This is a post-peer-review, pre-copyedit version of an article published in **2020 13th International Conference on Human System Interaction (HSI)**. The final authenticated version is available online at: https://doi.org/10.1109/HSI49210.2020.9142637

Respiratory signals derived from capacitive electrocardiogram on the smart chair

1st Adam Bujnowski
Biomedical Engineering Department,
Faculty of Electronics, Telecommunications
and Informatics, Gdansk University of Technology
Gdansk, Poland
adabujno@pg.edu.pl

2nd Mariusz Kaczmarek
Biomedical Engineering Department,
Faculty of Electronics, Telecommunications
and Informatics, Gdansk University of Technology
Gdansk, Poland
markaczm@pg.edu.pl

3rd Jerzy Wtorek
Biomedical Engineering Department,
Faculty of Electronics, Telecommunications
and Informatics, Gdansk University of Technology
Gdansk, Poland
jerzy.wtorek@pg.edu.pl

4th Kamil Osinski
Biomedical Engineering Department,
Faculty of Electronics, Telecommunications
and Informatics, Gdansk University of Technology
Gdansk, Poland
kamilosinski1@gmail.com

5th Clemens Nieke
iHomeLab,
Institute of Electrical Engineering IET
Lucerne School of Engineering and Architecture
Horw, Switzerland
clemens.nieke@hslu.ch

6th Edith Birrer
iHomeLab,
Institute of Electrical Engineering IET
Lucerne School of Engineering and Architecture
Horw, Switzerland
edith.birrer@hslu.ch

***Abstract*—Capacitive electrocardiogram (CECG) tends to deliver basic cardiac signals without need to use traditional glued electrodes. In the paper analysis of possibility if the ECG derived respiratory waveforms out of the CECG.**

***Index Terms*—smart chair, biosignals, ambient assisted living**

I. Introduction

An intelligent elders care is important part of researcher's interest. Current research trends are oriented towards extending independent live of elders in their natural environment as long as it is technologically possible. To achieve this a non-obstructive techniques of monitoring of their mental and physiological status need to be developed. This involves smart devices for ambient monitoring development including IoT devices. Also automated data processing with use of the neural networks and artificial intelligence should be considered [1], [2]. Another aspects are related to security systems, where e.g. false alarm rate should be reduced [3], [4]. Another interesting area is development of biomedical measurement systems for health status evaluation. This includes both - wearable biomedical devices and smart environment where applicable [5]–[7]

Research supported by The Ella4Life project - Co-funded by the European AAL Joint Programme and partially by Statutory Funds of Electronics, Telecommunications and Informatics Faculty, Gdansk University of Technology.

CECG is a widely explored and important area of research. It is also widely expored in the literature nowadays [8] [9] [10]. Major difference between traditional electrocardiogram (ECG) is lack of galvanic electrodes, usually attached to the skin surface. This technique is particularly applicable for long-term unobtrusive measurements. It can be applied on the daily used furniture e.g. chair [11] or bed [12].

In the paper arm-chair is considered as a reference measurement set-up. We are interested in recording of the ECG and ECG-related parameters.

The ECG-derived respiratory is a technique that is deriving the respiratory waves out of the electrocardiogram [13] [14]. There are several algorithms that can be used to derive respiratory signals out of the electrocardiogram. In general several information included in ECG signal can be utilized to calculate respiratory information. These are baseline drift, QRS complexes amplitude and QRS complexes frequency analysis.

In the paper we are going to investigate possibility of respiratory signal estimation out of recordings captured by the capacitive coupled electrodes. Recorded CECG signal is a high-pass filtered ECG record with additional noise. Thus we would like to explore the information included in CECG signal against the respiratory. Facial mask with thermistor measuring temperature of the airflow is used as a reference signal.

The rest of the paper is constructed as follows. In section

”Materials and Methods” we are showing principles of the CECG and describe typical algorithms of respiratory signal retrieval. Following this we are describing conducted experiment. Results of the experiment are collected in section named ”Results”, while ”Discussion and Conclussion” summarizes the paper.

