Influence of QT correction on temporal and amplitude features for human identification via ECG

Mario Sansone, Antonio Fratini, Mario Cesarelli, Paolo Bifulco,
Alessandro Pepino, Maria Romano, Francesco Gargiulo and Carlo Sansone
Department of Electrical Engineering and Information Technologies
University Federico II of Naples
Via Claudio, 21 - I-80125, Naples, Italy
Email: {msansone,a.fratini,cesarell,pabifulc,pepino,mariarom,francesco.grg,carlosan}@unina.it

***Abstract*—Identification of humans via ECG is being increasingly studied because it can have several advantages over the traditional biometric identification techniques. However, difficulties arise because of the heartrate variability. In this study we analysed the influence of QT interval correction on the performance of an identification system based on temporal and amplitude features of ECG. In particular we tested MLP, Naive Bayes and 3-NN classifiers on the *Fantasia* database. Results indicate that QT correction can significantly improve the overall system performance.**

I. Introduction

The idea of using medical attributes of the human body for identification purposes is recent [1], [2] and, among them, ECG has been investigated as a new biometric identification method for medium and high security applications. Along with the ECG, there is on-going research in the application of the electroencephalogram, heart rate, blood pressure and pulse oximetry for identity configuration [3].

A suitable biometrics should possess characteristics such as *uniqueness*, *permanence*, *universality* and *collectability*. Hoekema et al. [4] has suggested the *uniqueness* of ECG signal, based on geometrical and physiological factors. Wuebbeler et al. [5] studied the *permanence* characteristic of ECG pulses of a person. Particularly, the long term stability of the individual ECG was focused on by taking data repetitively recorded during several years. He observed similarities of healthy subjects pulses at different time intervals, thus demonstrating that ECG is invariant over a large period of time. Such demonstrations (uniqueness and permanence) motivated researchers to employ ECG for biometric purposes.

Another important aspect of using ECG as biometric is that, differently from conventional biometrics like fingerprint or hand geometry, ECG biometric can cover the whole portion of the population: it can be naturally monitored from every subject, as long as he is alive. ECG is universally present among all living individuals and a single-lead ECG (requiring only two electrodes) can be easily acquired, independently from any eventual physical disability. Thus, also the properties of *universality* and *collectability* are satisfied.

It is also important to recall that traditional biometrics are susceptible to *falsification* or *alteration*. In fact, what associates the conventional biometrics is that our facial and eye images, voice patterns, fingerprints etc. are publicly available. For instance, our facial images are recorded every time we enter a bank or a supermarket; our voices are recorded by many phone-based service providers; we leave our fingerprints on every surface we touch. So, conventional biometrics can be artificially recreated, such as images of a face or iris, lifted latent fingerprints, artificial fingers, high quality voice recordings, etc. This moved the researchers to introduce automatic *liveness detection* [6], whose aim is to determine if biometric data is captured from a live and legitimate user, who is physically present at the point of acquisition.

For the ECG signal, *liveness* detection is implied in the existence of the signal itself, since it is a life indicator: only alive users have it. Moreover, the ECG information is intrinsic to an individual, since it is controlled by the autonomic nervous system, therefore by a combination of sympathetic and parasympathetic factors. This suggests that it is highly secured and confidential, thus difficult to mimic or reproduce. Moreover, there is no falsification technology today that can steal and reproduce through muscles an electrocardiogram signal.

The use of ECG as biometric could arise privacy issues. Indeed, ECG signals convey a wealth of information about the cardiac health of the subject, which is considered as private. Moreover, the appearance of heart diseases such as arrhythmias significantly alters the appearance of the waveform, depending on the severity of the symptoms. However, the application of ECG signals in the presence of cardiac disorders is still an open research issue [7].

Aside the aforementioned advantages of using ECG as biometrics, the limits of using the ECG for human identification must be considered. First of all, electrodes have to be attached on the surface of the body, depending on the requirements of the system, making this biometric more invasive in terms of acquisition procedure. However, it has been shown [8] that single lead ECG can be acquired using only two electrodes easily and effectively. Moreover, there are conditions, such as mental stress or exercise, that can alter the morphological properties of the ECG waveform; thus any ECG-based system should be invariant to these conditions. In particular, although inter-individual variability allows the ECG to be used as a biometric for its uniqueness, intra-individual variability involves variations in different heartbeats of the same subject. This could limit the capability of an ECG based biometric system to identify subjects.

