# CARDIAC BIOMETRIC SECURITY IN WELFARE MONITORING

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# ABSTRACT

The electrocardiogram (ECG) is a new and promising modality for biometric recognition. This signal is typically collected within welfare monitoring environments along with other vital signals. As opposed to *static* biometric modalities like the iris or the fingerprints, ECG is time-dependent thereby presenting the opportunity of continuously authenticating subjects in such environments. However, ECG is affected by both physical and psychological activities, which have to be taken into consideration for successful deployment of this biometric. This paper demonstrates the effects of psychology on the performance of ECG biometric systems and proposes a novel methodology for automatic template updating in order to mitigate the risks associated with poor biometric matching.

*Index Terms*— Electrocardiogram, autocorrelation, discriminant analysis

# 1. INTRODUCTION

Medical biometrics comprise physiological characteristics that are typically used within health care environments for clinical diagnoses. However, there is evidence that some physiological signals such as the ECG, phonocardiogram (PCG), plotoplethysmogram (PPG) and blood pressure(BVP) carry information which is unique for every individual [1–5]. With the advances in the sensing technology, the potential of using these signals for biometric recognition is great. This work deals with the problem of human authentication using the ECG signal, however similar concepts are valid for most medical biometric modalities.

If the ECG signal is established as a biometric modality then the respective systems will have unique benefits. First, this biometric provides inherent liveness detection which has computational advantages, since most of the existing modalities would require additional mechanisms to validate the liveness of the sensor's reading. In addition, ECG is naturally immune to falsification or replay attacks, as it is extremely difficult to steal and inject someone's ECG into a biometric system. Francis M. Bui

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Heart signals are universal, stable over a large period of time, and sufficiently unique. The inter-subject variability comes from the fact that ECG pictures the electrophysiological variations of the myocardium and is affected by factors such as the heart mass orientation, conductivity of cardiac muscles and activation order [6, 7]. This variability has been extensively investigated in the medical research, for the establishment of universal diagnostic standards [8].

This work investigates the effects of psychological activity on the ECG signal. This aspect of the ECG is very important when deploying it for biometric recognition, because it can significantly affect the overall accuracy. In welfare monitoring environments, where the collection of the signal is continuous, and the modality is constantly flowing in the recognizer, one has the option of addressing the temporal variations of the ECG signal with biometric template updates. This work discusses the advantages of this operation and introduces algorithms for automatically detecting an emotional change which requires template updating.

## 2. THE AC/LDA ALGORITHM

The proposed solution is evaluated with the help of the Autocorrelation - Linear Discriminant Analysis (AC/LDA) algorithm which was originally proposed in [9]. However, the proposed solution can be generalized for any ECG biometric template. The AC/LDA is a fiducial points independent method for the design of ECG-based biometric templates. This method, relies on a small segment of the autocorrelation of 5 sec ECG signals. The 5 sec duration has been chosen experimentally, as it is fast enough for real life applications, and also allows for a sufficient amount of ECGs repetitive properties to be captured in AC. The reader should note that this ECG window is allowed to cut the signal even in the middle of pulse, and it does not require any prior knowledge on the heart beat locations. The autocorrelation (AC) is computed for every 5 sec ECG using:

$$\widehat{R}_{xx}(m) = \sum_{i=0}^{N-|m|-1} x(i)x(i+m)$$
(1)

where x(i) is an ECG sample for i = 0, 1...(N - |m| - 1), x(i + m) is the time shifted version of the ECG with a time lag m, and N is the length of the signal.

Out of  $\widehat{R}_{xx}$  only a segment  $\phi(m)$ , m = 0, 1...M, defined by the zero lag instance and extending to approximately the length of a *QRS* complex<sup>1</sup> is used for further processing. This is because this wave is the least affected by heart rate changes, thus utilizing only this segment for discriminant analysis, makes the system robust to the heart rate variability.

# 3. ECG TEMPLATE DESTABILIZATION

The heart rate changes is only one source of variability for the ECG biometric modality. In essence, the heart is affected by several sympathetic and parasympathetic factors of the autonomic nervous system, which suggests that the signal may vary under different psychological conditions. This variation may be significant enough, and may affect the accuracy of biometric matching if not treated appropriately.

