This full text paper was peer-reviewed at the direction of IEEE Instrumentation and Measurement Society prior to the acceptance and publication.

Cardiac Activity Classification using an E-Health App for a Wearable Device

M. Pirozzi, F. Pietroni, S. Casaccia, L. Scalise, G.M. Revel

Università Politecnica delle Marche
Ancona, Italy
s.casaccia@univpm.it

Abstract—**In the paper, authors discuss the development and performance evaluation of an e-health Android App, which allows to monitor and classify ECG-related features. The mobile platform is composed of a wearable and non-obtrusive sensor and a smartphone, which collects and process data during the daily life. The main goal of this work has been the development of a real-time, wireless monitoring tool that is not related to an indoor environment. Five physiological quantities are continuously measured: Heart Rate (HR) and 4 ECG time intervals (i.e., QT, ST, PR, QR); together with the complete ECG waveform, these parameters are displayed in real-time, while the user is performing different activities, indoor or outside. A visual feedback (i.e., colour bars, according to the level of the measured quantities) is provided to the user, together with the possibility to save data for further analysis. A pilot study has been conducted to evaluate the accuracy and the uncertainty of the data computed in real-time by the mobile application, to those derived from a reference system (i.e., ECG signal coming from a standard electrocardiograph), in post-processing. Results have shown a good agreement with gold standard instrumentation. The Bland-Altman test has identified a high correlation between the data computed by the App with respect to the ones from the gold standard (i.e., R^2 equal or higher than 90%), with a slight underestimation of the time intervals (3.6±1.5 ms for QT, 4.1±1.7 ms for ST, 3.0±1.2 ms for QR and 11.9±1.9 ms for PR interval).**

Keywords—physiological parameters; ECG waveform; smart devices; wereable sensors; real-time monitoring; signal processing

I. INTRODUCTION

Demand for health care has risen rapidly in recent years. Therefore, traditional diagnosis services have become insufficient. With the rapid increase of the silver age, coupled with a longer lifespan, e-health is targeted to provide low-cost tools for everyday household usage [1]. Nowadays, it is possible to monitor user's health condition in real-time through wearable technologies. Furthermore, coupling smart sensors to devices (i.e., smartphones), allows a continuous detection, even when the user is performing different activities, indoor or outside. This can help to provide doctors with a more complete diagnostic scenario [2], [3]. As a matter of fact, the idea of health monitoring has profoundly changed nowadays. In modern lives, health surveillance plays a key role in the daily life, even considering the increasing number of people with chronic diseases [4]. To achieve the purpose of monitoring patient's physiological information continuously, mobile health care is needed. The development of the Body Sensor Network (BSN) technology allows to monitor some important physiological quantities, such as electrocardiograph (ECG), respiration rate, blood oxygenation (SpO2), body temperature, electroencephalograph (EEG), etc., for a long time [5]. Patient comfort and persuasiveness of the used technologies are two other important aspects, as people may find wearing vests with several sensors physically uncomfortable, restrictive, or even irritating [1]. However, persuasive technologies are in continuous development, in particular to motivate users in improving their quality of life, wellbeing, to live independently, stay positive, etc. [6]. Many e-Health applications and systems have been developed and are available, but, in order to make them interesting, it is necessary to follow several aspects, e.g., acceptability, usability, efficacy, persuasiveness, attractiveness of the system [7]. Basing on these considerations, the authors have focused on the development and the study of a wearable system that allows the real-time monitoring of physiological quantities (i.e., from ECG signal) and that could provide useful feedback to the users, to motivate them in the use of the measuring system itself. Two choices have been made. The first concerns the physiological quantities to be measured. The ECG waveform is rich of diagnostic information. Consequently, five quantities have been taken into consideration. Heart Rate (HR) and ECG time intervals (QT, ST, PR and QR) have been measured and, together with ECG waveform, are shown to the user and saved locally on the mobile system. HR is an important parameter, commonly used to monitor the subject's health status [8], [9]. It is defined as the number of hearth beats per minute (bpm) and several conditions can affect it, such as stress, illness, anxiety, etc. At the same time, ECG has been used clinically by cardiologists for many years [10]. For example, the ST segment's change is used to determine whether myocardial ischemia has occurred; the QT interval is used to discover a possible long QT syndrome, i.e., a rare cardiac anomaly that can lead to ventricular fibrillation or even to cardiac arrest. The QT/QTc interval (where QTc is the QT interval corrected for heart rate, $QTc = QT/(HR)^{1/2}$) is also considered because of its potential for the detection of

