Machine Learning for Contactless Low-Cost Vital Signs Monitoring Systems

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Abstract. Following a growth of the elderly population in developed countries, a growth in research towards contactless measurement systems for this public has been observed. The development goes often in the direction of intelligent systems to support nursing staffs in assisted living residences. This can also be foreseen for those living alone at home. In this work, two contactless sensing systems are presented, one of them already with an optimized algorithm based on machine learning. Moreover, the optimization of a specific parameter and of an inclusion of a boundary condition for the algorithm are explained.

Keywords: Machine learning; Ballistocardiography; Contactless sensors; Cardiac measurements; Low-cost sensors.

1 Introduction

An increase of low-cost contactless/cuffless monitoring and alarming systems are required to keep up with the demographic changes in the world. It is estimated that the percentage of the German population above 60 years old will reach 34.6% in 2030 [1]. These systems are important to allow the independence and a normal life of especially elderly people living alone, but they could also be used in retirement homes to alarm nursing or medical assistances.

Different sensor designs have been previously presented to allow vital sign measurements using ballistocardiography (BCG) practically in any position on a bed [2], couch [3] or standing [4] anywhere in the house. In general, unsupervised machine learning (ML) algorithmics (also known as pattern recognition) are used for vital sign monitoring. The reason is that the signals are normally periodical within a known frequency range. Moreover, body movements due to respiration and heartbeat, make vital signals even easier to be sensed. In the case of cardiac measurements, they are realized through BCG. This allows the algorithm to cluster the diverse peaks generated by the human body according to their similarities (normally known as dissimilarities) and determine the cardiac periods. Such measurements can be realized with distinct body positions, in different parts of the house or furniture and diverse sensing principles. However, adjustments related to the clustering parameters and boundary conditions can be optimized to increase the recognition rate of the systems.

In this work, two sensors briefly shown as well as a shown introduction of the ML algorithm. Furthermore, the improvement due to an optimization of parameter and of an inclusion of a boundary condition in the algorithm is present.

2 Sensors and Machine Learning

Most of the sensors must be designed considering several different points such as the position of the sensor, sensing object, interface and nature of the signal. To exemplify these in the environments mentioned in the introduction, the furniture selection, measurements required, and interface must be considered in the design to allow proper measurements.

According to the literature, the strongest cardiac component from a human body can be measured along the foot-head axis [5]. Therefore, a low-cost strain-gauge sensor (for scales up to 5 kg) was placed at the top end of the mattress (see Fig. 1). This position choice had the goal of maximizing the cardiac component and reducing the respiration component magnitude in BCG measurements. This allows a higher cardiac recognition rate by the ML algorithm. A 24-bit HX711 analog-to-digital converter from AVIA Semiconductor was used. Electrocardiogram (ECG) measurements using an AD8232 Heart Monitor were synchronized with BCG using an Arduino Uno.

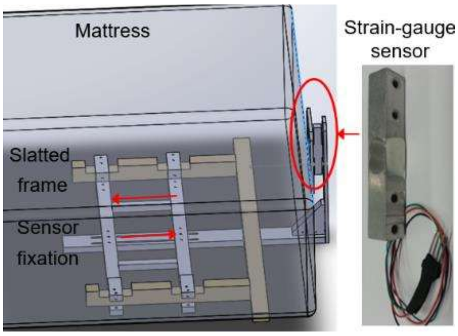

Fig. 1. Schematic of the measurement setup using a strain-gauge at the top end of the mattress [2]

For a person seating down, strain-gauges were replaced by piezo disks [3]. This type of setup has the advantage of reacting only to movement changes, and no offset signal due the person's weight is measured. Different signals are generated due to distinct positions. Other than his vital signs, a determination of the subject's position could also be indicated by specific patterns for each position. The dashed circles in Fig 2 were used to mark the different respiratory cycles.

