Motion Noise Cancellation in Seismocardiogram of Ambulant Subjects with Dual Sensors

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Abstract—This paper presents a dual-sensor method of extracting seismocardiographic (SCG) data from moving adult subjects using chest-worn wireless MEMS accelerometers. A digital signal processing (DSP) system including a normalized least means square (NLMS) adaptive filter is designed and tested in MATLAB. Data results from 10 subjects indicate a detection rate of 98.72% which outperforms our previously-proposed single-sensor scheme. Various sensor positions and possible failure mechanisms are also investigated to further evaluate the system performance. The results reveal that the quality of the SCG signal from moving subjects could be improved by integrating information from multiple sensors at the cost of increasing system complexity.

I. INTRODUCTION

Seismocardiography (SCG) is the recording of the vibrations of the chest wall occurring in response to the heart beat. Its measurement was first realized in the 1960s [1] and was applied to clinical studies in the 1990s [2]. Compared to other cardiac monitoring technologies, SCG directly reflects the mechanical activities of the heart, showing higher sensitivity in detecting cases of coronary artery disease [3]. It is also a good companion to electrocardiogram (ECG) with a combined sensitivity comparable to radionuclide and echo imaging technologies. Being compatible with magnetic fields is another advantage for SCG, as it can provide measurements during Magnetic resonance imaging (MRI) processes. The simple deployment of modern wearable SCG devices, which generally don’t need any preparation of the skin or electrode attachments would also be an advantage when a fast field emergency vital sign monitoring is needed such as in search and rescue situations.

Due to the rapid development of microelectromechanical systems (MEMS) in recent years, SCG can now be monitored using highly sensitive and low-cost MEMS accelerometers [4]. Several researchers have benefitted from MEMS accelerometers to investigate the clinical and homecare potential of SCG in robust setups including textile-based wearable devices [5] and wired data acquisition systems. However, most of the research so far has focused on subjects at steady positions in a clinical environment. The ability to track heart activity during movements would be beneficial in many cases, for example for monitoring high-risk patients in daily life, or for analyzing heart activity in subjects performing sports [6], or for preventing sudden heart failure during athletic activities [7].

Continuous monitoring of moving subjects brings the problem of motion artifacts (MA) into focus since accelerometers are sensitive to all environmental motions. Motion noise cancellation is therefore critical in such situations. In 2012, Di Rienzo et al. developed an algorithm that selects movement-free data segments from long-term recordings of SCG from ambulant subjects [8]. They applied a threshold-based algorithm which focuses on the standard deviation of the recorded signal as a spec for choosing movement-free segments. Pandia et al. implemented a DSP system based on a polynomial smoothing filter to extract heart sound signals from SCG recordings of walking subjects [9]. These methods result in a trade-off between signal quality and signal continuity, as they either realize a better detection rate by losing some signal information [9] or achieve a better signal quality at the cost of losing continuity in time [8].

Our group has recently proposed a single-sensor method of recovering SCG signals of moving subjects with a higher motion tolerance compared to the previous works mentioned above [10]. The method utilized a MEMS accelerometer on the front chest wall and processed data through a DSP system based on adaptive filtering. The present work focuses on using dual sensors to improve the signal quality and evaluates the effectiveness of the approach via experimental results.

II. METHOD

A. The Hardware System

Our proposed system contains two commercial, wearable wireless sensor nodes (Shimmer 3 from Shimmer Sensing [11]) which are attached on the front chest wall and back of the subject. The front node is capable of recording acceleration and ECG signals while the back node only measures acceleration using the same type of accelerometer as the front one. As illustrated in Fig. 1, the front sensor on the chest wall is placed to the left of the sternum along the third rib using a chest strap. The back sensor is placed at a symmetric position on the back along the direction of the shoulder. A three-axis MEMS accelerometer (Kionix KXR85-2042, Kionix, Inc [13]) records acceleration from the antero-posterior direction.

