Evaluation of a real-time low-power cardiorespiratory sensor for the IoT

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***Abstract*— A wide variety of sensors have been developed in the biomedical engineering community for telemedicine and personalized healthcare applications. However, they usually focus on sensor connectivity and embedded signal processing, at the expense of the sensing part. This observation lead to the development and exhaustive evaluation of a new ECG-based cardiorespiratory IoT sensor. In order to improve the robustness of our IoT-based sensor, we discuss in detail the influence of electrodes placement and nature. Performance assessment of our sensor resulted in a best-case sensitivity of 99.95 % and a precision of 99.89 % for an abdominal positioning of wet electrodes, while a sensitivity of 99.47 % and a precision of 99.31 % were observed using a commercial-grade dry electrodes belt. Consequently, we prove that our sensor is fit for the comfortable medical-grade monitoring of the cardiorespiratory activity in order to provide insights of patients health in a telemedicine context.**

***Keywords* — Cardiac sensor, Internet of Things, Electrocardiography, Internet of Medical Things**

I. INTRODUCTION

Personalized healthcare and telemedicine are leading research fields in the biomedical sensors community, aiming at the improvement of both patients' comfort and health using remote monitoring and diagnostics techniques. This is typically achieved with the remote continuous monitoring of the patients' physiological functions using wearable biomedical sensors [1], advanced signal processing and data analysis on the collected physiological data in order to trigger preventive or corrective medical actions. This novel approach to healthcare is of particular interest because of the improvements it brings over traditional healthcare, in terms of both therapeutic and financial efficiency [2]. Of all the numerous physiological functions that can be monitored, cardiac activity is of particular interest. Indeed, cardiac activity parameters such as heart rate variability (HRV) parameters are good indicators of both patients' emotional state and pathologies [3].

This paper only focuses on the development and evaluation of ECG-based cardiac activity sensor systems, as the reliability of other techniques such as photoplethysmography are sometimes challenged by the medical community [4].

The development of ECG-derived cardiac activity estimator sensor systems are quite common in the biomedical literature. For instance [5], [6] proposed a wirelessly powered ECG sensor patch, while [7] investigated the use of Bluetooth Low Energy to transmit raw ECG signals from a patch sensor to external tiers. In [8] and [9], patch-form heart rate wireless sensors were developed. Other example of ECG-based cardiac activity sensors can be found in [10], [11], [12], [13]. While all those sensors are introduced with some experimental results, such results usually focus on the comminucation of signal processing part of the design process, and the sensing part lacks formal validation. This slows the adoption of such devices by the medical community, where devices are expected to be extensively tested in order to verify their performance in terms of the quality of the measured signal.

In our paper, we thus propose a comprehensive evaluation of the heart rate computation performance of our IoT cardiorespiratory sensor system. The performance evaluation was realized both in terms of sensor precision and sensitivity against a reference instrumentation. The remaining of the paper describes the sensor development and the two experiments performed to verify our sensor system performance.

II. MATERIALS AND METHODS

A. Sensor Development

We developed a cardiorespiratory activity sensor system (called "sensor" hereafter) using embedded hardware and software. The Texas Instruments (Dallas, TX, USA) ADS1292R analog front-end was used for analog signal conditioning and acquisition. The ECG signal is acquired at a 1k SPS rate, and transmitted to the main MCU for signal processing. The Cypress Semiconductors (San Jose, CA, USA) PSoC 5LP was used for embedded hardware and software signal processing, and the Silicon Labs (Austin, TX, USA) BLE113 was used to provide Bluetooth Low Energy (BLE) wireless connectivity. A block diagram of this hardware architecture is given in Figure 1.

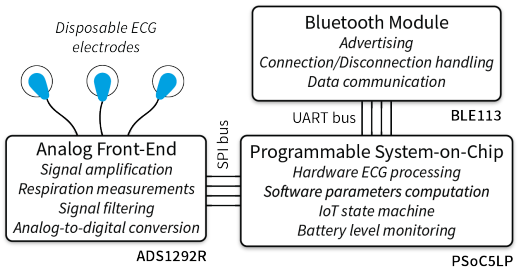

Fig. 1. Block diagram of the sensor

RR intervals were measured using an embedded version of the Pan-Tompkins real-time QRS detection algorithm [14]. In addition to heart rate measurements, our sensor also provides heart rate activity parameters estimation, given in Table I.