II. MATERIALS AND METHODS

A. Capacitive electrodardiography

In contrast to traditional electrocardiography , the capacitive one (CECG) is using a sensing electrodes that are not galvanicaly coupled to the patient’s skin. This allows to place electrodes over the clothes and makes possible to design standalone devices built into furniture to measure ECG.

Currently most of the systems is based on two electrode measurement delivering signal allowing to calculate heart-rate (HR) and HR-derivatives out of recorded signal. In order to achieve good-quality signal an proper shielding and common mode rejection techniques are a must.

Additionally instead of using long wires from actual electrode positioning to the central amplifier - an active electrode technique is utilized. It means that first stage amplifier is usually located very close to the electrodes. It also involves use of ultra-high input impedance amplifiers with sophisticated DC polarization circuits.

Due to nature od coupling the body-clothes-electrode channel is forming series capacitance. This capacitance in general is unknown as it depends on clothes thickness and area of electrode in good contact with the body. In previous works we have estimated value of this capacitance and it might wary from several picofarads to 1nF [11] [8].

The input capacitance together with the first stage input impedance forms high-pass filter. As result the low frequency components of the signal are filtered out. The characteristic frequency of the input coupling can be calculated as:

$$f = \frac{1}{2\pi RC}$$

where C is the coupling capacitance and R describes input resistance of the amplifier. In addition two electrodes located on different parts of the patient’s body can have different coupling capacitance’s causing different input impedance’s at each electrode. Resulting it is decreasing the CMRR of whole system.

B. EDR signal retrieval

In traditional ECG respiratory signal can be detected by analysis of the baseline of regular signal. The frequency of considered signal il lower than 1Hz. Unfortunately with CECG this frequency component is filtered out.

The respiratory signal can be derived by analysis of the amplitude or frequency of the QRS complexes [15].

Analysis of the EDR signal from amplitude of the QRS complex involves determination of such complexes out of ECG signal. A ”gold” standard of achieving this is to follow Pan-Tompkins algorithm [16]. This procedure has been designed for ”normal” ECG signal. Again, we have ECG which is altered by high-pass filtration. This process tends to differentiate signal where Pan-Tompkins algorithm applies additional filtration and differentiation of original signal. Thus original algorithm must be adopted in order to work with modified signals.

Second step is the QRS complex amplitude determination. High pass filtration in analogue domain degrades the QRS complex shape and if we assume additive noise in recorded signal correct amplitude determination is characterized by relatively large error.

Frequency changes detection og the QRS complex can be performed correctly even for differentiated ECG signal. This step also requires proper determination of QRS complexes. Then at time of R complex a value of distance between R{n} and R{n-1} complex is determined. Thus we obtain $\Delta R = f(R)$ function which is non uniformly sampled by definition. To obtain uniformly sampled function $\Delta R = f(t)$ we used spline interpolation.

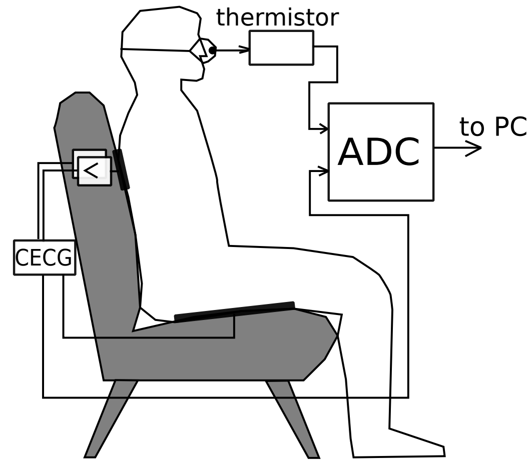

Fig. 1. Experiment setup

C. Experiment setup

An electronic smart chair is used for the experiment. It allows CECG measurements to be recorded for the person sitting in the chair. Additionally it can monitor contact quality of the electrodes to the body as described in [11]. In order to have reference respiratory signal a nasal mask equipped with thermistor was utilized as shown in Fig. 1. Thermistor is located along the air duct of the mask and is polarized by the external resistor forming voltage divider. Resulting voltage is a function of temperature and follows respiration forming ”resp” reference signal. The CECG signal after amplification, together with respiratory data were recorded using Analog Discovery 2 acquisition board [17].