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Fig. 1. Illustration of the proposed sensor placements (figure modified from [12]).
i.e. the z-axis of the sensor, with a sampling rate of 256 Hz and a measurement range of ±2 g. On the front node, a pair of lead II (RA-LL) electrodes along with a pair of LA-RA electrodes are connected to the sensor node to record a reference ECG signal. This ECG signal will serve as ground truth for evaluating the extracted SCG signals recovered from the accelerometer recordings to determine the heart beat detection rate as well as false positives and negatives. Synchronized data are transferred to a computer using a Bluetooth network. Data is then imported into a DSP system programmed using MATLAB (version R2015b, The Mathworks, Natick, MA).

B. The DSP system

Fig. 2 illustrates the proposed DSP system. Acceleration readings are first low-pass filtered at 25 Hz using a 10th-order finite impulse response (FIR) filter to capture the infrasonic range. This signal is then used as an input to a normalized least mean square (NLMS) adaptive filter.

In the following equations, $z_F$ denotes the z-axis acceleration of the front node and $z_B$ is the z-axis acceleration of the back node. The observed signals can then be described as follows:

$$\begin{align*}
\{z_F = s_F + m_F \\
z_B = s_B + m_B
\end{align*}$$

(1)

where $s_F$, $s_B$ represent the SCG signal components and $m_F$, $m_B$ are the MA parts. In order to apply the adaptive filtering approach, the following assumptions need to hold true:

1) $s_F$ and $m_F$ are not correlated. Same with $s_B$ and $m_B$.
2) $m_F$ and $m_B$ are highly correlated.
3) $s_B$ is weak enough to be ignored.

We can then feed $z_B$ into an adaptive filter with an output of $n_B$, and the final output $y$ can be described as:

$$y = s_F + m_F - n_B$$

(2)

Using the NLMS algorithm, the power in the $y$ signal can be minimized, thus minimizing the power of the noise component and increasing the signal-to-noise ratio (SNR) [14]:

$$\min E[y^2] = E[s_F^2] + \min E[(m_F - n_B)^2]$$

(3)

where E is the expectation of the signal. Previous research has indicated that as long as the signal component in reference input ($s_F$) is small enough (pre-supposition 3 above) and $m_F$ and $m_B$ are highly correlated (pre-supposition 2 above), the output SNR will be increased and only a small amount of signal distortion will be added [15]. This theory suggests that a proper placement of the reference channel is critical. Therefore a comparison between different reference sensor locations is needed.

In our previous work, we applied a self-tuning structure by feeding the reference input with a delayed version of the primary input. To compare the performance of our proposed dual-sensor method with the previous single-sensor method, we apply the front sensor measurement into our previous method with the same adaptive NLMS filter parameters. The filter length is set to 32 and the step size is 0.95 for both the previous and current filters.

A peak detection algorithm is then used after MA cancellation by the adaptive filter. We apply a maximum finding algorithm similar to our previous work, where the R-peak is detected on the ECG signal to provide the reference interval and the aortic valve open (AO) peak is detected on the SCG signal to mark cardiac intervals. A sliding window ensemble average is then implemented based on the detected intervals from SCG.

III. EXPERIMENTAL RESULTS

A. Experimental Setup

Human experiments were approved by the Committee for the Protection of Human Subjects at Stevens Institute of Technology under protocol number 2014-045 [16]. The first experiment is to compare different reference sensor placements around the chest wall. As shown in Fig. 3 (a), five different placement spots are selected as follows: 1) the right-side front chest wall; 2) under the right armpit; 3) right-side of the back; 4) left-side of the back; 5) under the left armpit. A 120-seconds test was conducted on each spot from a subject.

![Fig. 3. (a) Different reference sensor placements (figure modified from [12]) (b-f) Processed SCG signals based on spots 1-5, respectively.](image-url)
After that, ten healthy adult subjects were chosen to perform slow walking movements for more than 120 seconds with the reference sensor placement selected from the result of experiment 1. In addition to this standardized test for all subjects, some specific tests such as more extreme running and the application of an external force on the reference sensor node were also conducted on two of the subjects to investigate the failure conditions of the system. All measurements were performed in a lab environment with weak external vibrations.

