened to 11.07% and 12.06% respectively. Thus, pre-screening is important during enrolment, and in a practical scenario, the administrator would re-enrol the users with poor signals after pre-screening them.

3.2. Discussion

The best result in verification performance is in the case when users are standing. This is interesting as it was also observed during experimentation that SA-ECG while standing has a higher amplitude than the other two cases. Hence, a higher signal to noise ratio leads to a better EER, as expected. This is also supported by the fact that the heart works harder while standing up than while sitting down. SA-ECG from 'sitting after exercise' has lower performance due to considerable variability in ECG just after a period of exercise during the recordings, when the heart comes back to a normal heart rate. Hence, the dissimilarities in enrolling and testing windows correspond to the errors in classification.

Situations in which the proposed system can fail are: (a) Noisy acquisition methods such as using dry electrodes or non-conductive skin. (b) Users with non-existent ECG in the upper arm. This is possible but rare, as we encountered only a few such users. (c) Movement - the system can be adversely affected by contact noise and non-uniform EMG interference from muscles. While this scenario has not been studied in this work, the biometrics task in such cases is non-trivial. The performance was also not studied for users with arrhythmias, and this can be a subject of future research. Similarly, the effects of psychological changes in the user and their induced changes in the heartbeat are also not considered here, which is a topic of further study. The small database size is an area to improve on through further data collection of SA-ECG. However, the present work clearly supports the use of SA-ECG as a biometric modality.

This work establishes the presence of ECG signals of sufficient quality to be feasible for biometrics at the upper arm through three cases that cover a broad range of scenarios in day to day life. The results are encouraging as this offers a comfortable and practical way over methods described in literature, all of which need both sides of the user's body to be in contact with sensors. Hence, the system also provides a highly customizable way of implementing wearable biometrics solutions using the system parameters tuned to specific situations and signal characteristics.

4. CONCLUSION

In this paper, the feasibility of single-arm single lead ECG for biometrics has been studied and established. The signals were acquired from 23 subjects and a customizable system based on the AC/LDA algorithm tuned to Single-Arm ECG signals was applied for the performance analysis. An Equal Error Rate (EER) of 4.34% resulted in the 'standing' case whereas encouraging EERs of 8.17% and 10.56% were obtained from the 'sitting' and 'sitting after-exercise' cases respectively. Future work in this new method for ECG biometrics should be focussed on the creation of a larger database using single-arm and single lead electrodes to account for higher variability in large-scale deployment scenarios. Also, other electrode configurations can be explored exploiting a single side of the body that are better in terms of usability and accuracy.

REFERENCES

[1] S.A. Israel, J.M. Irvine, A. Cheng, M.D. Wiederhold, and B.K. Wiederhold, "ECG to identify individuals," *Pattern Recognition*, vol. 38, no. 1, pp. 133–142, 2005.

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

[3] C. Ye, M.T. Coimbra, and B.V.K.V. Kumar, "Investigation of human identification using two-lead electrocardiogram (ECG) signals," in *4th Int. Conf. Biometrics: Theory Applications and Systems*, Sep 2010, pp. 1–8.

[4] K.S. Kim, T.H. Yoon, J.W. Lee, D.J. Kim, and H.S. Koo, "A robust human identification by normalized time-domain features of electrocardiogram," in *27th Int. Conf. of the EMBS*. IEEE, 2006, pp. 1114–1117.

[5] Y. Gahi, M. Lamrani, A. Zoglat, M. Guennoun, B. Kapralos, and K. El-Khatib, "Biometric identification system based on ECG data," in *New Technologies, Mobility and Security*, Nov 2008, pp. 1–5.

[6] K.N. Plataniotis, D. Hatzinakos, and J.K.M. Lee, "ECG biometric recognition without fiducial detection," in *Biometrics Symposium: Special Session on Research at the Biometric Consortium Conf.*, 2006, pp. 1–6.

[7] Y. Wang, F. Agrafioti, D. Hatzinakos, and K.N. Plataniotis, "Analysis of human electrocardiogram for biometric recognition," *EURASIP J. Adv. Sig.Proc.*, Jan. 2008.

[8] F. Agrafioti and D. Hatzinakos, "Fusion of ECG sources for human identification," in *3rd Int. Symp. on Comm., Control and Sig. Process.*, 2008, pp. 1542–1547.

[9] G.G. Molina, F. Bruekers, C. Presura, M. Damstra, and M. v.d. Veen, "Morphological synthesis of ECG signals for person authentication," in *15th EUSIPCO*, Sep 2007, pp. 738–742.

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

[11] ChenXing Zhao, T. Wysocki, F. Agrafioti, and D. Hatzinakos, "Securing handheld devices and fingerprint readers with ECG biometrics," in *5th Int'l Conf. Biometrics: Theory, Appl. and Systems*, 2012, pp. 150–155.

[12] A. Lourenço, H. Silva, and A. Fred, "Unveiling the biometric potential of Finger-Based ECG signals," *Comp'l intelligence and neuroscience*, vol. 2011, pp. 5, 2011.

[13] A. D C Chan, M.M. Hamdy, A. Badre, and V. Badee, "Wavelet Distance Measure for Person Identification Using Electrocardiograms," *IEEE Trans. on Instrum. and Measurement*, vol. 57, no. 2, pp. 248–253, 2008.

[14] H.P. da Silva, A. Fred, A. Lourenco, and A.K. Jain, "Finger ECG signal for user authentication: Usability and performance," in *6th Int. Conf. Biometrics: Theory Applications and Systems*, Sept 2013, pp. 1–8.

[15] M. Hannula, H. Hinkula, and J. Jauhiainen, "Development and Evaluation of One Arm Electrode Based ECG Measurement System," in *14th Nordic-Baltic Conf. Biomed. Eng. Med. Physics*, pp. 234–7. Springer, 2008.

[16] H. Yang, T. Chien, S. Liu, and H. Chiang, "Study of Single-Arm Electrode for ECG Measurement Using Flexible Print Circuit," 2011.

[17] Plessey-Semiconductors, "Application note # 291491: Single arm ECG measurement using EPIC," 2012.

[18] F. Agrafioti and D. Hatzinakos, "ECG based recognition using second order statistics," in *6th Ann. Comm. Net. Services Research Conf.* IEEE, 2008, pp. 82–87.

[19] T. Li, S. Zhu, and M. Ogihara, "Using discriminant analysis for multi-class classification: an experimental investigation," *Knowledge and information systems*, vol. 10, no. 4, pp. 453–472, 2006.