978-1-5386-3392-2/18/$31.00

proarrhythmogenic effects of both cardiac and non-cardiac drugs [10]. The authors have already worked on the identification of the previously cited ECG time intervals for different sensors and instrumentation [11]. The algorithm proposed, which was a tuned version of an existing methodology [10], was suitable for ECG waveform, but was only tested in post-processing. For this reason, the choice has been to focus on the ECG time intervals analysis, while providing a real-time tool, basing on the previous studies conducted. The second aspect has been the selection of both the sensor and the smart device for the development of the overall measurement system. Considering the aim of the work (i.e., to provide the user with a real-time wireless monitoring tool that is not related to indoor environment), the authors have identified a multi-parametric belt (i.e., Zephyr Bioharness 3.0) as the sensor, and an Android smartphone as the device the user interacts with. The choice of the sensor has been related to the good measurement accuracy of the same, already evaluated by authors in previous tests, in both static and dynamic conditions [12]. As smartphone is considered the most used tool worldwide, it has been thought that the development of an Android application, together with the use of the BH3 sensor, was an optimal combination. The application has been developed in blocks and functions (e.g., data filtering, time intervals calculation, saving and export, etc.), so that in future the same implementation could be applied to different wearable ECG-sensors, without the need to modify the overall code. Next section provides a description of the instrumentation adopted, the description of the App and algorithms embedded, and the tests conducted in laboratory.

II. MATERIALS AND METHOD

The aim of the experiments conducted has been the evaluation of the user's cardiac activity, monitored through two different systems. Both acquires and save raw ECG waveform (lead I of the Einthoven's triangle). The first measurement system (composed by the wearable sensor BH3 [13] and smartphone) collects and processes ECG data in real time, to show to the user his/her physiological quantities (i.e., HR, QR, PR, QT, ST). The second one is composed by a standard electrocardiograph and a proper acquisition board. ECG signal is here acquired and then post-processed in a second time. Measurements have been conducted simultaneously. The synchronization process has been carried out in a post-processing phase, using the timestamp (i.e., UTC format) of the two measuring instruments. Linear correlation and Bland Altman tests have been conducted to validate the data acquired and to calculate the accuracy of the real-time tool.

A. Measurement setup

The BH3 [14] has been paired to the smartphone (i.e., through Bluetooth 3.0 standard communication) and data have been stored locally. The reference ECG waveform has been acquired with an ECG medical device (ADInstrument Acquisition Board, PowerLab 4/25, 4 digital inputs), connected to a PC for serial data transmission and saving of raw signals. Even if both the acquisitions have been conducted nearly simultaneously, data synchronization and resampling are needed. BH3 ECG signal has been acquired with a sampling frequency of 250 Hz, while ECG standard is characterized by a frequency sampling of 1000 Hz. So, a down-sampling of standard ECG signal has been applied.

Figure 1. The ECG reference device (left) and the BH3 (right).

Then, mean removal and a band pass IIR filter (Butterworth, 0.5-20 Hz) have been applied to reduce noise and remove both breathing and movement artefacts. While this process has been conducted in post-processing for the ECG reference signal, a filtering function has been developed in the App, which allows this step to be conducted in real-time.

B. Measurement procedure and subject population

One-minute acquisitions have been performed on 10 healthy volunteers (5 females and 5 males, 20-30 years old), who have been asked to sign informed consent and have then been instructed about the trials. The main characteristics of the participants are reported in Table 1. Each subject has been asked to sit on a chair and relax during the measurements. Standard ECG has been acquired by applying the electrodes on wrists and hip bone (reference signal). Multiparametric belt has been fixed on the subject thorax, below the pectoral line, as shown in Figure 2.

Table 1. Participants characteristics.

