Engineering Proceedings

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Smart Seismocardiography: A machine learning approach for automatic data processing

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† Presented at the 8th Electronic Conference on Sensors and Applications, 1–15 November 2021; Available online: https://ecsa-8.sciforum.net/.

Abstract: Seismocardiography (SCG) is a non-invasive method that measures local vibrations created by the mechanical cardiovascular exercises on the chest wall. Thereby, mechanical movements of the heart are recorded in real-time from vibration sensors positioned on the chest of the subject, to further compute the heart rate and retrieve the SCG waveform. Although such events have been widely studied, robust signal processing methods remain a challenging task. On the other hand, the use of piezoelectric sensors has been favored in recent years due to its features and low-cost. However, robust data processing techniques should be developed to increase their performance and reliability. In this work, we propose an attractive method for SCG data processing based on the K-Means clustering algorithm to automatically label waveform events. Interestingly, the SCG signals are recovered from a custom-made device built around an ultra-low-cost piezoelectric sensor. Once the signals are measured, they are pre-processed by spectral filtering. Afterwards, the signal spectrum is used to compute the heart rate (HR). Thereby, the filtered signal is sequentially segmented, and every frame is processed by a light-weight K-Means algorithm. Finally, we show the performance of the smart seismocardiography by analyzing SCG waveforms at different physiological conditions.

Keywords: Seismocardiogrphy; Piezoelectric sensor; K-Means algorithm

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Citation: López-Rico, O. and Ramírez-Chavarría, R.G. **Smart Seismocardiography: A machine learning approach for automatic data processing** . *Eng. Proc.* **2021**, *1*, 0. https://doi.org/

Received:
Accepted:
Published:

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1. Introduction

Cardiovascular disease (CVD) is a major cause of death worldwide [1]. Continuous cardiac monitoring is necessary for the diagnosis and to follow-up the CVD. However, common cardiac health monitoring systems are highly expensive and require specialized medical personnel for testing and diagnostic, which implies that patients should go to hospitals whenever they need a check-up. To circumvent such difficulties, several techniques have been proposed besides of the electrocardiography (ECG), among which stands out the seismocardiography (SCG).

SCG is a non invasive technique to measure vibrations on the chest wall, caused by cardiac mechanical processes, e.g.: heart valves closure and opening, blood momentum changes and myocardial movements [2]. The change in volume, pressure and shape of the heart, during this mechanical processes, produces vibrations on the tissues near the heart generating pulsations in the chest wall [3]. Then, the pulsations are recorded from vibration sensors to retrieve the SCG waveform, to further compute the heart rate and assess the cardiovascular phenomena.

To perform SCG measurements, accelerometers are widely accepted to recover the seismographic signal due to its performance [2]. Nevertheless, it requires a correct sensor placement in the chest wall of the test subjects, which is complicated due to its rigid structure. Recently, piezoelectric sensors have demonstrated its effectiveness to measure

SCG signals, enabling flexibility and reliable results [4–8]. Piezoelectricity is a phenomenon that occurs in certain crystals that, when subject to a mechanical stress, they produce a potential difference at their surface [9]. Piezoelectric materials are small, flexible, and relatively inexpensive. However, the use of piezoelectric brass diaphragms, for SCG, has not been studied as an alternative for developing werable devices (WD), despite their low cost and small size.

In general, an SCG waveform is labeled using ten cardiac mechanical processes as shown in Table 1, and three cardiac time intervals, delimited by the temporary appearance of signal peaks [10–14]: Isovolumetric Contraction Time (IVCT) (MC to AO), Left Ventricular Ejection Time (LVET) (AO to AC) and Isovolumetric Relaxation Time (IVRT) (AC to MO). Inherently, the SCG wave morphology is complex due to the large inter-subject and intra-subject variability. Depending on age, weight, gender and posture, heart rate, sensor type or position a SCG recording could contain many cardiac cycles with low-quality peaks [15]. Thereby, identifying peaks and events within SCG signals is not straightforward using semi-empirical-based methods, and robust methods should be introduced.

Table 1. Cardiac mechanical processes associated with the SCG signal events.

SCG event	Cardiac Mechanical Process	SCG event	Cardiac Mechanical Process
AS	Atrial systole	RE	Rapid ventricular ejection
MC	Mitral valve closure	PE	Peak ventricular ejection
IM	Isovolumetric movement	AC	Aortic valve closure
AO	Aortic valve opening	MO	Mitral valve opening
IC	Isotonic contraction	RF	Rapid ventricular filling

The use of ML approaches for data-driven problems has increased in recent years [3,10,14–19]. Particularly, ML has been applied to heart beat segmentation and cardiac events. For instance, in [10] and [15], an automatic annotation of peaks is proposed. Otherwise, unsupervised ML algorithms are used for clustering SCG signals in [3] and [14] using K-Means to detect patterns.