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Exhaustive evaluation of the embedded heart variability parameters evaluation was performed in [15]. The respiration waveform (RWF) is measured using impedance pneumography using the modulation and demodulation circuitry included in the ADS1292R. Remote configuration capabilities are embedded into the sensor, where both the sensor state (normal acquisition, lead off detect, failsoft acquisition and shutdown state) can either be remotely triggered or notified to the connected BLE master. The AFE gain can also be remotely configured. More details about the sensor implementation and IoT capabilities are given in [16], and a picture of the sensor and the application are given in Figure 2. In the normal acquisition mode, the sensor streams heart rate values as soon as they are available, it computes and streams HRV parameters every 5 minutes (in accordance with [3]), and the respiration waveform is streamed every second at a 6 SPS rate. In summary, the developed sensor is packaged in a 3D printed case weighing 26.7 g. The sensor embeds a 300 mAh battery, and with an average current consumption of 3.9 mA, our sensor is expected to be able to continuously measure ECG, compute heart rate and HRV parameters and stream data over BLE for more than 3 days.

TABLE I
COMPUTED HRV PARAMETERS

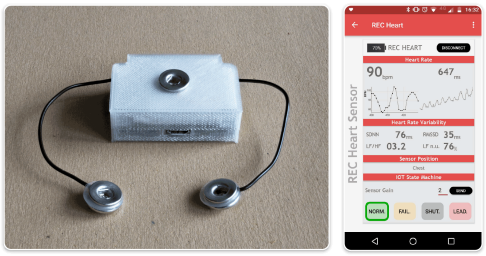
Variable	Unit	Domain	Description
SSDN	ms	Time	Standard deviation of RR intervals
RMSSD	ms	Time	Quadratic mean of differences between consecutive RR intervals
LF/HF	n.u.	Freq.	Ratio of the low-frequency (0.04 to 0.15 Hz) to high-frequency (0.15 to 0.4 Hz) components of the PSD of the RR intervals
Norm. LF	%	Freq.	Normalized low-frequency components to sum of low- and high-frequency components of the PSD ratio, i.e., LF/(LF+HF)

In addition to the sensor, a companion Android application based on the Nordic Semiconductor (Oslo, Norway) nRF Toolbox open-source framework was developed. Using BLE this application can be used to display and record all the sensor parameters and to remotely change the configuration of the sensor. The open-source Paho MQ Telemetry Transport (MQTT) client[1] was embedded into the application in order to provide Internet-based connectivity using lightweight publish/subscribe mechanisms, and in order to facilitate sensor integration into wide-scale healthcare systems.

B. Electrode Placement Evaluation

The first experiment consisted of the evaluation of the best electrodes placement for the developed sensor. Figure 3.a. gives a graphical representation of the evaluated electrodes placement. The LA-RA placement was chosen because of the emergence of sensors aimed at being attached to patches worn by the patients on their upper chest. The LL-RA electrodes configuration correspond to the standard lead-II derivation of traditional 3 electrodes ECG devices. Eventually, the last electrode configuration to be tested was the abdominal

[1]Available: https://www.eclipse.org/paho/



(a) (b)

Fig. 2. (a) Developed IoT sensor (b) Developed Android application

configuration, where the central electrode is placed just bellow the xiphoid process, and the lateral electrodes are placed 5 cm from each side of the central electrode.

This experiment aims at choosing the best electrode placement, for which movement artifacts are minimal, thus minimizing the amount of false positives and false negatives for heart beat detection. In order to compare the results from our sensor to a gold standard instrumentation, ECG was recorded using an ADInstruments (Sydney, Australia) PowerLab 26T data acquisition apparatus using the standard LL-RA configuration (illustrated in blue in Figure 3.a.). ECG was acquired at a 4 kSPS rate, and ECG signal was filtered using a bandpass filter (bandwidth: 5 to 20 Hz) to remove high and low frequency artifacts. During this experiment, patients were equipped with ConMed (Utica, NY, USA) Softrace Large repositionable ECG electrodes.

C. Electrode Nature Evaluation

In the second experiment, the influence of the electrodes nature was evaluated. Three kind of electrodes were compared: the ConMed Softrace Large electrodes (used in the previous experiment, and placed as shown in Figure 3.b.), Ambu (Ballerup, Denmark) Blue Sensor L electrodes and a Polar (Kempele, Finland) dry electrodes belt. ECG was also collected during this experiment, using the same apparatus and configuration from the previous experiment.