Subject	Gender	Age [years]	Weight [kg]	High [m]	BMI [kg/m^2]
1	F	22	51	1.60	19.9
2	F	24	50	1.64	18.6
3	F	23	55	1.62	20.9
4	F	25	53	1.58	21.2
5	F	27	54	1.66	19.6
6	M	26	85	1.80	26.2
7	M	30	70	1.76	22.6
8	M	30	78	1.79	24.3
9	M	23	72	1.72	24.3
10	M	27	80	1.81	24.4
Mean	5F/5M	25.7	64.8	1.70	22.2
STD	-	2.83	13.5	0.09	2.5

C. Data Processing

Several algorithms are available in the state of the art, which provides methodologies for the real-time extraction of both HR and time intervals [15], [16]. The one adopted by authors is based on the theory described in [10], in which slopes of straight line AB and AC (as identified in Figure 3) are calculated through the angle θ_1 and θ_2. The feature of interest has been detected by seeking the minimum of the angle θ, defined as the difference between θ_2 and θ_1. Further details of both implementation and modifications made to the native algorithm have been discussed by authors in [11]. Consequently, a proper searching window containing the minimum or the maximum of the angle has been used. The width of the window is automatically adapted to the signal under examination and varies according to the considered subject. Furthermore, 50% overlap of adjacent windows is applied in the analysis of the angle evaluation.

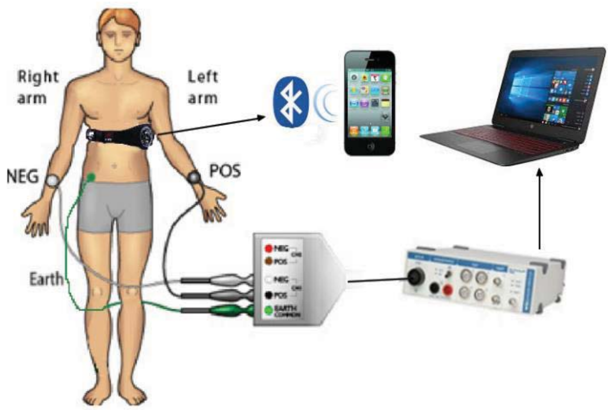

Figure 2. The measurement setup.

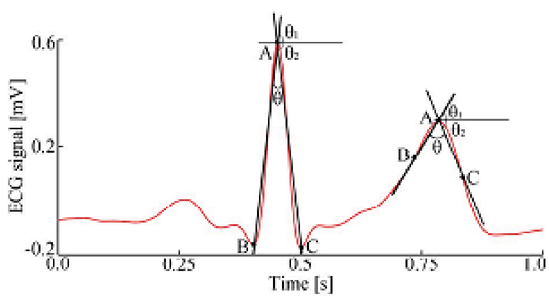

Figure 3. Straight line fitting and angle computation, according to the algorithm described in [10].

The just cited algorithm is the basic principle. It underwent very slight modifications in the version applied for the mobile platform since it has been necessary to:

1. Consider that, in the specific case, the algorithm should be able to work in real-time. That includes the chance to process ECG signal online and to equip the system with a user dialog interface, in which results (i.e., ECG time intervals) are shown to the user. This point will be better described in the next section;
2. Write the algorithm with a portable language for mobile devices. Java language for Android devices has been chosen. On the contrary, in the standard fixed platform, data have been processed in MATLAB (offline).

Data transferred from the wearable belt to the Android device are "clean" (i.e., no additional processing required), in a raw format. This suggests that the uncertainty, evaluated from these tests, will be due only to the algorithm and processing, not to the data exchange phase.

D. BioHarness ECG App

The mobile application, developed by authors and part of the complete measurement system, allows the user's monitoring in real time, anywhere, anytime. If adopting traditional techniques, a person would be forced to conduct measurements with standard instrumentation that relate them in closed environments. This limit has been overcome by the measuring system proposed. The algorithm developed has been based on the object-oriented Java paradigm, so that it could be possible to use different sensors, without the need to modify the entire code (i.e., only the function related to the raw ECG acquisition from the sensor). Moreover, the choice to make use of mobile devices, combined with wearable sensors, able to collect reliable ECG data, allows to carry out measurements, regardless of location or activity [12]. The App is composed of two principal functional blocks:

