Wearable Electro-Phonocardiography Device for Cardiovascular Disease Monitoring

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***Abstract*—In this paper, we present a new wearable multichannel phonocardiography (PCG) and electrocardiography (ECG) device for cardiovascular disease (CVD) pre-screening and monitoring developed recently by researchers at Curtin University in collaboration with Ticking Heart, a health-tech start-up. An iterative Wiener filter based noise cancelation algorithm is proposed to improve the integrity of heart sound signals. We show that compared with an existing approach, the proposed algorithm has a better performance in suppressing the noise at 200-300 Hz. A convolutional neural network based classifier is implemented which exploits both the ECG and PCG signals to improve the pre-screening accuracy of CVD.**

***Index Terms*—auscultation, cardiovascular disease, electrocardiography, phonocardiography.**

I. Introduction

Cardiovascular disease (CVD) is the leading cause of mortality and morbidity in the world, contributing 32% towards all global deaths [1]. Early diagnosis of CVD is important to prevent further development of this disease. Standard methods for diagnosis of CVD such as coronary angiography and myocardial perfusion imaging require specialized equipment and clinical setting. Although these methods are effective in diagnosing CVD, they are highly costly and expose patients to radiation.

On the other hand, heart auscultation is a cost-effective noninvasive tool for the pre-screening of CVD. However, the heart sound acquired by a stethoscope is often contaminated by various internal and external noises, making it hard for the human auditory system to identify abnormal heart sounds related to CVD. With the aid of computer technology and highly sensitive electronics, digital stethoscopes can be used to detect sounds that are low in volume which can be below the human hearing threshold. As a result, phonocardiogram (PCG) signal processing combined with computer-aided classification attract much interest over the last decade.

Sub-band based spectral features have been proposed in [2] to classify coronary artery disease using multi-channel PCG signals. A deep learning-based classifier for detecting abnormal heart sounds has been developed in [3]. A large public database was created for the 2016 PhysioNet/Computing in Cardiology (CIC) challenge to classify normal and abnormal heart sound recordings [4]. In [5], an adaptive noise cancelation algorithm has been proposed and analyzed in detecting coronary artery disease using PCG.

In this paper, we present a multi-channel PCG and electrocardiography (ECG) based CVD pre-screening instrument, developed by researchers at Curtin University in collaboration with Ticking Heart, a health-tech start-up. With the aid of a background-noise microphone integrated into each digital stethoscope, an iterative Wiener filter based signal processing method is proposed to suppress the environmental noise to improve the integrity of the recorded heart sound signal. Experiment results show an improved noise suppression capability of the proposed algorithm. Moreover, we develop a convolutional neural network (CNN) based CVD classifier using both the PCG and ECG signals, which achieves a higher classification specificity and accuracy compared with classifier based on only the PCG signals.

The rest of the paper is organized as follows. An introduction of the multichannel PCG and ECG instrument is presented in Section II. An iterative Wiener filter based PCG noise cancelation algorithm is proposed in Section III to improve the integrity of the signal-of-interest. A CNN based CVD classification algorithm is presented in Section IV. Conclusions are drawn in Section V.

II. Multichannel PCG and ECG instrument

A multichannel PCG and ECG measurement system has been built by Ticking Heart [6], a health-tech start-up. The system incorporates six digital stethoscopes and one three-lead ECG sensor onto a wearable vest that simultaneously measures heart sound signals (see Fig. 1) and applies machine learning methodologies for pre-screening CVD. The digital stethoscopes are placed in clinically advised positions. All signals from the stethoscopes and the ECG sensor are routed to a data collection board shown in Fig. 1. Compared with systems having only a single stethoscope or two stethoscopes

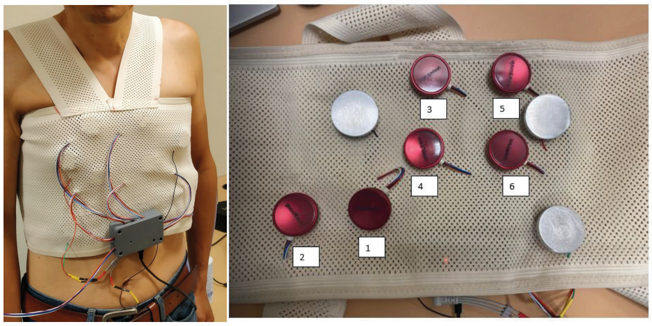

Fig. 1. Prototype wearable vest holding six digital stethoscopes and one three-lead ECG sensor.