The sampling frequency was set to $f_s = 1kHz$. The ECG bandwidth suggest much lower f_s but to higher sampling frequency allows obtaining higher accuracy of R episodes determination. To improve safety and improve noise immunity during experiment whole system was battery powered.

We have performed measurement with help of 13 healthy volunteers, both male and female, age from 22 to 69. We were used individual breathing masks for each volunteer to reduce risk of mutual infection.

Each record was lasted approx 40 seconds for each recording (some volunteers were measured few times) with custom set exercise regarding controlled breath.

III. Results

We have performed measurements using newly developed CECG active electrode probes and custom designed ECG differential amplifier. We were adopted amplification of about 3000 and narrowband filtering from 0.05Hz to approx 15Hz in 3dB bandtwidth. Analog probe has been connected to the Analog Discovery 2 ADC.

As a respiration signal reference we have used $100k\Omega$ glass tube thermistor inserted into single use plastic respiratory mask. We have polarized thermistor by means of constant resistor ($100k\Omega$) ant 5V supply. Resulting voltage was measured by second channel of the Analog Discovery 2 board.

For each case we have recorded approx 40 sec session with sampling rate of 1000kHz. Resulting session data for individual randomly selected volunteer is shown in Fig. 2 and in a more detailed version in Fig. 3.

From Fig. 3 it possible to observe differentiated ECG signal. The high-pass components are exposed, while low pas are vanishing. Thus for correct detection of QRS episodes an modified Pan-Tompkins algorithm should be applied.

Correct detection of R-waves is a key to proper analysis of the EDR signal. We have tested original Pan-Tompkins algorithm. Results were unsatisfactory. Mentioned algorithm performs data pre-processing , filtration , differentiation etc. Obtained during measurements signal is already differentiated, so several steps should be omitted as it causes detection errors.

Due to that authors decided to implement own algorithm with adaptive threshold and utilization of Octave's findpeaks function. In addition we have constrained algorithm by minimal peaks distance. Results of two implementation comparison is shown in Fig. 4. For future data analysis own algorithm was used as it is better suited for obtained data.

We have implemented detected QRS amplitude analysis. As signal is calculated by taking maximal to minimal signal value for a short period near detected R-wave. Example of obtained data is shown in Fig. 5. Data are presented together with reference respiratory signal. For further analysis data has been spline interpolated using 'interp1' function.

Additionally analysis of the HRV has been performed. To obtain this we have collected R-R distance versus detected R waves. Additionally to make it uniformly sampled spline interpolation has been performed. Example of obtained data is shown in Fig. 6.

Finally, we have implemented baseline trend analysis. We averaged all received ECG samples between 50 and 75% of the interval between detected R-episodes. Calculated average were mapped on time of R-peak for each heart bit. As in previous