With particular reference to the last two issues, in this

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work we focussed on the intra-individual variability of ECG. It is well known that ECG is a quasi-periodic signal. As the heart must supply oxygenated blood to the body, the cardiac output (the amount of blood ejected from the ventricles) must be continuously adjusted by the in order to satisfy organs' requirements. The vegetative nervous system accomplishes this task continuously adjusting the heart rate. Of course, this fact affects the intra-individual repeatability of the ECG heartbeats. A major effect of heart-rate variability on the shape of the ECG is the modification of QT intervals. This effect has been largely studied and several models have been proposed for QT interval correction [9], [10], [11]. We analysed the influence of the QT interval on the conventional amplitude and temporal features of ECG. In particular, we evaluated the performance of a set of classifiers with and without QT correction.

The rest of the paper is organised as follows. First we introduce the temporal and amplitude ECG features that have been used in this study. Successively we describe how temporal features can be corrected using QT information. After, we describe the database and the preprocessing used. Finally we present the classifiers used and their performance on the data-set.

II. ECG Features

ECG-based identification systems can be roughly categorised in two types: *fiducial-based* and *non-fiducial*. In fiducial based systems [2], the ECG is segmented into a number of simpler waves, and specific points must be detected in order to provide the basis for feature extraction. In non-fiducial systems [12], the ECG is considered as a whole and some sort of linear or non-linear transformation is accomplished in order to extract features.

QT interval variation can of course affect both types of identification systems. However, the consequences of QT variations can be more immediately appreciated in a fiducial system. Therefore in this study we considered a fiducial-based system.

A. Temporal features

The temporal relationships between the various ECG waves (P, QRS, T) are related to the electrical paths within the heart from the sino-atrial node to the Purkinje fibers: it is intuitively expected that these paths should be different from subject to subject due to geometrical configurations and electrical impedances of the tissues [13]. Temporal relationships (intervals) among waves can be derived locating appropriate fiducial points (typically wave peak or boundaries) (see fig. 1). A detailed list of features used in this study has been reported in table I.

B. Amplitude features

The rationale for amplitude features can be traced back to the study of Hoekema et al. [4]: as previously reminded they demonstrated that a large part of inter-individual variability is due to geometrical characteristics that can serve to discriminate individuals.

Typical amplitude features are shown in fig. 2. Amplitude features capture the relative height of the different wave-peaks

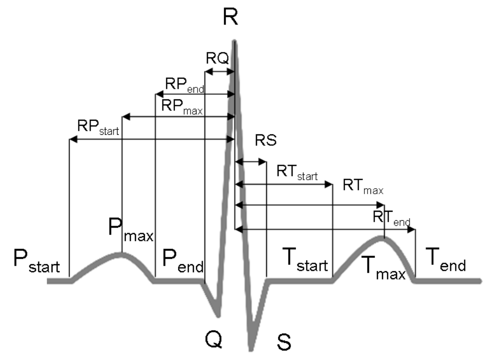


Fig. 1. ECG temporal features commonly used in literature. A detailed list of features used in this study is reported in table I.

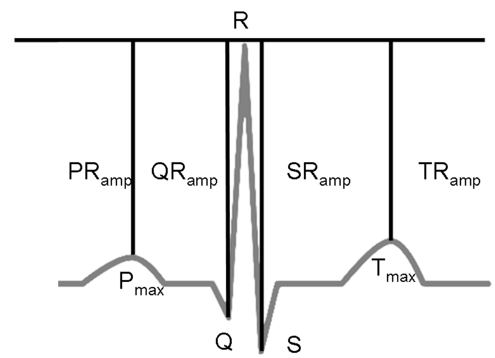


Fig. 2. ECG amplitude features commonly used in literature. A detailed list of features used in this study is reported in table I.

with respect to the R peak. Sasikala et al. [14] observed that ECG features may change if a person does physical work or with time (age). However, they observed that these changes should mainly affect the P-wave duration and the PR interval; P-wave amplitude, instead, should not change throughout life. However, most of studies used both temporal and amplitude features. Typically, a dimensionality reduction is used in order to obtain a mixed feature set.

