Wireless body sensor data analytics - challenges and approaches

Aleksandra Rashkovska, Viktor Avbelj, Roman Trobec
Jožef Stefan Institute
Jamova cesta 39
1000 Ljubljana, Slovenia
{aleksandra.rashkovska, viktor.avbelj, roman trobec}@ijs.si

ABSTRACT
The development of information technology and telecommunications has reached a level where its usefulness can be applied for health care needs. The trends in recent years are towards wireless body sensors applied for long-term patient monitoring during different activities. However, the measurements from wireless body sensors, which are novel both in terms of their duration and activity coverage, require also novel approaches to their analysis. These novel algorithms should be able to deal with noisy and sparsely sampled ECGs and with various beat shapes. Furthermore, these algorithms should be able to run in real-time and on a computationally limited portable devices, while maintaining power efficiency. This paper presents the challenges and discusses the possible directions in the design of robust methods for efficient analysis of noisy differential ECG measurements made with wireless body sensors.

Categories and Subject Descriptors
J.3 [**Life and Medical Sciences**]: Health

General Terms
Algorithms, Measurement

Keywords
ECG, long-term monitoring, wireless sensor

1. INTRODUCTION
High-quality electrocardiogram (ECG) was first measured by Willem Einthoven at the beginning of the 20th century with his invention of the string galvanometer. The whole ECG machine weighted some 300 kg. Today, a range of ECG devices are used in medicine, from the well-known standard 12-lead ECG, where wires are connected to electrodes placed on 10 locations of the body, to multichannel ECG body surface mapping systems [19], to the Holter monitor, where reduced number of electrodes are connected with wires to a small portable recorder that obtains continuous ECG measurement throughout several days [18], and finally to the (wireless) implantable loop recorder measuring ECG for a period of several years and weights only 17 g [25]. The last is an invasive ECG measurement where a special device is inserted under the skin.

The development of information technology and telecommunications has reached a level where its usefulness can be applied for health care needs towards Telemedicine and Telecare, which represent a promising alternative for today's traditional hospital admission [3]. This basic premise is included in all strategic plans of the EU and the rest of the world [23]. Research efforts are focused on the development of devices and instruments which are smaller, simple to use and reliable. The trends in recent years are towards wireless body sensors applied for patient monitoring [12].

Our latest contribution to this topic is an open source system for mobile monitoring of vital physiological parameters and environmental context [2]. The system has been registered as a technology innovation at the Jožef Stefan Institute since April 15th, 2015. In the center of the system is a wireless multi-functional body sensor (dimensions: 2x9cm, weight: 14 g) that measures vital physiological and environmental parameters, with two electrodes at the distance of 8 cm [20]. The device primarily measures differential surface potential (ECG) between the proximal electrodes. The sensor has a long autonomy (up to 7 days), a low power wireless connection (BT4) to a Smartphone or other personal device, and corresponding software for standard interpretation of measurements. The moderate resolution ECG is suitable for long-term personal cardiac activity monitoring, as well as for clinical use. Its exceptionally lightweight design allows for unobstructed use also during sports activities or during exhaustive physical work. Besides ECG, other features can be extracted from the measured potential, such as muscle activity and respiration [21]. The sensor can also detect information about the measurement conditions such as movement and temperature, thus providing information that allows for ambient intelligence [5]. The device can support solutions to every-day problems of the medical personal in hospitals, health clinics, homes for the elderly and health resorts.