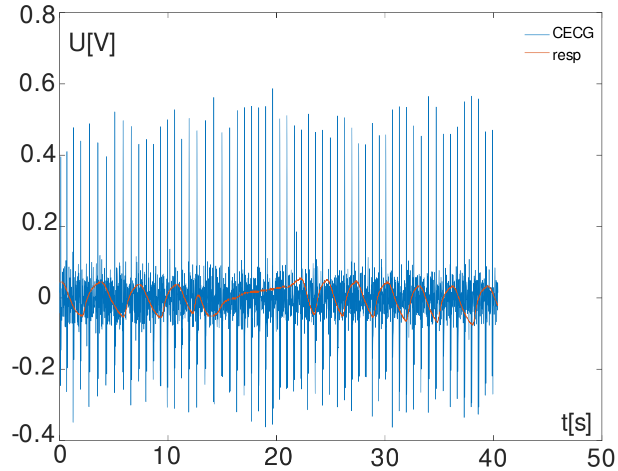

Fig. 2. Received signal example

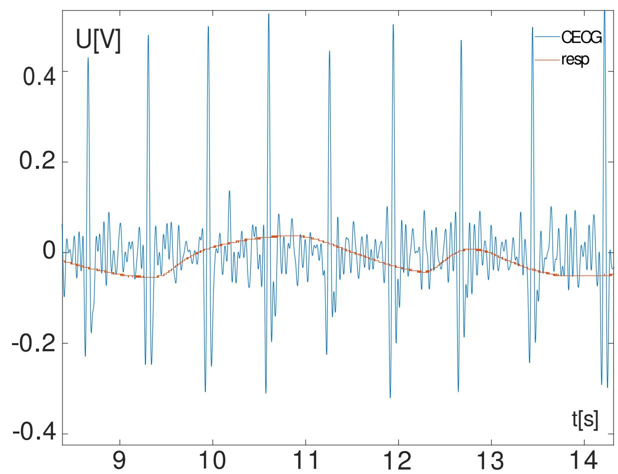

Fig. 3. Framgent of signals form Fig. 2 showing quality of ECG signal

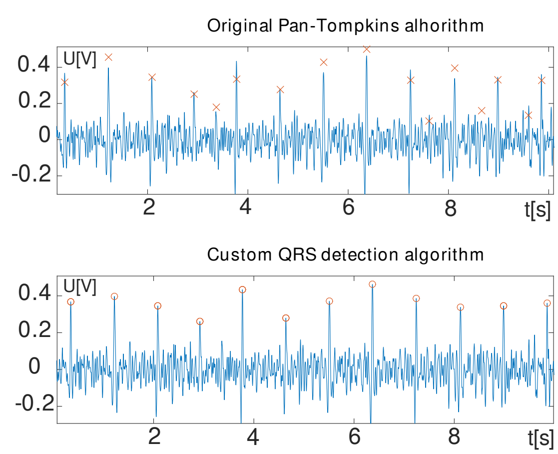

Fig. 4. Comparison of QRS complex detection algorithms

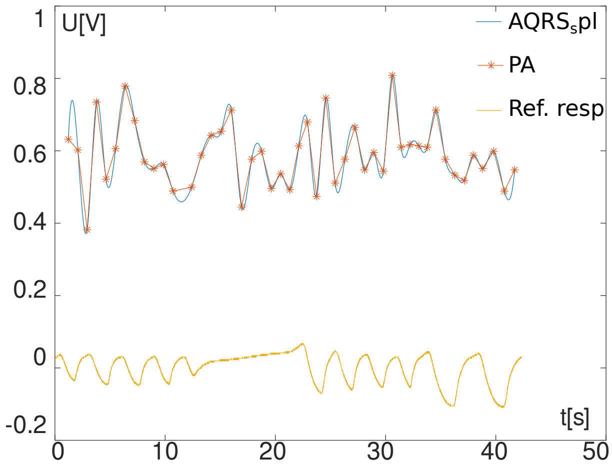

Fig. 5. The QRS amplitude test for case from Fig. 2

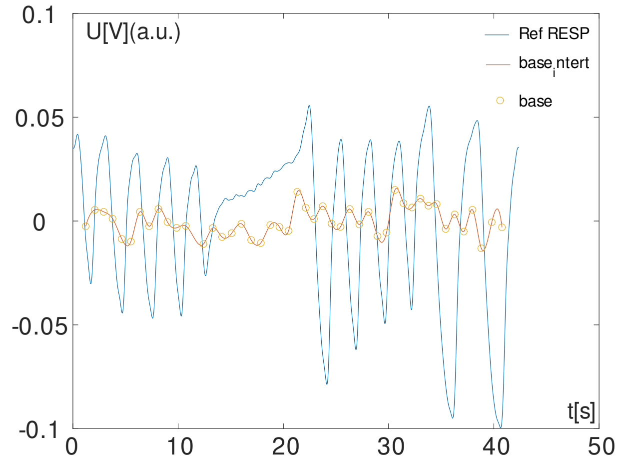

Fig. 7. Baseline changes analysis

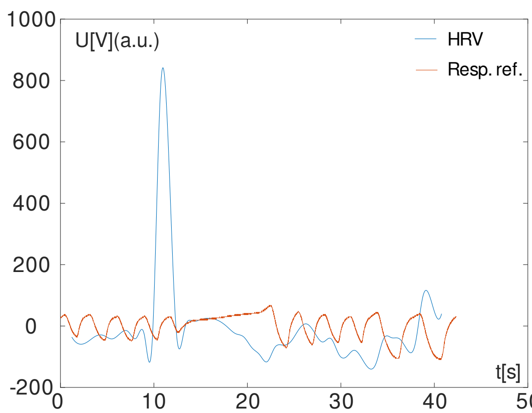

Fig. 6. The QRS HRV test for case from Fig. 2

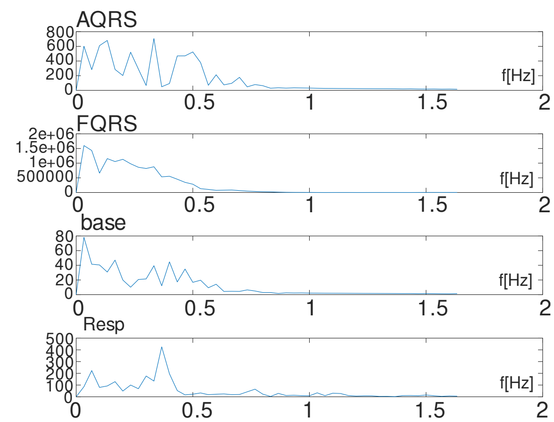

Fig. 8. Frequency analysis

cases data has to be interpolated using spline. Example of results are shown in Fig. 7.

We have compared obtained results. First of all - we calculated spectrum of the obtained signals. Results are shown in Fig. 8. Only relevant portion of spectrum has been shown.

IV. Discussion and Conclusion

In the paper we have checked possibility of respiratory signals retrieval out of the CECG signal captured on the smart chair.

By comparing data from a QRS amplitude variation, baseline drift and Heart rate variation (HRV) it van be shown that only HRV data seem to resemble reference data. As volunteer has been asked for breath for approx 10 seconds, hold breathing for another 10 s and breath normally again it is easy for visual inspection to see whether resulting EDR data resembles reference one.

From the calculated spectrum it is difficult to find similarity between reference and derived respiratory signal for all cases. This is due fact that whole signal has been taken into account - taking all the excercise.

There are several limitations regarding measurements. Person sitting in the chair must reduce body movements as electrodes are attached to the chair, not to the body.

Obtained example data are shown for randomly selected volunteer. We have analyzed in total data from 13 volunteers. For all cases results were similar except fact that motion artifacts occurred at different moments. From all observation HRV analysis seem to be best respiratory signal estimator.

References

[1] R. Fernandez Molanes, K. Amarasinghe, J. Rodriguez-Andina, and M. Manic. Deep learning and reconfigurable platforms in the internet of things: Challenges and opportunities in algorithms and hardware. In *IEEE Industrial Electronics Magazine*, volume 12, pages 36–49, June 2018.

[2] M. D. Valdes Pena, J. J. Rodriguez-Andina, and M. Manic. The internet of things: The role of reconfigurable platforms. In *IEEE Industrial Electronics Magazine, Sep. 21,*, volume 11, pages 6–19, 2017.