B. Results

Figs. 3 (b)-(f) illustrate the ensemble-averaged SCG plots obtained from sensor placement spots 1 to 5. The solid line is the ensemble average and the dotted lines are standard deviation boundaries. Our observations indicate that left and right back sides shown in Figs. 3 (d) and (e) share similar signal qualities with a relatively good SCG graph recovery. On the other hand, references from the two armpit positions fail to provide sufficient noise cancellation and the SCG graph is distorted as indicated in Figs. 3 (c) and (f). The right side of the front chest wall shows a larger distortion in Fig. 3 (b) compared to Figs. 3 (d) and (e), especially on the aortic valve closure and mitral valve opening (AC-MO) peak areas in the red rectangular zone. These results can be explained since armpit-position measurements have weakly-correlated movement noise components and the sensor on the right chest wall picks up strong SCG components even though it shares a good correlation with the noise component of the primary sensor node.

Based on this experiment, we performed standardized tests on 10 human subjects with the reference node on the left-side of their backs (position 4 in Fig. 3 (a)). Fig. 4 shows the time-domain plots of a representative measurement and its processed outputs. Figs. 4 (a) and (b) present the raw data after low-pass filtering from front and back sensor nodes, respectively. Fig. 4 (c) shows the waveform after being processed by our proposed method, and Fig. 4 (d) shows the result of the single-sensor solution previously suggested [10]. It can be observed that the double-sensor processing technique outperforms the single-sensor solution especially in the case of strong and more frequent MAs. Measurement results are analyzed using the following metrics as explained below.

1) Detection Rate

Table I illustrates the heart beat detection rates defined as the number of detected true SCG beats over the number of ECG beats observed during the same time interval. False-positive SCG beats are ruled out if the SCG peak is not precisely located on the AO peak position. Our method

<table>
<thead>
<tr>
<th>Subject</th>
<th>False-positives</th>
<th>Detection Rate</th>
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<tr>
<td></td>
<td>Proposed Method</td>
<td>Previous Method</td>
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Fig. 4. (a) Raw data from the front accelerometer, (b) Raw data from the back reference accelerometer, (c) SCG signal achieved using the proposed method (d) SCG signal achieved using the previous single-sensor solution described in [10], (e) Reference ECG signal.
achieves an average detection rate of 98.41% with a standard deviation of 0.89%. Using the same data, the previous single-sensor method has an average detection rate of only 90.98% with a standard deviation of 2.31%. Our previous method is relatively robust and has a motion tolerance of 20 to 40 milligrams in standard deviation. In addition, recordings from different spots around the chest through development of a sensor array will lead to 2D SCG graphs or imaging systems. This would bring SCG motion tolerance and robustness into a whole new level, further triggering its widespread use in various applications.

2) SCG Recovery

Figs. 5 (a) and (b) illustrate the ensemble-averaged recovery plots of the SCG signal from a moving subject and the same subject at rest, respectively. The dotted lines in these two plots are the standard deviation boundaries. In the moving subject (Fig. 5 (a)), it can be observed that there are more minor damping peaks between AO and AC peaks compared to the at rest condition and the standard deviation for the AC-MO peak area is also larger. However, the overall recovery quality of SCG from moving subject is quite satisfactory. Further investigations will be performed to analyze if the distortion and damping peaks are caused by the natural effect of heart activity during motion, or by unwanted processing via the DSP program.

3) Failure Conditions

Through our extreme tests, we observed two major failure conditions for our proposed system. The first condition is a larger MA strength. Experiments reveal a detection rate of below 60% when the subject is running, with a motion noise of 747 mg in standard deviation. In addition, if there is an external force on only one of the sensor nodes, i.e. physical impact on either the front or back side nodes, the false-positive detection rate increases and SCG graph quality decreases significantly. Further improvements in the DSP program and adding more sensor nodes may solve this vulnerability.

IV. DISCUSSION AND CONCLUSIONS

This paper presents a novel method of detecting and recovering adult SCG signals from moving subjects using dual sensor nodes placed on the front and back sides of the chest. Compared to our previously-proposed single-sensor solution, the proposed system has a higher motion tolerance. Our results suggest that a better system performance can be achieved at the cost of higher power consumption and more system complexity.

Future work could be performed on an optimized adaptive system that initially evaluates the MA strength and subsequently determines the number of sensor nodes to power on as well as selects the proper DSP processing technique. Furthermore, recordings from different spots around the chest through development of a sensor array will lead to 2D SCG graphs or imaging systems. This would bring SCG motion tolerance and robustness into a whole new level, further triggering its widespread use in various applications.

REFERENCES