While the exact effects of emotion on the ECG waveform are not explicit and cannot be analytically modeled, a biometric template designed under one psychological state will not correlate adequately with ECG readings under different emotional states. This problem has been identified in [2], and is herein referred to as *template destabilization*. Even though the degradation of the biometric matching is not extreme under various emotional states, one should take into account this variability before deploying real life ECG biometric systems.

One way to address this issue is to train the machine learning algorithm on ECG waveforms under various psychological conditions. This approach is similar to face recognition, when during enrollment the subjects may be required to perform several facial expressions, for the system to learn the particular variability. However, this option is not trivial for ECG biometrics; first, because it is inherently difficult to induce emotional states during enrollment, and second, because there is no straight-forward way of guaranteeing that one succeeded in doing so. In addition, there is no finite set of psychological conditions on which system training would suffice with high confidence. Therefore, in this work this problem is solved with template updating at strategic times i.e., when an emotional change is automatically detected.

#### 4. TEMPLATE UPDATING

The objective of the subsequent analysis is to update the biometric template at instances corresponding to the destabilization (or *decoherence*) of the ECG biometric template. Since the purpose is to detect state changes, and not to classify emotions, a coherence analysis approach is herein adopted. Every new ECG reading will be compared against the previous recordings in order to assess whether variability has been introduced or not. The reader should note that this solution applies to monitoring environments i.e., environments where the ECG is collected continuously from the subjects (ex. first responders, patients, law enforcement, military) as part of welfare monitoring.

The idea is to design variable-length accumulated durations (or ECG segments) based on some *fundamental* time duration [2]. ECG segments need to accumulate until decoherence is observed whereby a biometric template update is performed. There is a trade-off between frequency of templateupdates and computational effort. Frequent template updating implies accurate tracking of events, but increases the computational effort. On the other hand, infrequent template updating may cause inadequate system performance in terms of increased false rejection.

Taking these considerations into account, the idea of defining a fundamental time duration (which is application dependent) is to consider some acceptable *minimum duration*, over which the system makes a decision about whether the template needs to be updated. The extreme case is to define this fundamental duration to be equal to the smallest time-resolution in the system (for instance 5 seconds for the AC/LDA algorithm). However, this is computationally inefficient and therefore the updating instances need to be strategically chosen.

In essence, a variable-length accumulated duration (or *burst*) is constructed by accumulating various fundamental durations (for the proposed AC/LDA algorithm, these fundamental durations correspond to ECG segments of 5 seconds length). The following iterative description can be made.

Consider the following fundamental durations  $\{d_1, d_2, \ldots\}$ , where each  $d_i$  corresponds to time duration of 5 seconds. This duration is chosen to acceptably accommodate the time resolution requirement of the AC/LDA algoritm. Now suppose that at the current iteration, the current burst,  $\mathbf{D}_{\text{current}}$ , contains  $\mu$  fundamental durations, i.e.,  $\mathbf{D}_{\text{current}} = \{d_k, \ldots, d_{k+\mu-1}\}$ . For the subsequent segment,  $d_{k+\mu}$ , the two choices are:

- (C1) Add  $d_{k+\mu}$  to the current burst, forming  $\mathbf{D}_{\text{potential}} = \{d_k, \dots, d_{k+\mu}\}$ . Continue the operation with  $d_{k+\mu+1}$  as the next candidate.
- (C2) Reject  $d_{k+\mu}$ , and terminate  $\mathbf{D}_{\text{current}}$ . Re-initialize with  $d_{k+\mu}$  as the start of a new burst.

The correlation coefficient between all ECG segments within a burst are utilized to decide between (C1) or (C2). The following procedure is performed:

- Compute the correlation profile for D<sub>potential</sub> relative to starting point d<sub>k</sub>.
- 2. Find the minimum correlation value  $c_{\min}$  over  $\mathbf{D}_{\text{potential}}$ .