[3] D. Marino, C. Wikramasinghe, and M. Manic. An adversarial approach for explainable ai in intrusion detection systems. In *Proc. 44rd Annual Conference of the IEEE Industrial Electronics Society, IECON 2018, Washington DC, USA, Oct. 21-23*, 2018.

[4] K. Amarasinghe and M. Manic. Improving user trust on deep neural networks based intrusion detection systems.

[5] M. Kaczmarek, A. Bujnowski, K. Osi?ski, and J. Wtorek. A scale with ecg measurements capability for home cardiac monitoring. In *EMBEC 2017, NBC 2017. IFMBE Proceedings*, volume 65, pages 984–987, 2017.

[6] A. Bujnowski, J. Rumiński, A. Paliński, and J. Wtorek. Enhanced remote control providing medical functionalities. In *2013 7th International Conference on Pervasive Computing Technologies for Healthcare and Workshops*, pages 290–293, May 2013.

[7] Adam Bujnowski, Arkadiusz Palinski, Piotr Koscinski, Lukasz Skalski, Anna Skurczynska, and Jerzy Wtorek. Detection of person presence and its activity in the bathtub. *Journal of Physics: Conference Series*, 434(1):012035, 2013.

[8] Adam Bujnowski, Mariusz Kaczmarek, Kamil Osiński, Marta Gońka, and Jerzy Wtorek. Capacitively coupled ecg measurements - a cmrr circuit improvement. In Hannu Eskola, Outi Väisänen, Jari Viik, and Jari Hyttinen, editors, *EMBEC & NBC 2017*, pages 1109–1112, Singapore, 2018. Springer Singapore.

[9] A. Arcelus, M. Sardar, and A. Mihailidis. Design of a capacitive ecg sensor for unobtrusive heart rate measurements. In *2013 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*, pages 407–410, May 2013.

[10] Y. Sun and X. B. Yu. Capacitive biopotential measurement for electrophysiological signal acquisition: A review. *IEEE Sensors Journal*, 16(9):2832–2853, May 2016.

[11] Adam Bujnowski, Mariusz Kaczmarek, Jerzy Wtorek, Kamil Osiński, and Domnika Strupińska. Estimation of electrode contact in capacitive ecg measurement. In *Proceedings of 12th International Conference on Human System Interaction (HSI), Richmond, VA, USA, June 25-27*, pages 132–136, 2019.

[12] Antti Vehkaoja, A Salo, Mikko Peltokangas, J Verho, Timo Salpavaara, and Jukka Lekkala. Unconstrained night-time heart rate monitoring with capacitive electrodes. *IFMBE Proceedings*, 41:1511–1514, 01 2014.

[13] Piotr Przystup, Artur Poliński an Adam Bujnowski, Tomasz Kocejko, and Jerzy Wtorek. ”optimal ecg lead for deriving respiratory signal”. In *Proceedings of the 12th International Conference on Human System Interaction (HSI), Richmond, VA, USA, 2019,June 25-27*, pages 187–191, 2019.

[14] P. Przystup, A. Poliński, A. Bujnowski, T. Kocejko, and J. Wtorek. A body position influence on ecg derived respiration. In *2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 3513–3516, July 2017.

[15] J. M. Kim, J. H. Hong, N. J. Kim, E. J. Cha, and Tae-Soo Lee. Two algorithms for detecting respiratory rate from ecg signal. In R. Magjarevic and J. H. Nagel, editors, *World Congress on Medical Physics and Biomedical Engineering 2006*, pages 4069–4071, Berlin, Heidelberg, 2007. Springer Berlin Heidelberg.

[16] J. Pan and W. Tompkins. A real-time qrs detection algorithm. *IEEE Transactions on Biomedical Engineering*, 32(3):230–236, March 1985.

[17] Analog discovery product page, https://analogdiscovery.com/, access[20-02-2020].