In this work, we introduce the smart seismocardiography as an attractive tool for measurement and data processing to assess cardiovascular events. The SCG signal is measured from a custom-built WD built around an ultra-low-cost brass piezoelectric diaphragm. Once the signals are recorded, they are cleaned-up by spectral filtering. Thus, the filtered signal is sequentially segmented, and each frame is processed by a lightweight K-Means algorithm for clustering and automatic annotation of SCG events.

2. Materials and Methods

Figure 1 shows the block diagram of the smart seismocardiography system. First, the brass piezoelectric sensor is positioned on the lower sternum body from where the raw signal is measured. Then, the signal was conditioned using a voltage-mode amplifier and digitized with a digital-to-analog converter (ADC)-based acquisition system. Subsequently, the acquired signal was pre-processed with a spectral filtering technique to remove high-frequency components. Afterwards, a peak detection algorithm (PDA) was used to segment the SCG signal using the IC cardiovascular event as the reference (see Table 1). Finally, the SCG segments were examined to find the possible SCG event, which were then processed by the K-Means algorithm to provide a an automatic labeling method.

2.1. Sensor and signal conditioning

For SCG measurements, we used the CEB-27D44 device, an ultra-low-cost brass piezoelectric diaphragm sensor with 27 mm diameter [20]. The sensor was placed into the chest wall to measure the pulsations caused by the heart beat. These induced small deformations in the sensor material, thus producing voltages with an amplitude of around 10 mVpp. To measure the SCG signal, the output of the piezoelectric sensor was amplified

using a voltage-mode amplifier, which was built around the TLV2771 operational amplifier. Thereby, the output voltage V_o can be expressed as

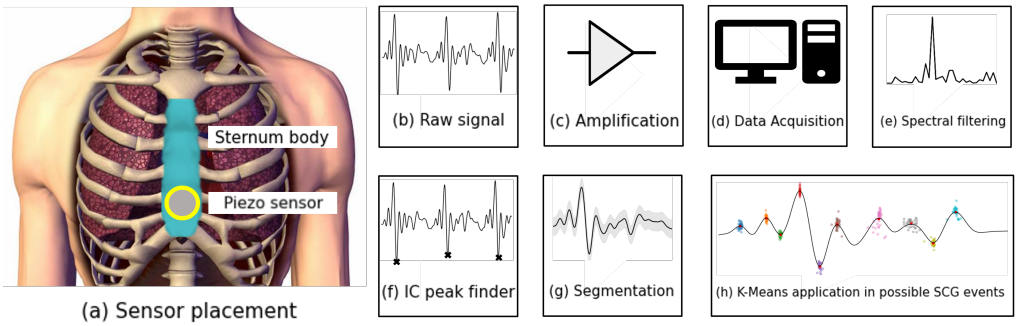

Figure 1. Block diagram of the proposed system for the smart seismocardiography.

$$V_o = V_p \times G + V_{\text{offset}}, \tag{1}$$

where $V_p = q_p/(C_p + C_c)$ is the voltage produced by the piezoelectric sensor, with q_p the electric charge produced by the sensor, C_p the capacitance determined by the area, the width, and the dielectric constant of the material, and C_c the lead capacitance. On the other hand, $G = 1 + (R_f/R_g)$ is the amplifier gain, which user-selected given the resistors R_f and R_g, thus producing an output voltage swinging around the voltage level V_{offset}.

2.2. Measurement protocol

Two test subjects participated in our study: S1 (male, 24 years old, 70 Kg) and S2 (female, 25 years old, 60 Kg). The subjects provided their consent, and verbally reported no history of cardiovascular disease. The subjects were comfortably seated in a chair with a back. The sensing device was placed on the low sternum fixed with a medical grade transparent film adhesive. The test subjects were asked to relax and hold their breath during data recording. The signal was acquired by means of an ADC with 16-bit resolution and a frequency sampling of 11 kHz, thus leading to a record of approximately $N = 300000$ samples per measurement.

2.3. SCG signal pre-processing

Once the SCG signal was recorded, it was pre-processed using a spectral filtering technique with a low-pass frequency of 25 Hz. Since the SCG spectrum covers the infrasonic range [5], we limited the high-pass frequency from the highest peak, in the spectral range of 0.8 to 2.0 Hz, which corresponds to the heart rate (HR) under regular conditions. Owing that each SCG cycle exhibits a minimum peak that corresponds to an IC event [12], the PDA detects the IC events as a reference to indicate the start of the SCG segment in the AS event, this allowing to perform an automatic segmentation procedure.