<sup>&</sup>lt;sup>1</sup>A QRS complex lasts for approximately 100 msec

3. Compare to a threshold  $c_{th}$  for decision:

$$c_{\min} - c_{th} \underset{C_2}{\stackrel{C_1}{\underset{C_2}{\overset{C_1}{\underset{C_2}{\overset{C_2}{\overset{C_1}{\underset{C_2}{\overset{C_2}{\overset{C_1}{\underset{C_2}{\overset{C_2}{\underset{C_2}{\overset{C_1}{\underset{C_2}{\overset{C_2}{\underset{C_2}{\overset{C_1}{\underset{C_2}{\atopC_1}{\overset{C_1}{\underset{C_2}{\underset{C_2}{\atopC_1}{\atopC_1}{\atopC_1}{\atopC_1}{\atopC_1}{\atopC_1}{\\C_$$

It should be noted that, in using the described algorithm, a maximum burst size  $dsize_{max}$  should be enforced. In other words, after  $dsize_{max}$  bursts, template updating is executed. Such a strategy could be necessary to deal with buffering requirements (since the entire accumulated data needs to be stored), as well as to reset the algorithm in case of misdetections.

### 5. PERFORMANCE EVALUATION

The performance of the proposed template-updating scheme is evaluated over ECG recordings with psychological labeling. The purpose of the following analysis is to validate that every coherent burst, as detected by the proposed algorithm, describes an true emotional state.

### 5.1. ECG Signals

For the evaluation of the proposed algorithm, ECG signals under different emotional states were recorded at the Biometrics Security Laboratory of the University of Toronto.In this experiment, a commercial video game was used to elicit active mental arousal. The game was designed to present increasing difficulty. The goal was to have the player gradually immersed in the gaming experience, by increasingly concentrating in order to meet the game requirements. The subjects got motivated with deception, by letting them know that the purpose of the experiment is to measure game completion time. In total 43 volunteers participated in this study. Data from one person were discarded due to noise.

Depending on the familiarity of the subject with game playing, the duration of the experiment varied between 20-45 minutes. During the game, ECG was monitored using Hidalgo's Equivital<sup>2</sup> sensor, which is portable and wireless. ECG was recorded from the chest, and digitized at 256Hz. Because of the chaotic nature of the game, and the unforeseeable order of events that can take place, arousal annotation was self-determined. For this reason, a video of the player's facial expressions was captured during the game (synchronous to ECG). Upon game completion, the subjects were asked to watch a playback video of the game and their facial expressions while continuously reporting arousal using FEELTRACE [10]. The arousal states were classified as either *high* or *low*.



**Fig. 1**. Verification performance without template updating (EER = 15.1%).

#### 5.2. Experimental Results

In order to quantify the performance of the proposed system, a measure  $q_i$  is herein introduced to describe the system's confidence that burst *i* represents consistently one emotional state (i.e, high or low arousal). Let  $N_H^i$  and  $N_L^i$  be the number of ECG windows marked as high and low arousal respectively. Then  $q_i$  can be calculated as:

$$q_{i} = \frac{\max(N_{H}^{i}, N_{L}^{i})}{N_{H}^{i} + N_{L}^{i}}$$
(3)

Essentially, every burst that is identified by the updating algorithm will be shown to have a high  $q_i$ , which means that with high confidence each burst corresponds to either high or low arousal. Even though this measure relies on the subjects' self-reports, and discrepancies are expected, the average state confidence for the bursts was estimated to be 96.47%. This performance is illustrative of the accuracy of detecting homogeneous emotional states, which leads to successful template updating.

Returning to our original problem, we are interested in template destabilization for biometric recognition. When a burst is terminated due to decoherence, the biometric template is updated. While the above results show that each burst corresponds to either high arousal or low arousal, the question that naturally arises is the following: *do two consecutive bursts correspond to opposite arousal labels?* In other words, *is change in arousal the only factor that is responsible for burst termination?* 

In practice, the template updating algorithm is not only affected by emotional states. A burst may be interrupted due to one of the following three reasons:

- 1. *A state change* i.e., a transition from one psychological state to another.
- 2. Buffer overflow i.e., when  $dsize_{max}$  is reached.  $dsize_{max}$  can be adjusted according to the requirements of the application environment. For the present simulation  $dsize_{max}$  was set to 10 minutes.