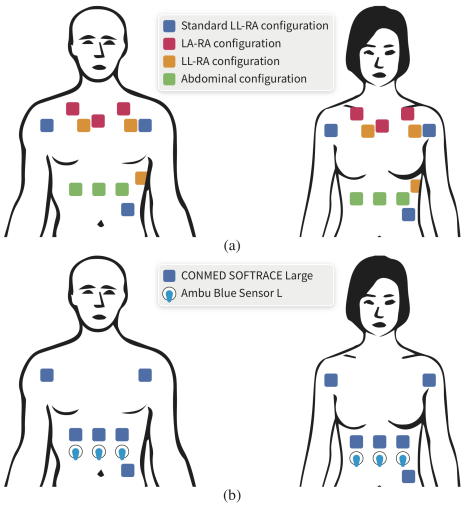


Fig. 3. (a) Electrodes placement for electrodes position experiment (b) Electrodes placement for electrodes nature experiment

Eventually, data from both experiments was processed in order to extract the true positive rate, false positive rate and false negative rate. More details about data processing are given in the next section.

D. Data Collection and Data Processing

Reference ECG and sample data was collected on 8 voluntary subjects, who provided informed consent. Three of the subjects self-reported as females, while 5 of the subjects self-reported as males. Ages ranged from 22 to 47 years, with an average of 31 years.

For both experiments, subjects were asked to perform the same three-minute long exercise. The first minute of the experiment consisted in a baseline rest period where subjects were asked to sit still. For the second minute of the experiment, subjects were asked to stand still. Finally, for the third and last minute of the experiment, subjects were asked to sit back down and perform a series of longitudinal arm rotations, in order to test the robustness of the sensor when faced with movement artifact.

The formal evaluation of sensor performance was executed in terms of sensitivity and precision, where the sensitivity is the ratio between the true positives and the sum of the true positives and false negatives. The precision is the ratio between true positives and the sum of the true positives and false positives. In our case, true positives are heart beat correctly identified as such, while false positives are heart beats detected by the sensor while no heart beats is detected in the reference ECG signal. Eventually, false negatives are heart beat present in the reference ECG signal missed by the sensor. Peak detection in the reference ECG was performed on the filtered signal. In order for a peak to be detected, the signal has to verify the following condition:

$$\begin{cases} x_{n-1} - x_n < 0 \\ x_n > thres \\ y_m - y_{m-1} > 250 \text{ ms} \end{cases} \tag{1}$$

where x_n denotes the ECG signal, $thres$ is a predefined threshold (manually adjusted for each subject), and y_m denotes the time occurrences of the detected peaks. The first condition corresponds to an inversion of the ECG signal derivative, while the second condition is used to isolate the R peaks of the signal. Finally, the last condition improves the robustness of ECG peak detection by rejecting consecutive peaks closer than 250 ms.

After reference ECG peak detection, extracted time occurrences between R peaks can be compared to RR intervals value detected by our sensor, and results of this comparison are given in the next section.

III. Results and Discussion

A total of 9428 heart beats were extracted from ECG signals and were compared to peaks detected by the sensor. From the extracted true positives and both false positives and negatives, the sensor sensitivity and precision were computed. Results from both experiments (electrodes placement and electrodes nature) are given in Table II. It is worth noting that, apart from the LA-RA configuration, all the tests resulted in sensitivity and precision values higher than 99 %. The best electrode placement both in terms of sensitivity and precision is the abdominal position using ConMed Softrace Large electrodes, with a precision of 99.89 % and a sensitivity of 99.95 %, and this mandates the promotion of the abdominal position as the reference position for our sensor.

The upper-chest position, also designated as LA-RA, yielded very poor results, both in terms of sensitivity (94.57 %) and of precision (89.39 %). This points to the fact that if a patch form factor is used for ECG measurement, a careful evaluation of the patch placement must be performed.

Sensor robustness with respect to motion artifact is likely to be related with the electromyographic activity introduced by motions. Indeed, the influence of EMG signals on ECG signals is a known problem in the research community, and numerous attempts at reducing such artifact can be found in the literature [17]. However, while most of these techniques are relevant when full ECG signal is available, their embedded implementation are resources-consuming, making them unfit for in-sensor implementation. Because of the proximity of the pectoral muscles when placed in the LA-RA position, the sensor is faced with great EMG signal, which introduce both false positives and false negatives detections. This is not the case when placed in the abdominal position, because the sensor lies in proximity of the ribcage, where low muscle thickness is usually observed.

