# Improvement of ECG Signal Quality Measurement using Correlation and Diversity-based Approaches

F.J. Martínez-Tabares, J. Espinosa-Oviedo, and G. Castellanos-Dominguez Signal Processing and Recognition Group, Universidad Nacional de Colombia, Km. 9, Vía al aeropuerto, Campus la Nubia, Manizales, Colombia

Abstract-A large proportion of cardiovascular diseases might be preventable, however, majority of this diseases occurs in rural areas where there is a poor presence of cardiologists. To overcome this issue, the use of wearable devices within the telemedicine framework would be of benefit. However, implementation of processing algorithms in smart-phones at mobile environments imposes restrictions ensuring high measurement quality of acquired ECG data, while maintaining low computation burden. This work presents an algorithm for scoring the quality of measured ECG recordings is developed. Particularly, a quality score is provided that takes into account the proportional correlation observed in acceptable signals based on a diversity scheme, and their inverse relation with standard deviation. Testing of proposed algorithm is carried out upon two different databases, the first one is of own production, while the second one is obtained from Physionet. As a result, high values of sensitivity and specificity are achieved.

#### I. INTRODUCTION

Global atlas on cardiovascular disease prevention and control states that Cardiovascular Diseases (CVDs) are the leading causes of death and disability in the world. Although a large proportion of CVDs is preventable, a big amount (some close to 82%) takes place in rural areas, where a lack cardiologists persists and continues to rise, mainly, because preventive measures seem to be inadequate [1].

In this regard, wearable mobile health-care systems along with telemedicine have a high impact in monitoring cardiac health status, where real-time implementation of algorithms, by example in smart-phones at mobile environments, is critical for early detection. Particularly, real-time automatic classification should be of benefit in early diagnosis [2]. Nowadays, there is a tendency for nurses or patients by themselves carrying out measurements and transmitting biosignals to specialized personnel, who is thousands of miles away, through wearable devices (smart phones and innovative mobile information services) that improve patient access to medical specialists [3].

Electrocardiogram (ECG) is the best way to measure and diagnose abnormal rhythms of the heart, but derived from ECG data high volumes of information lead to an unaffordable computational cost when wearable mobile health-care systems are required [4]. In this connection, the Physionet 2011 Challenge was carried out with the aim of determining the proper ECG data set acceptable for interpretation, in terms of low-cost computational complexity algorithms to be implemented in mobile phones [5].

Since the non standard conditions during ECG data acquisition, robustness to different kind of artifacts is another aspect to take into consideration. This paper discusses an algorithm based on diversity schemes and correlation techniques, which provides information about the adequate/inadequate acquisition of ECG signals, allowing to detect failures caused, mainly, by sensors displacement and baseline wandering.

## II. MATERIALS AND METHODS

#### A. Correlation-based Measurement of ECG signal quality

Quality during ECG signal acquisition using mobile devices is determined from the perspective of measurement instrument fidelity (associated with morphology, amplitude and frequency of ECG signals), adjustment, as well as coupling between the electrodes and the patient, evidencing the proper acquisition of an ECG recording (without saturation and deviation from the baseline signal) [6]. Acquisition system must guarantee high values of Common Mode Rejection Ratio and Signal to Noise Ratio, usually quantified with spectral, time and waveform distortion measurements.

As discussed in [7], [8], quality of measured ECG recordings can be provided grounded on detailed analysis of their shape, by instance, using the correlation between ECG data within the T frame of analysis:

$$E\{x(t)y(t+\tau)\} = \int_T x(t)y(t+\tau)dt, \forall t, \tau \in T$$
(1)

where  $E\{\cdot\}$  stands for expectation operator. For the sake of easier interpretation, we use the Pearson coefficient correlation,  $\rho$ , which is estimated by dividing the covariance (cov $\{\cdot\}$ ) of two given recordings,  $x_1(t), x_2(t)$ , by the product of their standard deviations,  $\sigma_i$ , with i = 1, 2, as follows:

$$\rho_{1,2} = \frac{\operatorname{cov}\{x_1(t), x_2(t)\}}{\sigma_1 \sigma_2} \tag{2}$$

#### B. Diversity systems

Correlation-based measure of quality given in (2) is applied between signals under assumption that ECG signal channels can form a diversity scheme. Used in telecommunication system analysis, diversity techniques exploit the apparently random nature of some channels, having more than one version of the signal originally transmitted; each copy of the signal will experience differences in terms of attenuation and phase delay while travel from source to receiver.