The multichannel ECG inspired our solution with 64 electrodes on the surface of the body. We recognized that a significant amount of information about heart activity could be measured just through the electric potential between two neighboring multichannel electrodes. Such an approach enables non-invasive measurement with a single-channel of bipolar ECG without wires. Thus, our solution is situated between the Holter monitor and the implantable loop recorder with the possibility of immediate access to the measured data. With appropriate placement of the device on the chest, good visibility of all electrocardiographic waves (P, QRS and T) can be achieved, allowing for quality ECG recording sufficient for medical analysis. In contrast, implanted ECG

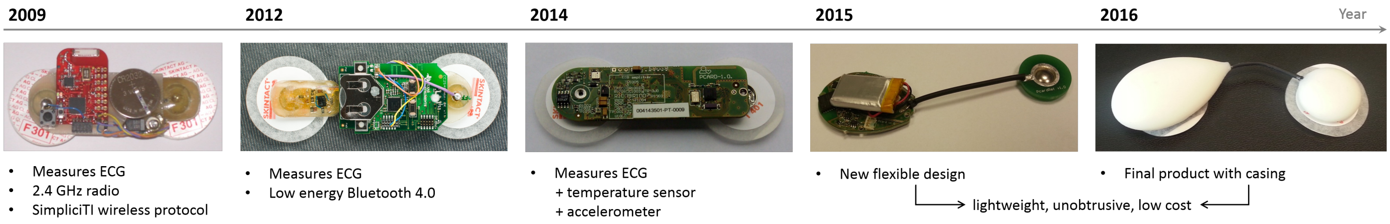

Figure 1: Wireless sensor evolution.

recorders often record P waves that are poorly visible or not visible at all. Compared to the Holter monitor, our solution is open source and wireless, low-cost and is already used for research purposes. Moreover, a commercial version of our sensor will be available soon on the market. The device in its current design is a result of almost 7 years of research, development, testing and upgrades. The evolution of the sensor design is presented in Fig. 1.

2. CHALLENGES

The Holter monitor has been the standard for long-term ECG monitoring for more than 50 years. It is time to move forward, follow the technological advances, and place wireless ECG monitoring devices in the health care system, like the previously described wireless body sensor. One of the main issues for the breakthrough of these sensors will be the availability of methods for analysis of the acquired data. Namely, current methods for ECG analysis are tailored for multichannel ECG equipment. On this type of equipment, more electrodes are used to obtain the signals. Usually one to three wired leads are utilized for ECG analysis since multiple channels provide multiple viewpoints on the signal.

In contrast, the acquired signal from the wireless sensor is differential ECG that offers just a single viewpoint of the state. This sets the crucial challenge for the ECG analysis of such signals. Moreover, in contrast to the standard 12-lead ECG signal, which is most often short and measured on a resting subject, the lightweight design of wireless sensors allows for several days long measurement on active subjects. Therefore, ECGs are noisier because measurements are made on physically active subjects, and additionally, because the electrodes are placed close together. Next, the sensor is not always placed on the subject by a trained professional and can be miss-oriented, thus producing a wide range of ECG orientations and noise levels. Finally, such devices are designed to be very energy efficient. Therefore, the measurements are sampled with lower frequency (app. 125 Hz) compared to the standard 12-lead ECG, which helps conserve battery life. All of the above issues pose serious challenges for the currently existing analysis methods to be directly applied on differential single-channel ECG.

It is clear that the measurements from wireless body sensors, which are novel both in terms of their duration and activity coverage, require also novel approaches to their analysis. These novel algorithms should be able to deal with noisy and sparsely sampled ECGs and with various beat shapes. Furthermore, these algorithms should be able to run in real-time and on a computationally limited portable devices, while maintaining power efficiency. So, the main goal should be to design robust methods for efficient analysis of noisy differential ECG measurements made with wireless body sensors.

3. TASKS AND METHODS

The methods for differential ECG analysis should be based on existing approaches, tailored for differential single-channel measurements, addressing their specific characteristics. Moreover, if none of the investigated approaches yields good performance, a novel method should be designed and implemented, which also needs to be verified by medical professionals. In particular, the tasks that should be addressed are discussed in the following, together with the corresponding analysis methods.

3.1 Preprocessing

The task of preprocessing includes reducing noise and baseline wandering. Noise is especially difficult to be filtered out of such measurements because of the absence of multiple channels that would provide multiple viewpoints on the signal. Additional challenge represents the wide spectrum of device orientations and consequently also noise levels. The methods for preprocessing range from the simplest and most widely used finite impulse response (FIR) recursive digital filters [10], through wavelet transformations [16], nonlinear Bayesian filters [15], and finally, to the extended Kalman filters [17].