2.4. K-Means algorithm for SCG clustering

The algorithm uses an iterative process, which aims to cluster an input data set into K groups [23–25]. To execute the algorithm we pass as input the data set and a value of K. The data set will be the characteristics or features for each point, in this case, the amplitude and sample number of the presumed cardiovascular events. The initial positions of the K centroids will be randomly assigned from any point in the input data set. Then it iterates in two steps: Data assignment and update centroids.

In the first step, each row in our data set was assigned to the closest centroid based on the Euclidean distance (d) of data vectors X and Y as follows

$$d(X,Y) = \sqrt{\sum_{i=1}^{i=n}(x_i - y_i)^2}, \quad (2)$$

where x_i represent the $i-$th value of horizontal axis in the coordinate plane, y_i stand for the value of vertical axis in the coordinate plane, and n is the number of observations. Subsequently, the centroids of each group are recalculated. This is done by taking an average of all the points assigned in the previous step. The algorithm iterates between these steps until it meets the following stop criterion: if there are no changes in the points assigned to the groups, or if the sum of the distances is minimized.

3. Results and discussion

In Figure 2(a), we show the low-pass filtered SCG signal (continous line) and the IC peaks retrieved by the PDA (marks). As can be seen in Figure 2(b), the SCG signal was segmented using the detected peaks, and then, the average of the segments was computed to account for the variability of the measurement. Also, from Figure 2(b), it is worth to notice that the SCG signal showed negligible differences in the morphology of each segment, and instead, it was systematic and uniform throughout the segments. Therefore, once the segmentation succeeded, the presumed SCG events, from each cycle, were used as the input data set for the clustering algorithm.

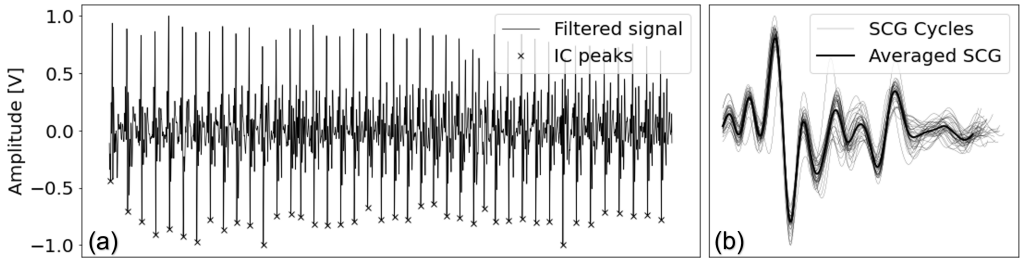

Figure 2. SCG signal measurement and segmentation. (a) Filtered signal (continuous line) and the peaks (marks) found by the pre-processing algorithm. (b) SCG cycles and their average.

As the input of the K-Means algorithm, we considered the signal amplitude and sample number of each presumed SCG event. Moreover, each event was discriminated depending on whether it is an event associated with a minimum peak or a maximum peak. Subsequently, the algorithm clusters first the presumed events associated with maximum peaks (AS, MC, AO, RE, PE, AC, RF), and then, those associated with minimum peaks (IM, IC, MO). Results of the K-Means algorithm are depicted in Figure 3, alongside the SCG average, as a reference. Each label was then assigned in the order of appearance of the clusters. As shown in Figure 3, the clustering procedure showed an excellent performance by grouping each of the cardiovascular events with enough accuracy and sensitivity. Interestingly, the IC cluster does not show temporal variability because the IC peaks were used as a reference for segmentation, so the temporal variability in the rest of the clusters is relative to the IC cluster.

To assess the variability of the proposed method, in Figure 4 we show box plots for the statistically analyze the SCG clusters of subjects S1 and S2. The analysis was made by considering the variation of the amplitude in each cardiovascular event (Figures 4(a) and 4(d)). Therein, the analysis shows low variability between and within subjects (tens of mV), despite physiological conditions. The amplitude of the AO peak in S1 is the highest peak, while in S2 it is the RF peak. In both cases, the lowest peak correspond to the IC peak. On the other hand, Figures 4(b) and 4(e) show the variability in the time differences for each SCG cluster. The IC cluster shows temporal variability approximately equal to zero due to the IC peaks were used as a reference for segmentation. It is worth to notice that PE and AC clusters are those with the large temporal variability (20 to 50 ms), whereas, the other clusters, does not exceed 20 ms. Finally, as shown in Figures 4(c) and 4(f), it was