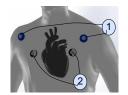


Fig. 1. Single input multiple output diversity scheme

Diversity can be used to improve system performance in fading channels, instead of transmitting and receiving the desired signal through just one channel; processor obtains L copies of the desired signal through M different channels. The idea is that while some copies may undergo deep fades, others may not. Thus, out of M branches, M replicas of the transmitted signal are obtained by the receiver,  $\mathbf{x} = [x_1(t) \dots x_{M-1}(t)]$ . Consequently, the proposed scheme places the human heart as the Single Input system, while the ECG sensors represent Multiple Output scheme, as shown in Fig. 1. As a result, uncorrelated data are matched allowing to detect relations of proportionality, to reconstruct the original signal rejecting disturbances or artifacts.

## C. Rating criteria of the signal

The purposed score, based on diversity and correlation ratios, for a measured ECG recording is given by the following expression:

$$\boldsymbol{\varsigma} = \frac{\boldsymbol{\varphi} + \boldsymbol{\chi}}{2} - \boldsymbol{\sigma}, \ \boldsymbol{\varsigma} \in [0, 1]$$
(3)

where  $\varphi$  is the mean of the zero-lag autocorrelation coefficient (i.e.  $\tau = 0$ ), computed for each one of the 12 channels during the time lapse *T* (i.e. 10 *s*). Correlation is evaluated using the pattern vector  $\alpha_n$  of 1 *s* duration extracted from the same channel  $x_n$ , and rotated along the whole signal, as follows:

$$\varphi = \frac{\sum_{n=1}^{12} \sum_{t=1}^{10} E\{\alpha_n(t)x_n(t)\}|_{\tau=0}}{10 \cdot 12}$$
(4)

In turn, scalar value  $\chi$  is the mean of the cross correlation between the reference channel (in the concrete case, the channel 1 is preferred) and the remaining ECG channels:

$$\chi = \frac{\sum_{n=1}^{12} E\{x_1(t)x_n(t)\}|_{\tau=0}}{12}$$
(5)

Lastly, the term  $\sigma$  is the mean standard deviation of  $E\{\alpha_n(t)x_n(t)\}|_{\tau=0}$ , estimated for each second interval during the defined time lapse *T*.

The purposed score ranges from 0 until 1, where the lowest the score - the worse the quality of measured ECG recording. Particularly, given a 10-*s*-length ECG recording acquired from a patient, for which the following values are estimated,  $\chi =$ 0.5,  $\varphi = 0.95$ , with high value of  $\sigma = 0.4$ , then the following score is obtained:  $\zeta = 0.325$ . Thus, it is likely the recording is corrupted by any interference or artifact.

#### III. EXPERIMENTAL SETUP

Quality estimation is delivered in the following steps: *i*) calibration of the acquisition system through correlationbased measure of quality; calibration is carried out with a simulated ECG signal, and *ii*) signal scoring using iterative cross correlation and autocorrelation among all ECG channels. Data sources for machine calibration are created using a standardized signal generator and ECG system to determine the quality of ECG acquisition system under consideration. It should be quoted that the former step is not mandatory, but it is desirable to guarantee the quality of the measuring instrument.

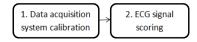


Fig. 2. Experimental scheme.

Latter step (signal scoring) is important to ensure the proper sensor acquisition. In addition, this step permits to differentiate these artifacts, due to disconnection or movement, that are clinically relevant, and therefore should be corrected.

## A. Acquisition system calibration

First step can be carried out periodically to verify the signal generator scale with a standardized caliper; reference arrays with ideal sinusoidal, square functions, and ECG waveforms are constructed. These arrays are correlated with data obtained by the signal generator trough a standardized computer-based ECG Machine. For instance, this work uses the Lionheart 1 (BIO-TEK) simulator that is tested using the QRS-Card (Pulse Biomedical Inc). Acceptable correlation coefficients (heuristically, it is determined as acceptable a threshold  $\geq 0.8$ ) lead to consider the signal generator adequate for calibrate ECG devices.

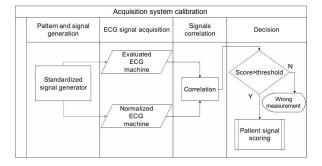


Fig. 3. Step 1: calibration of data acquisition device.

It is intended to embed a reliable signal generator into mobile ECG machines for self calibration process. In this regard, with the aim of determining the feasibility of this proposal, we use the Lionheart signal generator with two ECG acquisition systems in validation process: INNOVATEC S.L. (Spain) [9] and CELBIT LTDA. ELECTRODOCTOR (Colombia) [10]. Once the proper acquisition system is assured, the next step is to determine whether signals are properly acquired trough the signal scoring action.