<sup>&</sup>lt;sup>2</sup>http://www.equivital.co.uk/



**Fig. 2**. Histogram of Equal Error Rates after template updating (Average is 3.96%)

3. *Noise artifacts* (e.g. due to a sudden movement), that are not sufficiently treated by the filter.

Nevertheless, a template update is necessary in all cases. For the purpose of comparison, the verification performance is estimated for two cases namely *with* and *without* template updating. Figure 1 demonstrates the baseline false acceptance and rejection rates (i.e., without template updating). The equal error rate is 15%, which is typical for LDA training without template updating.

For every individual in the database, a template is updated every time a new burst is detected. As such, the number of updates is highly dependent on the subject. To quantify the verification accuracy after template updating, false acceptance and rejection rates are estimated for every individual separately. Figure 2 shows a histogram of the equal error rates that were achieved with this treatment, for all subjects in the database. The average equal error rate in this case is 3.96%, which represents a significant improvement from 15%.

### 6. CONCLUSION

This paper presented a solution to the problem of template destabilization of ECG biometrics. The perils of ignoring the destabilization of the template were originally demonstrated in [2].

In monitoring environments where the ECG signal is constantly acquired, it is critical to address this problem. In most real life settings, the emotional activity that affects the ECG signal is characterized by high arousal, since the individual is usually actively engaged in some everyday task. Automatic detection of template destabilization due to psychological variations is therefore very important in order to control false rejection.

The proposed template updating methodology was evaluated over an active arousal database of ECG signals. The purpose of this analysis was two-fold. First, it was shown that the accumulated bursts that were detected with the proposed solution correspond to homogeneous emotional states with high probability. Furthermore, the verification accuracy was evaluated for every subject when the respective biometric template was updated in the beginning of a burst. On average an equal error rate of 3.96% was achieved, which represents a dramatic reduction from the EER of 15% for the particular dataset in the absence of template updating.

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#### 8. REFERENCES

- 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] F. Agrafioti, F.M. Bui, and D. Hatzinakos, "Medical biometrics: The perils of ignoring time dependency," in *Proceedings* of 3rd Int. Conf. on Biometrics: Theory, Applications, and Systems, 2009. BTAS '09, Washington, Sept. 2009, pp. 1–6.
- [3] F. Agrafioti, F. M. Bui, and D. Hatzinakos, "Medical biometrics in mobile health monitoring," *Security and Communication Networks*, July 2010, 10.1002/sec.227.
- [4] G. Wübbeler, M. Stavridis, D. Kreiseler, R.D. Bousseljot, and C. Elster, "Verification of humans using the electrocardiogram," *Pattern Recogn. Lett.*, vol. 28, no. 10, pp. 1172–1175, 2007.
- [5] C. Ye, M.T. Coimbra, and B.V.K.V. Kumar, "Investigation of human identification using two-lead electrocardiogram (ECG) signals," in *Proceedings of 4th Int. Conf. on Biometrics: The*ory Applications and Systems, Sept. 2010, pp. 1–8.
- [6] G. Kozmann, R.L. Lux, and L.S. Green, "Geometrical factors affecting the interindividual variability of the ECG and the VCG," *J. Electrocardiology*, vol. 33, pp. 219–227, 2000.
- [7] R. Hoekema, G.Uijen, and A. van Oosterom, "Geometrical aspect of the interindividual variaility of multilead ECG recordings," *IEEE Trans. Biomed. Eng.*, vol. 48, pp. 551–559, 2001.
- [8] H. Draper, C. Peffer, F. Stallmann, D. Littmann, and H. Pipberger, "The corrected orthogonal electrocardiogram and vectorcardiogram in 510 normal men (Frank lead system)," *Circulation*, vol. 30, pp. 853–864, 1964.
- [9] F. Agrafioti and D. Hatzinakos, "Fusion of ECG sources for human identification," in *Proceedings of 3rd Int. Symp. on Communications Control and Signal Processing*, Malta, March 2008, pp. 1542–1547.
- [10] R. Cowie, E. Douglas-Cowie, S. Savvidou, E. McMahon, Sawey M., and M. Schroder, "FEELTRACE: An instrument for recording perceived emotion in real time," in *Proc. of iSCA Workshop Speech and Emotion.*, 2000, pp. 19–24.