3.2 Segmentation

Segmentation means detection of peaks of individual ECG waves and their duration (R peak or QRS complex, T peak, RT interval). Good layout of an ECG sensor with two electrodes should compromise between comfort, good visibility of the ECG waves, and minimal disturbance caused by movement. Different device orientations produce different ECG waveforms. Additional challenge to the segmentation task represents the low sample rate of such measurements. The segmentation stage is of a paramount importance for further analysis, like ECG classification.

Segmentation methods that need to be investigated include – for QRS detection, starting from simple ones, like nonlinear translations and adaptive detection threshold [11], to more sophisticated like methods based on neural networks [6], genetic algorithms [13], filter banks [1], Quad Level Vector [7]; and methods for detection of other waves, such as the P wave and the T wave [8].

3.3 Classification of heartbeats

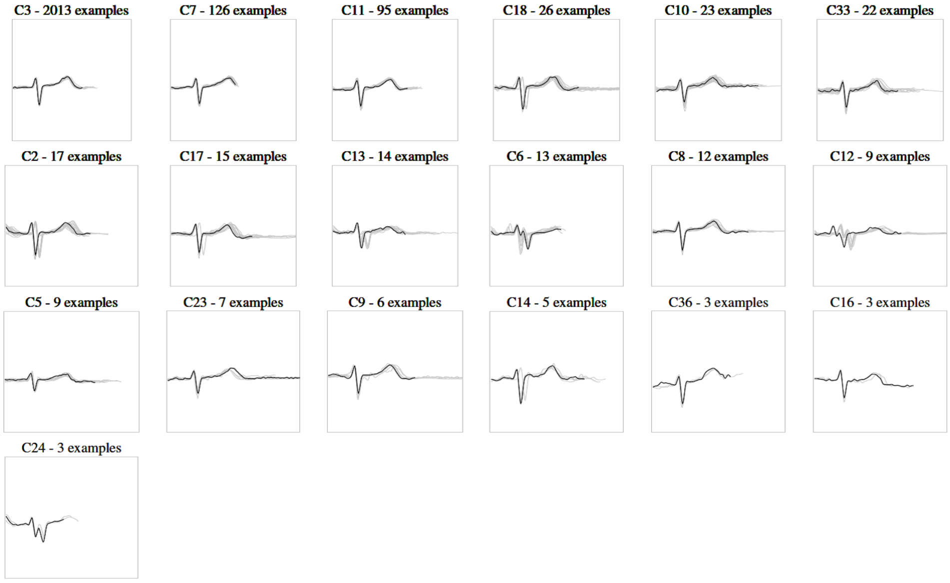

Figure 2: Clusters from differential ECG measurement.

The task of ECG classification should help in detection of unusual events (arrhythmias, heart rhythm disorders, and significant deviations from normal ECG morphology). Long-term ECG recordings are significantly longer and more heterogeneous than the measurements performed at a controlled hospital environment. Consequently, manual inspection of these recordings in order to identify different groups/clusters of heartbeats (that can be used for better describing the health status of the subject) is a tedious, hard and expensive job. Therefore, an alternative is to use computational techniques for automatic classification.

The most popular algorithms employed for this task are: support vector machines (SVM) [24], artificial neural networks (ANN) [22], linear discriminant analysis (LDA) [9], and reservoir computing with logistic regression (RC) [4]. Combining classifiers has been little explored for the task in question. Important stages in the classification task are also: clustering (grouping of similar beats) - the clustering results will form the base for annotation of the ECG beats and formation of a database; and feature extraction and selection, if the method is feature based. Special attention should be given to the potential influence of the preprocessing and segmentation tasks on the final classification results.