# B. Estimation of Signal Scores

Based on the correlation and diversity approaches, and taking as reference the Physionet-CINC challenge, named "Improving the Quality of ECGs Collected Using Mobile Phones" [6], it is proposed to enhance results of participants like Langley et al. [11] and Xiao et al. [3] to measure signal quality.

Auto correlation between same channel aims to determine base line wandering caused by electrodes movement, whereas cross correlation allows to estimate changes in specific channels showing problems of missing channels or saturation.

It must be quoted that recordings measured with acceptable quality should have a high correlation on the same channel and between different leads; therefore standard deviation is low, and the correlation standard deviation is inversely proportional to signal quality. Thus, for estimation of signal scoring, correlation values are to be added while deviation ones are to be subtracted.

As a result, unacceptable values derived from score-based criteria for this multistage algorithm include the followings:

- flat line, that is, constant voltages at least for 1 *s*, saturation;
- constant voltage superior to 2 mV by more that 200 ms;
- baseline drift and channel off the chart;
- drifts over to 2.5 mV, low amplitude;
- if the maximum amplitude is lower than  $125 \,\mu V$ .

#### C. Database

In practice, there are many situations leading to improper acquisition system setup (electrode disconnection, movement, baseline wandering, among others), which are present in the MIT-Physionet database including numerous scenarios intended to train the classifier. So, the signal scoring algorithm is tested using Physionet database that is a collection of 1000 registers, 12-lead ECGs, each 10-s-long, recorded by people with different amounts experience, intended to be used as a training set for the PhysioNet/Computers in Cardiology Challenge 2011 [5]. The training set includes 775 recordings labeled as acceptable, 223 labeled as unacceptable, and 2 recordings labeled as indeterminate.

## IV. RESULTS AND DISCUSSION

After the first step, acquisition systems calibration is done successfully using the proposed quality criteria of ECG measurement based on a high correlation. Measurements of the standardized ECG system show correlations above 95%, while correlation for machines under validation process are around 80%, and thus, still suitable.

Relating mobile devices with included ECG systems such as smart phones, it must be quoted that the proposed measure of quality leads to implementation of devices that can be self calibrated through a reliable signal generator, by example, digital to analog converters embedded in the electronics of the mobile device.

For second step (signal scoring), we find that absolute value of the score goes to zero when there is no correlation, whereas a correlation of zero means no relationship between channels; that situation occurs in cases of flat line when values are constants.

Initial testing gives values of sensitivity and specificity around 86%, which are not so high as expected. Thus situation may be explained since some recordings are very close to the decision threshold, caused by a low score due to any zerocorrelation value, obtained with some channel.

However, some of recordings labeled as acceptable in the database (see PhysioNet/Computers in Cardiology Challenge 2011 [5]) reach low signal scoring values close to 0.5 (lower that the fixed threshold). Detailed analysis of those recordings shows that there is artifact influence in, at least, one channel, in particular, a flat line is measured. So, that recordings should be relabeled as unacceptable for diagnosis.

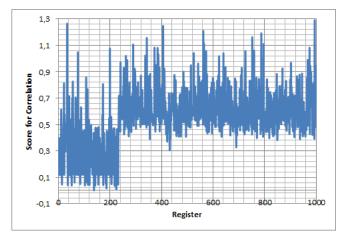


Fig. 4. Estimated values of correlation-based quality score for labeled recordings as Acceptable / Unacceptable in [5]

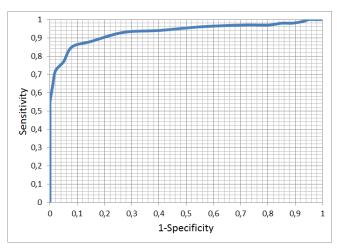


Fig. 5. ROC curve for quality estimation

Estimation of signal scores for testing of the PhysioNet database is is shown in Fig. 4, computed for all 1000 patients. According to the provided information in [5], the first 233 recordings are labelled as unacceptable for diagnosis, whereas

reaming 764 can be considered as acceptable. Nonetheless, one can see some recordings in the first part with correlationbased scores exceeding the threshold, and, at the same time, other recordings labeled as acceptable reach low quality score of measure.

Overall, from signal scoring and performed classification, we obtain a sensitivity value of 86% and specificity of 91%. ROC curve (shown in Fig. 5) shows accuracy superior to 90%. Accuracy of the algorithm allows to confirm that some recordings of Physionet database, labeled as acceptable, have no data, and therefore, should be considered unacceptable (see Table I).