It is expected that the combination of the two types of features should improve the performance of the whole system. For example, Wang et al. [15] compared the use of temporal features only with the combination of temporal + amplitude features on two public databases (PTB and MIT-BIH): while temporal features only gave 84% of subject identification on PTB they obtained 100% subject identification on both DBs using a mixed feature sets. Other type of amplitude related feature can be conceived: for example, Zhang et al. [16] added the QRS area to time/amplitude features.

C. QT interval correction

Although it is known that ECG fiducial points can have a little misalignment among different leads [17], it has been shown that sensor location should not affect the observed timing of the P-QRS-T complexes to an extent such as to prevent subject recognition [13]. This is clearly an advantage

TABLE I. FEATURES USED IN THIS STUDY AS SHOWN IN FIG. 1 AND 2.THE QRS SUBSET OF FEATURES ARE COLOURED IN GREEN AND THE FEATURES INVOLVED INTO THE CORRECTION PROCESS (QTC) ARE COLOURED IN RED. IT IS WORTH NOTING THAT THE QRS SUBSET DOES NOT INCLUDE ANY FEATURE THAT NEEDS A CORRECTION (QTC).

Time	Amplitude
$(P_{max}-P_{start})$, $(P_{end}-P_{start})$, $(P_{end}-P_{max})$, $(Q-P_{start})$, $(Q-P_{max})$, $(Q-P_{end})$, $(R-P_{start})$, $(R-P_{max})$, $(R-P_{end})$, $(R-Q)$, $(S-P_{start})$, $(S-P_{max})$, $(S-P_{end})$, $(S-Q)$, $(S-R)$, $(T_{start}-P_{start})$, $(T_{start}-P_{max})$, $(T_{start}-P_{end})$, $(T_{start}-Q)$, $(T_{start}-R)$, $(T_{start}-S)$, $(T_{max}-Pstart)$, $(T_{max}-P_{max})$, $(T_{max}-P_{end})$,$(T_{max}-Q)$, $(T_{max}-R)$, $(T_{max}-S)$, $(T_{end}-P_{start})$,$(T_{end}-P_{max})$, $(T_{end}-P_{end})$,$(T_{end}-Q)$, $(T_{end}-R)$, $(T_{end}-S)$, $(T_{end}-T_{start})$, $(T_{end}-T_{max})$	$(R-P_{start})$, $(R-P_{max})$, $(R-P_{end})$, $(R-Q)$, $(R-S)$, $(R-T_{start})$, $(R-T_{max})$, $(R-T_{end})$

of ECG temporal features from the point of view of data acquisition in the context of subject recognition.

It is also well known that the distances between fiducial points can vary with heartrate (HR) [18]. Israel et al. [13] assumed that a linear relationship exists between the heartrate and all the time intervals computed with respect to the R peak (apart from the QRS complex, see below). Therefore, they considered interval normalisation to the length of the P-QRS-T complex in order to remove the dependence with respect to the heartrate. Moreover, they observed that, as the QRS complex is only a function of the geometrical characteristics of the electrical path [4], it does not depend on the heartrate and therefore QRS-related distances should not be normalised.

However, the assumption of a simple linear relationship could be questionable and therefore, in this work, we used another approach based on [19]. They observed that QRS complex is fairly constant because it reflects the time from the depolarisation of the first ventricle muscle to the last one, and the action potentials travels a very short distance (endocardium to epicardium) through the fast Purkinjie fibers. On the other hand, QT interval is strictly related to the plateau period of the ventricular action potentials, whose duration is controlled by the autonomous nervous system, changing with the heartrate (see fig. 3). Therefore, we used the correction formula (1) proposed by Sagie et al. [20], where QT_c is the corrected QT interval, RR is the RR interval and α is a factor that is estimated from the ECG data (see fig. (3)) for normalising the QT interval with respect to the HR. The factor α has been estimated from the training set of each subject in order to have a personalised correction. All the features related to the QT interval (such as $Q-T_{max}$, $T_{end}-T_{start}$, etc...) have been corrected in a similar way (see table I). We assumed that the same α could be used to correct these other intervals as well. Future investigations could use different αs for different intervals.