Hierarchical agglomerative clustering on differential ECG measurements in conjunction with dynamic time warping distance has already been demonstrated in [14]. An example of obtained clusters from differential ECG measurement acquired while sitting is shown in Fig. 2. Results show that the clustering method identified different cardiac events in the measurements (98.72 % clustered beats). The clusters with the highest number of examples do not have the P wave present, indicating atrial fibrillation (87%). Some other smaller clusters, like C11 and C5, can also be identified as atrial fibrillation. The rest of the clusters (12%) belong to normal sinus beats, except for C6, C12 and C24, which indicate SVES (Supra Ventricular Extra Systole).

3.4 Extraction of new knowledge

Additional information can be derived from the measured bio-potential difference on the body surface. The measured bio-potential on the surface of the body can give most of the information on the health status of the individual. For example, extracting the respiration rate based on the amplitude changes in the body surface potential differences between two proximal body electrodes - a technique known as ECG-derived respiration (EDR), already tested on simulated differential ECG from measured multichannel ECG [21]. These technique should be tested also on real differential ECG and the method should be adjusted accordingly.

3.5 Ambient intelligence

The sensor is characterized by the fusion of different sensing functions in a single multi-functional sensor. Measured signals can be combined in order to improve the reliability and robustness of the readings, and make reliable conclusions about the overall health condition [5]. Methods for ambient intelligence include predictive and decision models built upon all the sensor-gathered data and data from health information reference models to better understand the condition of the user and therefore better understand the user's current health and behavior. Three monitoring and data analysis classes are envisioned:
- short-term behavior and health analysis – focusing on the last few minutes of data (alarming situations, falls, arrhythmias),
- medium-term behavior analysis – focusing on the past day (gait analysis), and
- long-term behavior analysis (daily/weekly anomalies) related to occasional health problems in real life, such as prolonged emotional stress, events of prolonged higher or lower physical activity, etc.

Although these tasks can be treated separately, they are also interconnected. Namely, the preprocessing task usually precedes the segmentation task; the segmentation task precedes the classification, etc. Consequently, the selection of methods in each of the tasks can have a crucial implication on the results from the particular task in question and consequently, the medical interpretation of such results. Therefore, the ultimate goal should be to investigate how selection of different methods in one task can influence the results in the forthcoming tasks.

4. CONCLUSIONS

Efficient and reliable methods for analysis of signals acquired by wireless body sensors will increase the interest for such devices and will push them forward to become the new standard in patient monitoring and health care. The wider penetration of these devices is expected to reduce health care costs and at the same time increase the effectiveness of health care. The system will be useful for users at home, in nursing homes and health centers, and homes for the elderly. The work of medical personnel will be less stressful and more effective. Medical personnel will be relieved of repetitive work that can lead to mistakes and delays in the treatment process. In the longer term, all above is expected to increase the performance level of the health care.

5. ACKNOWLEDGMENTS

This work was partially supported by the Slovenian Research Agency under the Grant P2-0095.

6. REFERENCES

[1] V. X. Afonso, W. J. Tompkins, T. Q. Nguyen, and S. Luo. ECG beat detection using filter banks. *IEEE Transactions on Biomedical Engineering*, 46:192–202, 1999.

[2] M. Depolli, V. Avbelj, R. Trobec, J. M. Kališnik, T. Korošec, A. P. Susič, U. Stanič, and A. Semeja. PCARD Platform for mHealth Monitoring. *Informatica*, 40:117–123, 2016.

[3] A. Ekeland, A. Bowes, and S. Flottorp. Effectiveness of telemedicine: A systematic review of reviews. *Int. J. Med. Inform*, 79:736–771, 2010.

[4] M. A. Escalona-Moran, M. C. Soriano, I. Fischer, and C. R. Mirasso. Electrocardiogram classification using reservoir computing with logistic regression. *IEEE Journal of Biomedical and Health Informatics*, 19:892–898, 2015.

[5] H. Gjoreski, A. Rashkovska, S. Kozina, M. Luštrek, and M. Gams. Telehealth using ECG sensor and accelerometer. In *Proceedings of MEET & GVS on the 37th International Convention MIPRO*, pages 270–274, 2014.