1. Data Visualization Activity;
2. Export Activity.

The first one is used for both monitoring (in real-time) ECG waveform and providing feedback to the user. At first, HR value is collected from the device, without additional processing. In fact, the BH3 device allows to retrieve HR directly, it is calculated by means of internal embedded algorithms and provided as raw data every second [13]. Then, according to the HR of the user, the searching moving window, described in [11], is created and auto-adjusted. Finally, after ECG time intervals have been calculated, their values are shown to the user. To make data easily readable for the end user, colour markers have been adopted and brought next to the measured quantities. The standard acceptability range for ECG intervals (Figure 4) are:

- PR: 120 ms ÷ 200 ms;
- QR: 30 ms ÷ 60 ms;
- QT $\leq$ 420 ms;
- ST $\leq$ 350 ms.

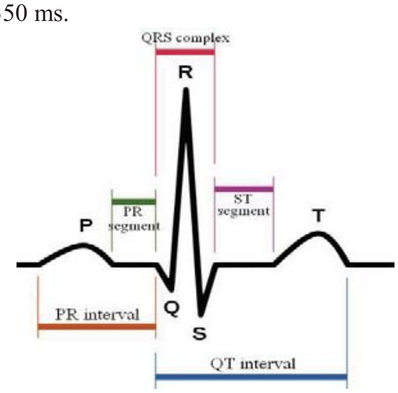

Figure 4. ECG waves and time intervals.

On this basis, to make the analysis more intuitive, if the detected interval is well-outside the range, it is marked by a red spot. If it is slightly outside the range, by a yellow spot. Otherwise, if it is within the standard interval, it is marked by a green spot (Figure 5). In this version, the application has been developed only to alert, through visual feedback, possible values of ECG intervals out of range. In case of high accuracy and reliability of such indicators, an asynchronous task for the automatic management of the alerts will be subsequently implemented. In this case, to make the processing results repeatable, the red colour is attributed when the deviation from the standard value falls between 5% and 10%, while yellow one for deviations less than 5%. The time intervals considered are calculated and averaged for every 5 seconds of acquisition.

Figure 5: Data Visualization Activity.

Considering for example the QT interval, for each subject and for the entire duration of the test, the application has been designed to calculate all the QT intervals in the ECG waveform. On the contrary, the value that is saved on DB and shown to the user is the result of the average of every 5 seconds of QT collected. All the values are updated automatically.

The second window - the Export Activity window (Figure 6) has been implemented to give the user the possibility to save his data, in an appropriate database (i.e., local DB in mobile device). Moreover, this section can be used, e.g., by clinicians, to derive more information than the mere temporal intervals here considered (i.e., the full ECG raw trace).

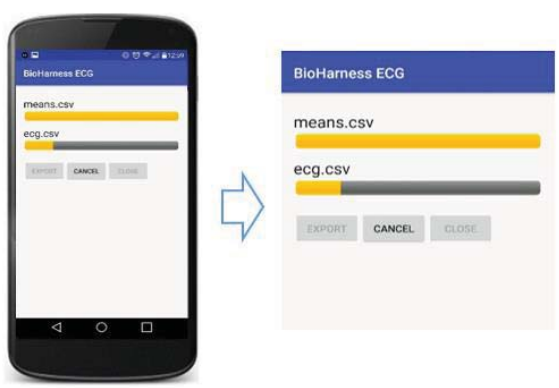

Figure 6. Export activity.

III. RESULTS

The results of the measurements are discussed below. The validity and performance of the designed App in ECG interval computation are reported by making a comparison with those computed from the Golden Standard instrumentation. The results are reported for all subjects, considering 40 s of acquisition. The first 15 s and last 5 s have been discarded to let the subject relax and to avoid movement artefacts that could affect measurement (in particular, the one through ADI board, which is the reference system).

A. Linear Correlation

Linear correlation analysis has been used to evaluate how strong is the relationship between two variables. Pearson correlation, also called Pearson's R, has been computed for the ECG time intervals within the trials. They have all been calculated, comparing the ones from the mobile platform (e.g., referred in Figure 7 as QT_APP) with those deriving from standard system (QT_ADI). A strong correlation has occurred for the time intervals computed, as reported in Table 2.