$$QT_c = QT + \alpha(1-RR) \quad (1)$$

III. DATA AND PREPROCESSING

A. ECG Database

As the objective of this work is to study the influence of QT interval correction on ECG-based identification systems, and because it is well known that heartrate (RR intervals) is prone to short (5 minutes) and long variability (one day) [21], it was necessary to use ECG records of long duration. Moreover, as we would facilitate comparisons with other studies, we choose to use a public database. Previous considerations should have suggested the normal sinus MIT-BIH database, which is a collection of Holter ECG acquired at 128 Hz. However, literature review and preliminary exploration of data has suggested that a higher sampling frequency should be considered in order to capture ECG feature with a sufficient detail for subject identification.

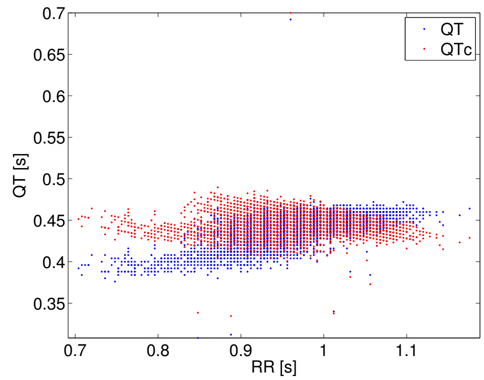


Fig. 3. QT intervals has been reported as a function of RR intervals. Blue dots represent measured QT values. Red dots represent corrected QTc according to eq. 1.

In this study we used the Physionet [22] database *Fantasia* [23]. This database includes 40 short-term ECG recordings (120 minutes) from 20 young (21 - 34 years old) and 20 elderly (68 - 85 years old) rigorously-screened healthy subjects. All subjects remained in a resting state in sinus rhythm while watching the Disney's movie *Fantasia*, while continuous electrocardiographic and respiration signals were collected. The signals were digitized at 250 Hz. Only one signal was digitized at 333 Hz and thus it was excluded from the analysis. Each heartbeat was annotated using an arrhythmia detection algorithm, and each beat annotation was verified by visual inspection. Each recording was collected from Physionet using the free software CYGWIN (www.cygwin.com).

B. Detection of fiducial points

After preprocessing, the fiducial points were located on each ECG signal from the records of both databases by using a detector, ECGPUWAVE developed by Laguna et al. [24]. It detects onset, peak and offset of the P, QRS and T waveforms, characterizing the patterns of the P wave (regular or inverted), the QRS complex (Q, R or S position), and the T wave (regular, inverted or biphasic).

IV. IDENTIFICATION SYSTEM

A. Classifiers

We used the following classifiers: Naïve Bayes, MultiLayer Perceptron (MLP) and 3-Nearest Neighbour. They were readily available in WEKA. We used 10-fold cross validation on the training data in order to choose the parameters of the MLP classifier.

B. Training set and test set

The training set was composed by the first 300 s (5 min) of each record, whereas the test set was made up of the other 6700 s (about 115 min) of each record, divided into segments of 200 s.

C. Performance evaluation

First of all, we evaluated the performance of the classification system by using the first and the last segment of the test set. This test outlined an *aging* effect on the classifier model, due to the variation of the features over time. Since the objective of this paper was to evaluate the possibility of mitigating this effect by using QT correction, results were calculated with and without QT correction. Moreover, in order to better evaluate the behaviour of the system in the different conditions, we also evaluate the performance by using only QRS features, which, as above reminded, is considered to be fairly constant. As it is common in literature on identification systems, the performance were evaluated as subject identification rate [2], [13].

In these tests, the performance was evaluated by using a majority voting on five consecutive heartbeats. The suitability of this number, preliminary chosen on the basis of a literature review [25], was also confirmed by the test presented in Figure 5, as it will be discussed later.