[6] Y. H. Hu, W. J. Tompkins, J. L. Urrusti, and V. X. Afonso. Application of artificial neural networks for ECG signal detection and classification. *Journal of Eletrocardiology*, 26:66–73, 1990.

[7] H. Kim, R. F. Yazicioglu, P. Merken, C. van Hoof, and H. J. Yoo. ECG signal compression and classification algorithm with quad level vector for ECG holter system. *IEEE Transactions on Information Technology in Biomedicine*, 14:93–100, 2010.

[8] P. Laguna, R. Jané, and P. Caminal. Automatic detection of wave boundaries in multilead ECG signals: Validation with the CSE database. *Computers and Biomedical Research*, 27:45–60, 1994.

[9] M. Llamedo and J. P. Martínez. Heartbeat classification using feature selection driven by database generalization criteria. *IEEE Transactions on Biomedical Engineering*, 58:616–625, 2011.

[10] P. Lynn. Recursive digital filters for biological signals. *Medical and Biological Engineering and Computing*, 9:37–43, 1979.

[11] J. Pan and W. J. Tompkins. A real-time QRS detection algorithm. *IEEE Transactions on Biomedical Engineering*, 32:230–236, 1985.

[12] A. Pantelopoulos and N. G. Bourbakis. A Survey on Wearable Sensor-Based Systems for Health Monitoring and Prognosis. *IEEE Transaction on Systems, Man, and cybernetics–part C: Applications and reviews*, 40(1), 2010.

[13] R. Poli, S. Cagnoni, and G. Valli. Genetic design of optimum linear and nonlinear QRS detectors. *IEEE Transactions on Biomedical Engineering*, 42:1137–1141, 1995.

[14] A. Rashkovska, D. Kocev, and R. Trobec. Clustering of heartbeats from ECG recordings obtained with wireless body sensors. In *Proceedings of MEET & GVS on the 39th International Convention MIPRO*, pages 481–486, 2016.

[15] R. Sameni, M. B. Shamsollahi, C. Jutten, and G. D. Clifford. A nonlinear Bayesian filtering framework for ECG denoising. *IEEE Transactions on Biomedical Engineering*, 54:2172–2185, 2007.

[16] O. Sayadi and M. B. Shamsollahi. Multiadaptive bionic wavelet transform: Application to ECG denoising and baseline wandering reduction. *EURASIP Journal on Advances in Signal Processing*, 14:1–11, 2007.

[17] O. Sayadi and M. B. Shamsollahi. ECG denoising and compression using a modified extended Kalman filter structure. *IEEE Transactions on Biomedical Engineering*, 55:2240–2248, 2008.

[18] SCHILLER AG, Switzerland. *ECG Measurements and Interpretation Programs, Physician's Guide*, 2009.

[19] R. Trobec. Computer analysis of multichannel ECG. *Comput Biol Med*, 33(3):215–226, 2003.

[20] R. Trobec, V. Avbelj, and A. Rashkovska. Multi-functionality of wireless body sensors. *The IPSI BgD transactions on internet research*, 10:23–27, 2014.

[21] R. Trobec, A. Rashkovska, and V. Avbelj. Two proximal skin electrodes - a respiration rate body sensor. *Sensors*, 12:13813–13828, 2012.

[22] E. D. Übeyli. Combining recurrent neural networks with eigenvector methods for classification of ECG beats. *Digital Signal Processing*, 19:320–329, 2009.

[23] WHO. eHealth tools and services: Needs of the Member States. Report of the Global Observatory for eHealth, 2006.

[24] C. Ye, V. Bhagavatula, and M. T. Coimbra. Heartbeat classification using morphological and dynamic features of ECG signals. *IEEE Transactions on Biomedical Engineering*, 59:2930–2941, 2012.

[25] C. Zellerhoff, E. Himmrich, D. Nebeling, O. Przibille, B. Nowak, and A. Liebrich. How can we identify the best implantation site for an ecg event recorder? *Pacing Clin Electrophysiol*, 23:1545–1549, 2000.