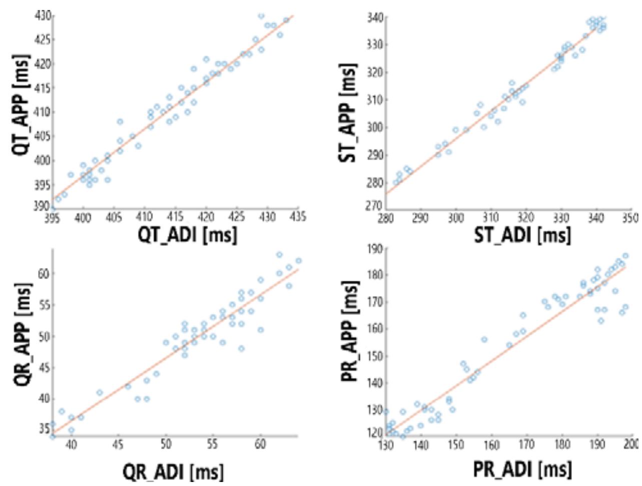

Figure 7. Linear correlation results; QT, ST, PR and QR intervals are expressed in ms.

Table 2. Pearson index (R) and Correlation coefficient (R^2) for the data computed by the App and the ones from the gold standard.

Time Interval	Pearson index (R)	R^2[%]
QT	0.97	95%
ST	0.98	97%
QR	0.95	90%
PR	0.97	94%

According to these considerations, it can be deduced that the results obtained with the proposed measuring system (i.e., mobile App and wearable ECG sensor) are satisfactory and enough accurate.

B. Bland-Altman test

The Bland-Altman test is a method used to compare two measures of the same nature. In Figure 8, results of this test on QT, QR, ST and PR intervals are reported.

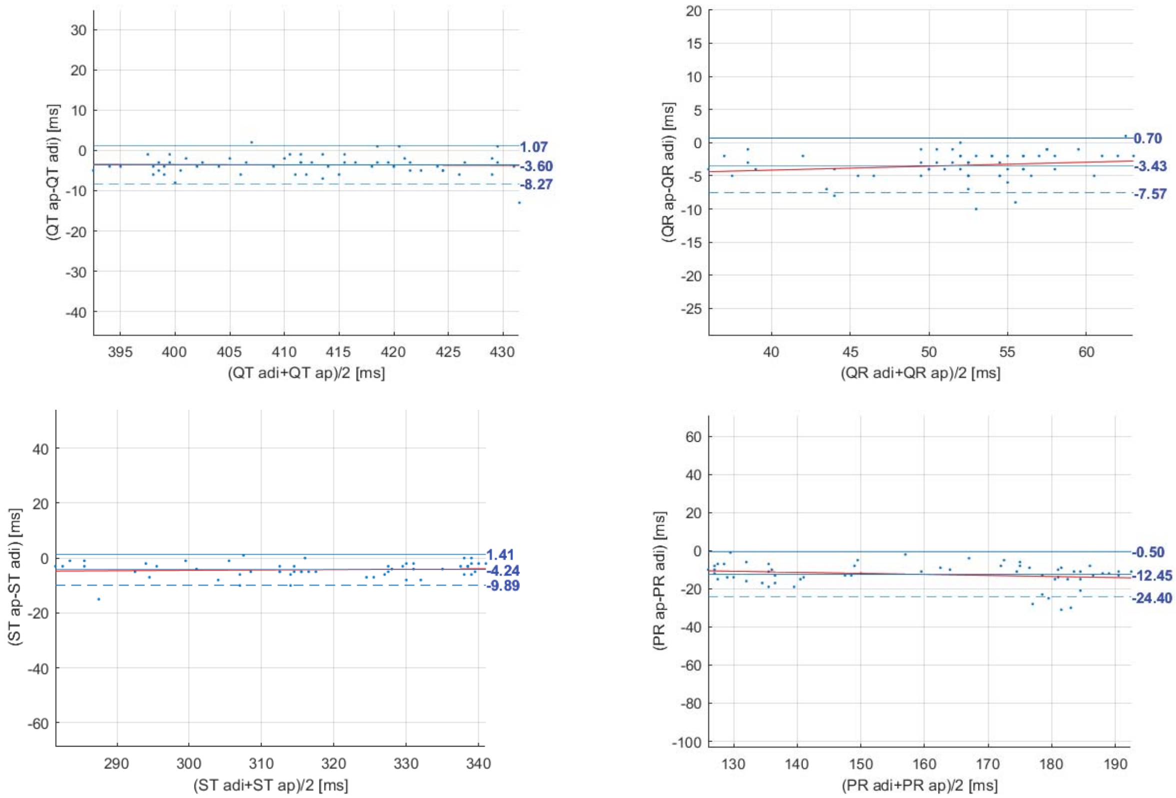

Figure 8. Bland-Altman test for QT, QR, ST and PR intervals.