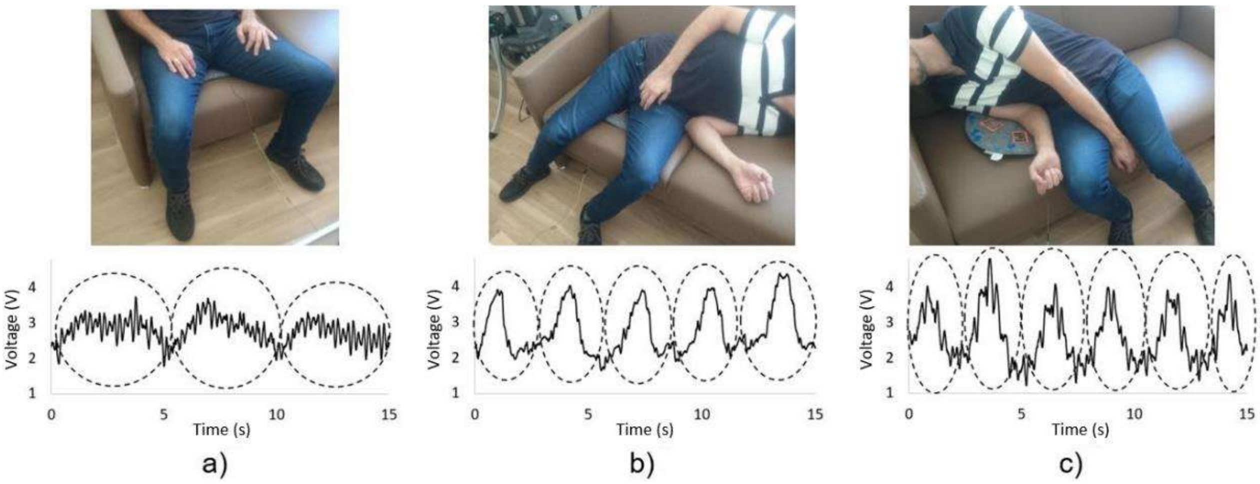

Fig. 2. Measurement of a subject a) seating on the coach with the sensors placed right below his trunk, b) seating on the sensor but leaning away from it and c) laying on the coach with the side body over the sensing area [3]

After measuring BCG, different filters were used to separate cardiac and respiratory components [2]. The solution adopted consists of a peak detection function and the allocation of the measurement points in the next 0.66 s in a vector [6]. This corresponds to vector with lengths of 56 for our settings. Then, an arccosine function [7] was chosen to calculate the angle between vectors x and y according to their dissimilarity d for a period of 10.66 s. These angles are compared using equation (1) and its boundaries [2]. For the boundary conditions, $\alpha = 3$ and $t_{min} = 0.33$ s were used. After calculating d for all the vectors is this certain window (i.e. 10.66 s), these vectors are clustered, the largest cluster with the lowest d is chosen as the beginning of the cardiac cycle.

$$d(x,y) = \begin{cases} cos^{-1}\left(\frac{x^T y}{\|x\|\|y\|}\right), & if \ \frac{1}{\alpha} < \frac{\|x\|}{\|y\|} < \alpha \ \ and \ \ |t_{x_1} - t_{y_1}| > t_{min} \\ \pi \ , & otherwise \end{cases} \tag{1}$$

where the vectors first elements are represented by x_1 and y_1.

3 Results and Discussion

The results presented in this section are only from measurements realized on a bed with the strain-gauge setup. An assumption made in our previous work [2], does not consider that the algorithm can select different BCG waves for the following window. In this case, an error is introduced during the transition to the next window. For this reason, effective heartbeat calculations were realized for 10 s, while the detected peaks in the overlapped region of 0.66 s were not considered for calculation (see circle in Fig. 3). Thus, the next calculation is done between first and second selected BCG waves of the second 10 s window shown in Fig. 3. This will be shown in detail in our upcoming study [8].

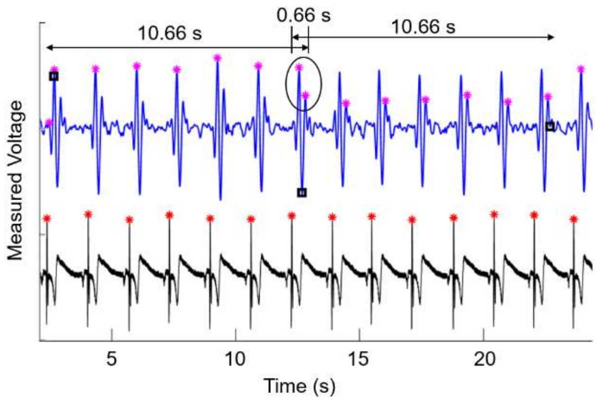

Fig. 3. Synchronized ECG and filtered cardiac component from a BCG measurement, *squares* indicate the beginning of a new window and the *pink stars* represent the selected cardiac cycle start