TABLE II
Precision and Sensitivity of the Sensor

Configuration	Sensitivity	Precision
LL-RA	99.47%	99.89%
LA-RA	94.57%	89.39%
Abd. (I)[1]	99.95 %	99.89 %
Abd. (II)[2]	99.89 %	99.84 %
Abd. (III)[3]	99.47 %	99.31 %

[1]Abdominal position using ConMed electrodes
[2]Abdominal position using Ambu electrodes
[3]Abdominal position using Polar dry electrodes belt

In addition to performance evaluation in terms of sensitivity and precision, a quantitative comparison of the reference instrumentation and the sensor was performed. This assessment is presented under the form of a Bland-Altman plot in Figure 4. This evaluation was realized on a single subject for which both reference ECG and sensor data were recorded during 10 minutes. During this experiment, the subject was asked to sit still. The sensor electrodes were placed in the abdominal position, using Ambu Blue Sensor L electrodes. It can be seen that the greatest positive difference is of 5.25 ms for an average measurement of 783.6 ms, which results in an error smaller than 1 %. Similar observation can be drawn for the greatest negative difference (−2.25 ms for an average of 668.9 ms, resulting in a relative error of less than 1 %). It is worth observing that an average positive shift of about 1.4 ms is present on the graph. This is likely caused by the precision of the internal clock of the AFE, which is of 1.5 %

on the component standard temperature range. This internal clock was used rather than an external clock for both energy and components footprint saving reasons.

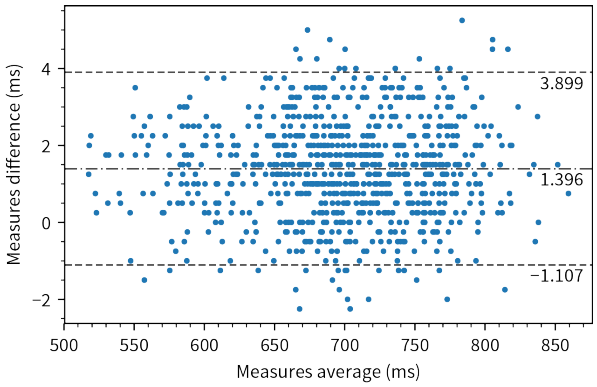


Fig. 4. Bland-Altman plot of the sensor compared with gold standard instrumentation

These results, especially the excellent sensitivity and specificity achieved using a commercial-grade dry electrodes belt are encouraging because of the implications, in terms of adoption rate and patient compliance, it could have. Indeed, one of the causes of the limited patient adoption rate of wearable sensors for telemedicine are their difficult use and sometimes uncomfortable interface (for instance, the long term use of wet electrodes often causes skin irritation). With a measurement apparatus connected to an easy to use dry electrode belts, patients compliance could increase.

IV. Conclusion

This paper presents the extensive evaluation of an IoT cardiorespiratory system of sensors. The sensor design and its implementation were briefly introduced, and supported with a comprehensive evaluation of the influence of both electrodes placement and nature was performed, using both our developed sensor and medical-grade reference instrumentation.

In sum, we were able to promote an abdominal positioning of the electrodes, motivated by the excellent performance of this location both in terms of sensitivity (99.95 % at best) and of precision (99.89 % at best). In addition to this result, a Bland-Altman plot illustrated and evaluated the accuracy of sensor measurement. We found that both positive and negative greatest differences between the sensor and the reference instrumentation were less than 1 %. As a result, we believe the developed sensor is reliable enough to perform medical grade long-term monitoring of the cardiac activity.

Future research directions include an exhaustive evaluation of the sensor in true ambulatory condition using a Holter monitor as the reference instrumentation in order to further validate the robustness of our sensor in ambulatory situations.

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References

[1] B. Massot, N. Noury, C. Gehin, and E. McAdams, "On designing an ubiquitous sensor network for health monitoring," in *Proceedings of the International Conference on e-Health Networking, Applications and Services*, Oct 2013, pp. 310–314.