Table 3. ECG time intervals, mean absolute errors (MAE) and mean relative errors (MRE) for one subject.

Time Interval	Mean ADI intervals [ms]	Mean APP intervals [ms]	MAE [ms]	MRE [%]
QT	421	417.4	3.6	1%
ST	320	315.8	4.2	4%
QR	55	51.6	3.4	3%
PR	160	147.5	12.5	12%

For ST and QR, mean deviations are 4.2 ms and 3.4 ms respectively. The larger mean deviation is reported for the PR interval (12.5 ms). This could be attributed to the difficulty of identifying the P wave in the considered paths. It is to note that the mean error of each interval (if not considering the absolute value) is negative. This implies that the application slightly underestimates, in average, the ECG time intervals. Figure 8 reports the application of Bland-Altman test for the time intervals, while, in Table 3, the mean values of ECG intervals are reported, considering both standard method (ADI) and mobile system.

Table 4 QT, ST, QR and PR MAE for all the subjects involved in the trial.

Subject	MAE QT [ms]	MAE ST [ms]	MAE QR [ms]	MAE PR [ms]
1	3.6	4.2	3.4	12.5
2	4.7	4.0	4.0	12.6
3	2.6	2.7	3.8	13.0
4	3.9	4.1	3.2	11.0
5	4.0	4.3	2.1	12.6
6	4.3	3.8	2.8	12.9
7	2.6	4.2	2.9	12.4
8	4.0	5.8	2.3	10.6
9	2.7	3.0	3.2	10.8
10	3.8	4.6	3.6	11.1
Mean [ms]	3.6	4.1	3.0	11.9
STD (2σ)	1.5	1.7	1.2	1.9

These values are related to one of the subjects involved in the trial. For the other subjects, results are reported in Table 4. From such data, it can be observed that the application, considering that it is based on a wearable sensor and without FDA approval, provide data more than satisfactory. As shown, mean error for all subject is 3.6 ms for QT interval, 4.1 ms, 3 ms and 11.9 ms for ST, QR, PR intervals respectively.

IV. CONCLUSIONS

In this paper, an e-health App to monitor physiological quantities of users, together with a methodology to provide feedback about their physiological status, have been presented. A multi-parametric belt (BH3) has been used to provide a continuous monitoring of ECG waveform. The Android application developed allows to give the user a high-quality monitoring of his physiological quantities under different conditions (e.g., at home, outside, in movement, etc.). A specific algorithm, already described by authors in [11], has been here tuned to calculate in real-time the ECG time intervals (PR, QR, QT and ST) and to find singularities, in case these intervals are out of range. The measured quantities, coming from the test conducted, have been post-processed and compared to the ones obtained from standard instrumentation. QT, ST, QR and PR intervals calculated in real-time with the App are highly correlated to the ones post-processed from gold standard instrumentation (i.e., R^2 equal or higher than 90% in all the cases). The mean average errors (MAEs) of the computed quantities for all subjects involved in the tests (i.e., 10 healthy young adults) are, respectively: 3.6±1.5 ms for QT, 4.1±1.7 ms for ST, 3.0±1.2 ms for QR and 11.9±1.9 ms for PR interval. The application slightly underestimates the values, with respect to the ones from standard method, but is accurate enough and reliable. Apart from the PR interval (i.e., the difficulty in the identification of the P-wave), the system developed allows to provide a real-time measurement of ECG relevant features, with errors lower than 5% for the QT, ST and QR intervals. Future works will interest the possibility to manage such quantities and apply them in real-contexts and scenarios, for example in working conditions or for athletes [17]. Besides, the same data could lead to the development of a Cloud-based health care service, similarly to what is described in [18].