This modification allowed the inclusion of a further boundary condition. All detected peaks received an index number (see Fig. 4, left graph) after peak detection. However, d is directly assumed as π if the index difference is smaller than 3. Let us take peak 9 as an example, d is not calculated for peaks 7, 8, 10 and 11. A further improvement was then possible with this boundary condition, a parameter which determines the cluster sizes due to dissimilarity was initially set as 1 rad [2]. This value has been suggested as $\pi/4$ rad for BCG measurements using piezoelectric pressure sensors [7]. However, the optimal value for strain gauges placed at the top end of the bed for a set of almost 10 subjects was determined as 1.2 [8]. The reason for this value might be related to the sensor system, which requires higher dissimilarities to allow the suppression of false positive detections. These adjustments have allowed an average improvement of heartbeat recognition above 8% for different patients laying on a bed in supine, prone, right and left side positions (see Table 1). Even though the same algorithm could be directly used with to analyze the measurements shown in Fig. 2, settings improvements would be required to reach acceptable recognition rates.

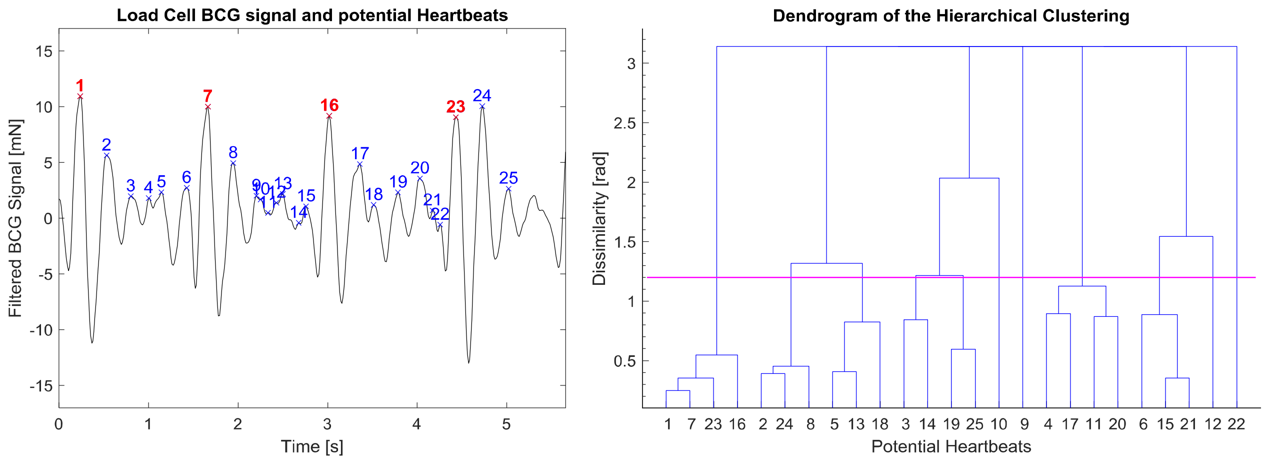

Fig. 4. Cardiac component extracted from a BCG measurement after peak recognition, used as starting point for the feature vectors (left side) and dendrogram with clustered vectors (right side)

Table 1. Heartbeat recognition in % using either none [2] or index equals 3 [8] for the clustering process

Subjects	Index	Supine	Prone	Left Side	Right Side
1	None	96.1	75.0	89.3	90.0
	3	98.2	88.6	96.6	98.0
2	None	89.2	91.7	78.0	77.3
	3	94.3	96.4	91.2	90.0

4 Conclusion and Outlook

The requirement of contactless monitoring systems especially for elderly people is real, and several measurement principles are already available. Sensor setups still can be improved and optimized to reach better results and more affordable prices. Moreover, it was shown that the actual machine learning algorithms must be adjusted for a certain system and are not universal. Therefore, it is expected that these settings optimizations to improve signal analysis and, consequently, vital sign monitoring be done automatically by the system using artificial neural networking in the future.

Acknowledgments

This work was partly financed by the Federal Ministry of Education and Research of Germany under the IKT2020 – Innovations in Care for People with Dementia. The authors are grateful for the support from the Alexander Bejan and the staff from the Future Care Lab at the Hochschule Furtwangen where several measurements were carried out.

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