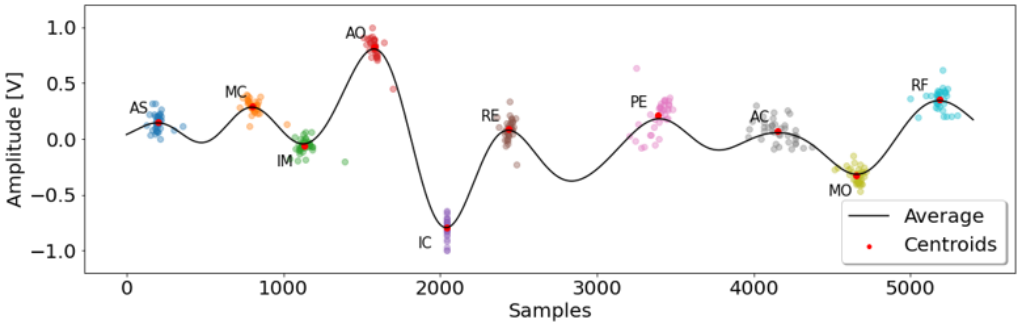

Figure 3. Results of the K-Means algorithm for SCG clustering. Centroids and peaks associated with unrepresentative events are hidden.

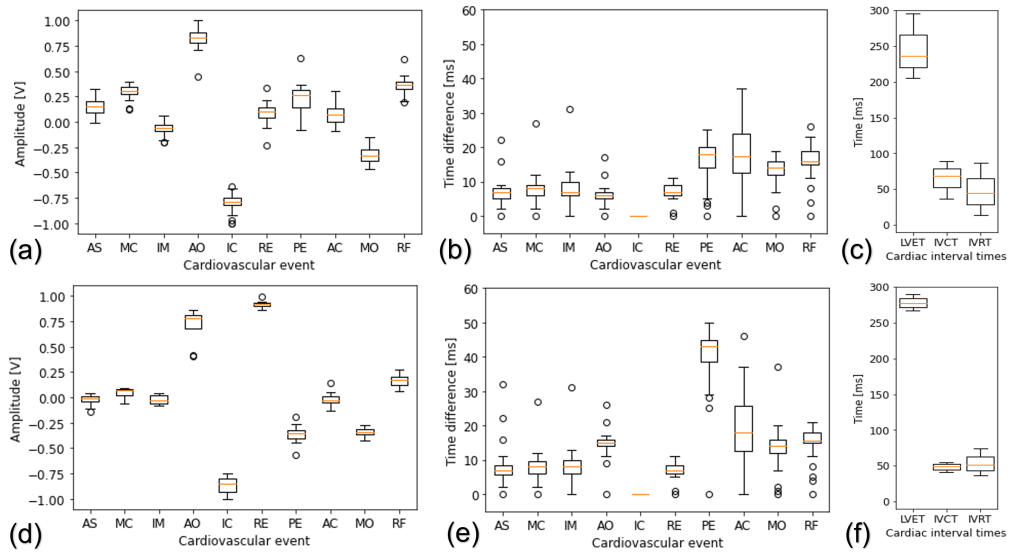

Figure 4. Statistical analysis of SCG clusters for subjects S1 and S2, in the upper and lower plots, respectively. (a) and (d) Variation of the amplitude in each cardiovascular event. (b) and (c) Time difference between each grouped cardiovascular event. (c) and (f) Temporal variation between each calculated cardiovascular time interval.

possible to estimate the cardiac time intervals, thus retrieving three clusters with similar mean values each, for both test subjects. This makes sense since S1 and S2 were subjects with normal cardiovascular conditions, which guarantees reproducible results for the smart seismocardiography.

4. Conclusions

In this work, we introduced the so-called smart seismocardiography (SCG) as an attractive method for clustering cardiovascular events. The proposal worked around a wearable device (WD) based on an ultra-low-cost brass piezoelectric sensor that captures the mechanical vibrations of the heart. We showed how the K-Means algorithm can automatically cluster SCG events using unsupervised ML techniques, which remains a scientific challenge. Preliminary results indicated that WD coupled with ML leads into a powerful tool to retrieve information on cardiac mechanical processes and cardiac time intervals. We showed how the smart seismocardiography could serve as proof-of-concept to design novel home-made and cost-effective and smart devices, exhibiting enough sensitivity and accuracy to automatically assess physiological signals.

Acknowledgments

This works was supported by the grant UNAM-PAPIIT TA100221. OYLR thanks CONACyT for the MSc studies grant (CVU: 1084874).

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