REFERENCES

[1] Zhang, Y., Liu, H., Su, X., Jiang, P., & Wei, D. (2015). Remote mobile health monitoring system based on smart phone and browser/server structure. *Journal of healthcare engineering*, 6(4), 717-738.

[2] Lin M, Qiao ZZ. The demand and development thinking of mobile medical. *Mobile Communications*, 2010, 34(6):31–35.

[3] Konstantas, D., & Herzog, R. (2003, September). Continuous monitoring of vital constants for mobile users: the MobiHealth approach. In Engineering in Medicine and Biology Society, 2003. *Proceedings of the 25th Annual International Conference of the IEEE* (Vol. 4, pp. 3728-3731). IEEE.

[4] Rasid, M. F. A., & Woodward, B. (2005). Bluetooth telemedicine processor for multichannel biomedical signal transmission via mobile cellular networks. *IEEE transactions on information technology in biomedicine*, 9(1), 35-43.

[5] Karaoguz, J. (2001). High-rate wireless personal area networks. *IEEE communications Magazine*, 39(12), 96-102.

[6] Matthews, J., Win, K. T., Oinas-Kukkonen, H., & Freeman, M. (2016). Persuasive technology in mobile applications promoting physical activity: a systematic review. *Journal of medical systems*, 40(3), 72.

[7] op den Akker, H. J., Klaassen, R., & Nijholt, A. (2016). Virtual coaches for healthy lifestyle. *In Toward Robotic Socially Believable Behaving Systems-Volume II* (pp. 121-149). Springer, Cham.

[8] Cullington, D., Goode, K. M., Zhang, J., Cleland, J. G., & Clark, A. L. (2014). Is heart rate important for patients with heart failure in atrial fibrillation?. *JACC: heart Failure*, *2*(3), 213-220.

[9] Cowie, M. R., & Davidson, L. (2012). Clinical perspective: the importance of heart rate reduction in heart failure. *International journal of clinical practice*, *66*(8), 728-730.

[10] Hu, X., Liu, J., Wang, J., Xiao, Z., & Yao, J. (2014). Automatic detection of onset and offset of QRS complexes independent of isoelectric segments. *Measurement*, 51, 53-62..

[11] Cosoli, G., Casacanditella, L., Pietroni, F., Calvaresi, A., Revel, G. M., & Scalise, L. (2015, May). A novel approach for features extraction in physiological signals. *In Medical Measurements and Applications (MeMeA), 2015 IEEE International Symposium on* (pp. 380-385). IEEE.

[12] Casaccia, S., Pietroni, F., Calvaresi, A., Revel, G. M., & Scalise, L. (2016, February). Smart Monitoring of Userźs Health at Home: Performance Evaluation and Signal Processing of a Wearable Sensor for the Measurement of Heart Rate and Breathing Rate. *In Proceedings of the International Joint Conference on Biomedical Engineering Systems and Technologies* (pp. 175-182). SCITEPRESS-Science and Technology Publications, Lda.

[13] Johnstone, J. A., Ford, P. A., Hughes, G., Watson, T., Mitchell, A. C., & Garrett, A. T. (2012). Field based reliability and validity of the BioHarness™ multivariable monitoring device. *Journal of sports science & medicine*, 11(4), 643.

[14] Khandpur, R. S. (1992). *Handbook of biomedical instrumentation*. Tata McGraw-Hill Education.

[15] Song, M. H., Cho, S. P., Kim, W., & Lee, K. J. (2015). New real-time heartbeat detection method using the angle of a single-lead electrocardiogram. Computers in biology and medicine, 59, 73-79.

[16] Karimipour, A., & Homaeinezhad, M. R. (2014). Real-time electrocardiogram P-QRS-T detection–delineation algorithm based on quality-supported analysis of characteristic templates. Computers in biology and medicine, 52, 153-165.

[17] Peritz, D. C., Howard, A., Ciocca, M., & Chung, E. H. (2015). Smartphone ECG aids real time diagnosis of palpitations in the competitive college athlete. Journal of electrocardiology, 48(5), 896-899

[18] Xia, H., Asif, I., & Zhao, X. (2013). Cloud-ECG for real time ECG monitoring and analysis. Computer methods and programs in biomedicine, 110(3), 253-259..