V. Results

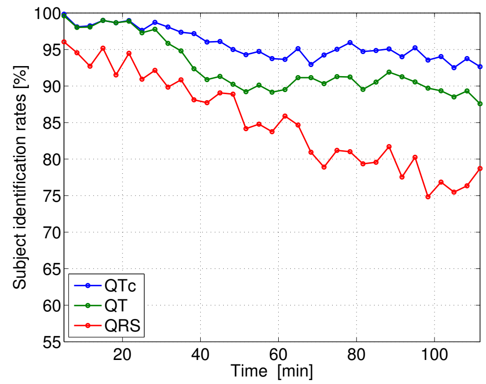
Figure 3 illustrates the variability of the QT interval along one record ('f2o01') of *Fantasia*. Each QT interval is plotted against the last RR interval.

Table II reports the results obtained by different classifiers on the first and the last segment of the test set. An analysis of this table reveals that MLP is the best performing and robust classifier with all sets of features. A detailed analysis of the behaviour of the classifiers along the whole test set is depicted into Figures 4(a), 4(b) and 4(c).

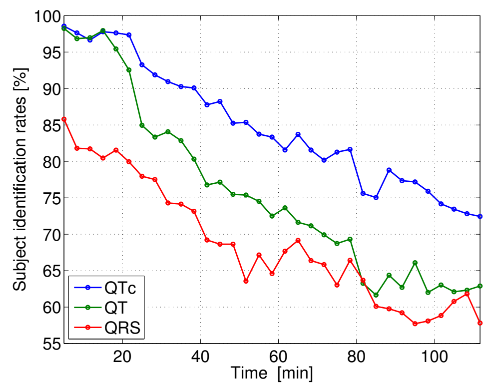
It can be clearly seen that identification performance is not constant, but dramatically decreases over the time, especially for Naive Bayes and 3-NN classifiers. In particular, Figure 4(a) shows that MLP is again the best performing classifier. As regards the feature sets, it is evident that QT correction can increase performance over non-corrected QT features; moreover, both QTc and QT feature sets give rise to better results with respect to QRS features, for all the considered classifiers. It is worth noting that, by using the MLP classifier, the error rate always remains below 8%, which is in line with results coming from previous studies.

We also performed a statistical significance test, obtaining that the difference between performance on QTc and QT features becomes statistically significant ($p < 0.05$) starting from the 25th minute.

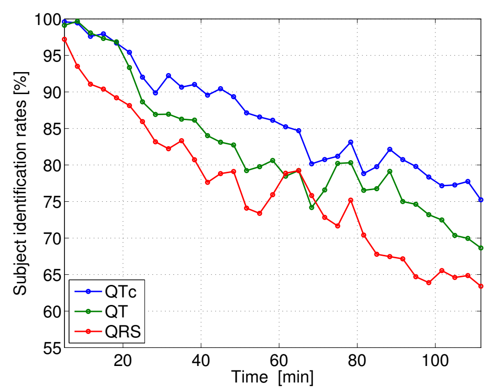
Finally, we have made an analysis about the impact on the performance of the number of heartbeats used for the majority voting for the best classifier, i.e. the MLP. As it can be seen in Figure 5, the use of only one heartbeat gives rise to results that are always worse with respect to the use of 5 heartbeats. On the other hand, the use of 10 heartbeats does not seem to produce any improvement. In order to confirm these findings, we verified that there is no statistical significance in performance between the *5 hb* and *10 hb* cases, whereas the difference between the *1 hb* and the *5 hb* curves is statistically significant for the most part of the time.



(a) MLP



(b) NB



(c) 3NN

Fig. 4. Subject identification rates of MLP (a), NB (b) , 3NN (c) using majority voting with 5 heartbeats. The performance of QRS-based vs QT and QT corrected features are compared.

VI. Discussion and Conclusion

In this work, we evaluated the influence of QT correction on the performance of an ECG-based subject identification system. The data from one public databases were pre-processed in order to detect fiducial points (the onset, the peak and

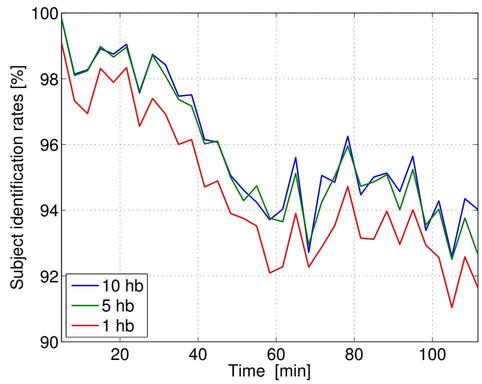


Fig. 5. Comparison of subject identification rates of MLP using QTc features and majority voting with 1,5,10 heartbeats respectively.