[2] C. Van Hoof and J. Penders, "Addressing the healthcare cost dilemma by managing health instead of managing illness: An opportunity for wearable wireless sensors," in *Proceedings of the Conference on Design, Automation and Test in Europe*. EDA Consortium, 2013, pp. 1537–1539.

[3] Task Force of the European Society of Cardiology the North American Society of Pacing Electrophysiology, "Heart rate variability: Standards of measurement, physiological interpretation, and clinical use," *Circulation*, vol. 93, no. 5, pp. 1043–1065, 1996.

[4] A. Schäfer and J. Vagedes, "How accurate is pulse rate variability as an estimate of heart rate variability?: A review on studies comparing photoplethysmographic technology with an electrocardiogram," *International Journal of Cardiology*, vol. 166, no. 1, pp. 15 – 29, 2013.

[5] J. Yoo, L. Yan, S. Lee, H. Kim, B. Kim, and H.-J. Yoo, "An attachable ECG sensor bandage with planar-fashionable circuit board," in *Proceedings of the International Symposium on Wearable Computers*, 2009, pp. 145–146.

[6] J. Yoo, L. Yan, S. Lee, H. Kim, and H.-J. Yoo, "A wearable ECG acquisition system with compact planar-fashionable circuit board-based shirt," *IEEE Transactions on Information Technology in Biomedicine*, vol. 13, no. 6, pp. 897–902, 2009.

[7] Y.-J. Park and H.-S. Cho, "Transmission of ECG data with the patch-type ECG sensor system using bluetooth low energy," in *Proceedings of the International Conference on ICT Convergence*, oct 2013, pp. 289–294.

[8] M. Altini, S. Polito, J. Penders, H. Kim, N. V. Helleputte, S. Kim, and F. Yazicioglu, "An ECG patch combining a customized ultra-low-power ECG SoC with bluetooth low energy for long term ambulatory monitoring," in *Proceedings of the 2nd Conference on Wireless Health*, 2011, pp. 15:1–15:2.

[9] H.-P. Kew and D.-U. Jeong, "Wearable patch-type ECG using ubiquitous wireless sensor network for healthcare monitoring application," in *Proceedings of the 2nd International Conference on Interaction Sciences Information Technology, Culture and Human*, 2009, pp. 624–630.

[10] B. Massot, T. Risset, G. Michelet, and E. McAdams, "A wireless, low-power, smart sensor of cardiac activity for clinical remote monitoring," in *Proceedings of the International Conference on E-health Networking, Application Services*, Oct 2015, pp. 488–494.

[11] M. Magno, C. Spagnol, L. Benini, and E. Popovici, "A low power wireless node for contact and contactless heart monitoring," *Microelectronics Journal*, vol. 45, no. 12, pp. 1656–1664, Dec. 2014.

[12] J. Tuominen, E. Lehtonen, M. J. Tadi, J. Koskinen, M. Pnkl, and T. Koivisto, "A miniaturized low power biomedical sensor node for clinical research and long term monitoring of cardiovascular signals," in *Proceedings of the International Symposium on Circuits and Systems*, May 2017, pp. 1–4.

[13] Y. Jang, H. W. Noh, I. B. Lee, Y. Song, S. Shin, and S. Lee, "A basic study for patch type ambulatory 3-electrode ECG monitoring system for the analysis of acceleration signal and the limb leads and augmented unipolar limb leads signal," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology*. IEEE, 2010, pp. 3864–3867.

[14] J. Pan and W. J. Tompkins, "A real-time QRS detection algorithm," *IEEE Transactions on Biomedical Engineering*, vol. BME-32, no. 3, pp. 230–236, 1985.

[15] B. Massot, T. Risset, G. Michelet, and E. McAdams, "Mixed hardware and software embedded signal processing methods for in-situ analysis of cardiac activity," in *Proceedings of the 9th International Joint Conference on Biomedical Engineering Systems and Technologies*, Feb. 2016, pp. 303–310.

[16] A. Gatouillat, B. Massot, Y. Badr, E. Sejdić, and C. Gehin, "Building IoT-enabled wearable medical devices: an application to a wearable, multiparametric, cardiorespiratory sensor," in *Proceedings of the 11th International Conference on Biomedical Electronics and Devices*, 2018.

[17] S. L. Joshi, R. A. Vatti, and R. V. Tornekar, "A survey on ECG signal denoising techniques," in *Proceedings of the International Conference on Communication Systems and Network Technologies*, 2013, pp. 60–64.