Recording	Channel	Value
1968453	11	-16000
2080991	7	0
2151032	8	-15996
2536401	8	-16000
2537839	10	-16000
2883516	9	-15992

TABLE I NUMBER OF MISLABELED RECORDINGS.

From estimated results shown in Fig 4 and 5, one may infer that the inclusion of embedded signal generator, in the wearable ECG devices for self-calibration purpose, should be considered as a proper way to increase the hardware acquisition quality, in terms of reducing the influence of possible disturbances caused by any patient's movement.

## V. CONCLUSIONS

An algorithm for scoring the quality of measured ECG recordings is developed. Particularly, a quality score is provided that takes into account the proportional correlation observed in acceptable signals based on a diversity scheme, and their inverse relation with standard deviation. Testing of proposed algorithm is carried out upon two different databases, the first one is of own production, while the second one is obtained from Physionet. As a result, high values of sensitivity and specificity are achieved.

Detailed analysis of each recording belonging to Physionet database shows that some signals are wrongly labeled, mainly, because any of the electrodes remains unplugged during data acquisition (verification shows constant value during recordings). Moreover, some of labeled as unacceptable recordings show a high correlation-based score meaning that, mainly, the recording structure remains uncorrupted. In other words, it is likely that recordings holds high values of baseline wandering, which can be removed by any conventional high pass filtering approach. The proposed algorithm for quality scoring includes also a diversity scheme, requiring low computation burden, but improving the quality of estimated scores. Overall, the quality scoring algorithm can be programmed into wearable devices improving their effectiveness and robustness. Discussed quality score holds easy interpretation: the higher the score the more reliable its acquisition. In practice, to make a concrete

decision of whether any recording is suitable for diagnosis purpose, a working threshold is to be empirically fixed, which in a concrete case is fixed as 0.8.

Future work may focus on how to increase the rate of effectiveness, correlating additional measures to electrocardiogram, such as motion detectors with embedded accelerometers, and sensors for respiratory rate.

#### ACKNOWLEDGMENTS

This research is carried out under the grants of the program "Generación del Bicentenario" and "Bank of Eligible Projects for Entrepreneurship and Business Units Based on Technology", funded by COLCIENCIAS.

#### REFERENCES

- [1] Who report, Tech. rep., World Health Organization (2011).
- [2] B. Raghavendra, D. Bera, A. Bopardikar, R. Narayanan, Cardiac arrhythmia detection using dynamic time warping of ecg beats in e-healthcare systems, in: World of Wireless, Mobile and Multimedia Networks (WoWMoM), 2011 IEEE International Symposium on a, 2011, pp. 1–6.
- [3] H. Xia, G. A. Garcia, J. C. McBride, A. Sullivan, T. De Bock, J. Bains, D. C. Wortham, X. Zhao, Computer algorithms for evaluating the quality of ecgs in real time, in: Computing in Cardiology, Vol. 38, 2011, pp. 369–372.
- [4] R. Bonow, E. Braunwald, D. Mann, D. Zipes, P. Libby, Braunwald's Heart Disease: A Textbook of Cardiovascular Medicine, no. v. 2, Saunders/Elsevier, 2011.
- [5] Physionet/computing in cardiology challenge 2011 (2001).
- URL physionet.org/challenge/2011
- [6] I. Silva, G. B. Moody, L. Celi, Improving the quality of ecgs collected using mobile phones: The physionet/computing in cardiology challenge 2011, in: Computing in Cardiology, Vol. 38, 2011, pp. 273–276.
- [7] J. L. Rodríguez-Sotelo, D. Cuesta-Frau, D. H. Peluffo-Ordoñez, C. G. Castellanos-Domínguez, Unsupervised feature selection in cardiac arrhythmias analysis, in: Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE, 2009, pp. 2571 –2574.
- [8] F. J. Chin, Q. Fang, T. Zhang, I. Cosic, A fast critical arrhythmic ecg waveform identification method using cross-correlation and multiple template matching, in: Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE, 2010, pp. 1922 –1925.
- [9] Innovatec s.l. (2012).
- URL http://www.celbit.net [10] Celbit ltda. (2012).
- URL http://www.celbit.net
- [11] P. Langley, L. DiMarco, S. King, D. Duncan, C. DiMaria, W. Duan, M. Bojarnejad, D. Zheng, J. Allen, A. Murray, An algorithm for assessment of quality of ecgs acquired via mobile telephones, in: Computing in Cardiology, CinC, 2011, pp. 281–284.