TABLE II. SUBJECT IDENTIFICATION RATES ON THE FIRST AND THE LAST SEGMENT OF THE TEST DATA WITH AND WITHOUT QT CORRECTION AND BY USING ONLY QRS FEATURES.

	First Segment			**Last Segment**		
	QTc	QT	QRS	QTc	QT	QRS
MLP	99.84%	99.60%	96.04%	92.65%	87.57%	78.71%
NB	98.56%	98.24%	85.79%	72.44%	62.89%	57.82%
3-NN	99.60%	99.12%	97.21%	75.23%	68.64%	63.40%

the offset of each waveform) using a publicly available detector. From each recording temporal and amplitude features were computed. Data were divided into training- and test-set. Classification was performed using three classifiers: Multilayer Perceptron, Naive Bayes classifier and 3-Nearest Neighbour. Our results show that the performance of the system improves and is more robust when using QT corrected features.

Our results are in line with the intuitive feeling that subject identification can be affected by the heart rate. In particular, on the database used in this study, the heartrate evaluated at the beginning of the record is different from the heartrate evaluated at the end (about two hours later).

Figure 3 clearly shows that the QT interval varies in a complex manner with the RR interval. In this study we have used a linear correction formula proposed by [20]. however, other possible relationships QT-RR have been proposed and should be evaluated in the future. In this study we used a subject-specific QT correction based on appropriately estimated α factors.

One of the major issues is the data acquisition required for evaluation of QT correction formulas. The appropriate duration of an ECG suitable for estimation of α correction factor remains an open issue. In our study we used the whole record (about 2 hours) but this duration seems to be inadequate for practical purposes.

Moreover, in our study we used an available software for fiducial points estimation. Better segmentation algorithms could be developed and this could dramatically improve the performance, at least as regards the temporal features.

REFERENCES

[1] L. Biel, O. Pettersson, L. Philipson, and P. Wide, "ECG analysis: a new approach in human identification," in *Instrumentation and Measurement Technology Conference, 1999. IMTC/99. Proceedings of the 16th IEEE*, vol. 1, 1999, p. 557561.

[2] ——, "ECG analysis: a new approach in human identification," *Instrumentation and Measurement, IEEE Transactions on*, vol. 50, no. 3, p. 808812, 2001.

[3] A. Jain, L. Hong, and S. Pankanti, "Biometric identification," *Commun. ACM*, vol. 43, no. 2, pp. 90–98, Feb. 2000.

[4] R. Hoekema, G. J. H. Uijen, and A. Van Oosterom, "Geometrical aspects of the interindividual variability of multilead ecg recordings," *Biomedical Engineering, IEEE Transactions on*, vol. 48, no. 5, pp. 551–559, 2001.

[5] G. Wübbeler, M. Stavridis, D. Kreiseler, R. D. Bousseljot, and C. Elster, "Verification of humans using the electrocardiogram," *Pattern Recognition Letters*, vol. 28, no. 10, p. 11721175, 2007.

[6] E. Marasco and C. Sansone, "Combining perspiration- and morphology-based static features for fingerprint liveness detection," *Pattern Recognition Letters*, vol. 33, no. 9, pp. 1148–1156, 2012.

[7] S. C. Fang and H. L. Chan, "Human identification by quantifying similarity and dissimilarity in electrocardiogram phase space," *Pattern Recognition*, vol. 42, no. 9, p. 18241831, 2009.

[8] A. Loureno, H. Silva, and A. Fred, "Unveiling the biometric potential of finger-based ecg signals," *Computational Intelligence and Neuroscience*, p. 8, 2011.

[9] S. Al-Khatib, N. LaPointe, J. Kramer, and R. Califf, "What clinicians should know about the qt interval," *JAMA*, vol. 289, no. 16, pp. 2120–2127, 2003. [Online]. Available: + http://dx.doi.org/10.1001/jama.289.16.2120

[10] B. Hosmane, C. Locke, and D. Morris, "Qt interval: Correction for heart rate," *The Journal of Applied Research*, vol. 6, no. 4, pp. 288–299, 2006.

[11] D. Wang, J. Taubel, and R. Arezina, "Comparison of six commonly used qt correction models and their parameter estimation methods," *Journal of Biopharmaceutical Statistics*, vol. 22, no. 6, pp. 1148–1161, 2012, pMID: 23075014. [Online]. Available: http://www.tandfonline.com/doi/abs/10.1080/10543406.2011.577261

[12] A. D. C. Chan, M. M. Hamdy, A. Badre, and V. Badee, "Wavelet distance measure for person identification using electrocardiograms," *Instrumentation and Measurement, IEEE Transactions on*, vol. 57, no. 2, p. 248253, 2008.

[13] 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, p. 133142, 2005.

[14] P. Sasikala and R. S. D. Wahidauanu, "Identification of individuals using electrocardiogram," *International Journal of Computer Science and Network Security*, vol. 10, no. 12, p. 147153, 2010.

[15] Y. Wang, K. N. Plataniotis, and D. Hatzinakos, "Integrating analytic and appearance attributes for human identification from ECG signals," in *Biometric Consortium Conference, 2006 Biometrics Symposium: Special Session on Research at the*, 2006, p. 16.

[16] G. H. Zhang, C. C. Y. Poon, and Y. T. Zhang, "A biometrics based security solution for encryption and authentication in tele-healthcare systems," in *Applied Sciences in Biomedical and Communication Technologies, 2009. ISABEL 2009. 2nd International Symposium on*, 2009, p. 14.

[17] W. Ye, S. Li, X. Wu, and J. Ye, "Detection of multilead ecg character points and assessment based on a reference database." in *Conf Proc IEEE Eng Med Biol Soc.*, vol. 4, 2005, pp. 3895–8.

[18] S. Z. Fatemian and D. Hatzinakos, "A new ECG feature extractor for biometric recognition," in *Digital Signal Processing, 2009 16th International Conference on*, 2009, p. 16.

[19] M. Tawfik, H. Selim, and T. Kamal, "Human identification using time normalized qt signal and the qrs complex of the ecg," in *Communication Systems Networks and Digital Signal Processing (CSNDSP), 2010 7th International Symposium on*, 2010, pp. 755–759.

[20] A. Sagie, M. G. Larson, R. J. Goldberg, J. R. Bengtson, and D. Levy, "An improved method for adjusting the {QT} interval for heart rate (the framingham heart study)," *The American Journal of Cardiology*, vol. 70, no. 7, pp. 797 – 801, 1992.

[21] "Heart rate variability: standards of measurement, physiological interpretation and clinical use. task force of the european society of cardiology and the north american society of pacing and electrophysiology," *Circulation*, vol. 93, no. 5, pp. 1043–1065, Mar. 1996, PMID: 8598068.

[22] A. L. Goldberger, L. A. N. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, "PhysioBank, PhysioToolkit, and PhysioNet components of a new research resource for complex physiologic signals," *Circulation*, vol. 101, no. 23, pp. e215–e220, Jun. 2000, PMID: 10851218.

[23] N. Iyengar, C. K. Peng, R. Morin, A. L. Goldberger, and L. A. Lipsitz, "Age-related alterations in the fractal scaling of cardiac interbeat interval dynamics," *American Journal of Physiology - Regulatory, Integrative and Comparative Physiology*, vol. 271, no. 4, pp. R1078–R1084, Oct. 1996.

[24] P. Laguna, R. Jan, and P. Caminal, "Automatic detection of wave boundaries in multilead ECG signals: Validation with the CSE database," *Computers and Biomedical Research*, vol. 27, no. 1, pp. 45–60, Feb. 1994.

[25] H. Silva, A. Lourenco, R. Lourenco, P. Leite, D. Coutinho, and A. Fred, "Study and evaluation of a single differential sensor design based on electro-textile electrodes for ecg biometrics applications," in *IEEE Sensors 2011*, 2011, pp. 1764–1767.