[7], using multiple stethoscopes can improve the performance of classification [2]. Moreover, multichannel PCG and ECG signal processing has potential to separate the heart sound signals with a stronger mapping to the cause of the signal waveform.

Each stethoscope has two microphones, where one is the heart-sensor microphone (HM) located behind a diaphragm (facing towards chest), and the other one is the background-noise microphone (BNM) located at the other end of the stethoscope (facing away from chest). The HM acquires the heart signal plus part of the background noise, while the BNM mainly picks up the background noise. Using such two-microphone configuration, the background noise can be reduced from the HM, which contributes to successful diagnosis techniques, as acquired signals from the system are cleaner with higher signal integrity.

An example of the PCG and ECG signals measured simultaneously by the first author from the six digital stethoscopes and one ECG sensor held by Ticking Heart's wearable vest is given in Fig. 2, which shows the waveforms of the signals acquired by the HM of each stethoscope. As the three-electrode configuration [8] is used for the ECG sensor to improve the common mode interference rejection, there is only one ECG signal. The positions of the six stethoscopes are shown in Fig. 1. In particular, stethoscopes 1-4 are located on the left side of the chest to detect sounds from the tricuspid, mitral, pulmonary, and aortic valves, while stethoscopes 5 and 6 are placed on the right side of the chest to detect sounds from the ascending aorta artery. The positions of the three electrodes of the ECG sensor are chosen mainly for fitting into the vest with the stethoscopes. We do not observe much difference in the ECG signal when electrodes are placed on different parts of the chest.

We can observe that in one heart cycle, the first peak in the ECG signal (i.e., the R peak) appears slightly ahead of the S1 peak in the PCG signals, while the second peak in the ECG signal nearly coincides with the S2 peak in the PCG signals. In the case of Fig. 2, the ECG signal appears to be less noisy than PCG signals, indicating that jointly processing the ECG and PCG signals would provide more information on the feature of the heartbeat. Both the PCG and ECG signals can be fed into a classifier to improve the performance of CVD classification.

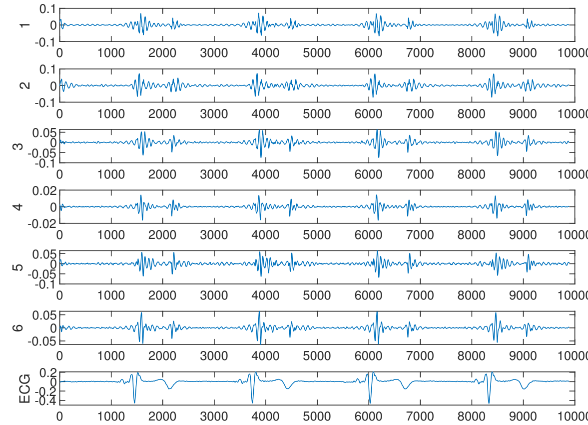

Fig. 2. Waveform of PCG signals and ECG signal recorded simultaneously.

In the two sections below, we focus on systems with a single stethoscope and a single ECG sensor. Extension to multichannel PCG and ECG system will be presented in our future work.

III. Stethoscope Noise Cancelation

Background noise can decrease heart signal integrity and affect the outcome of diagnosis. Conventional frequency-selective filters cannot filtered out noises that lie in the frequency band of interest. By using the BNM as a reference for noise, noise cancelation filtering techniques can be applied to attenuate unwanted background noise and restore integrity to the desired signal.

A normalized least mean squares (NLMS) based adaptive noise cancelation algorithm has been proposed in [5] as below

$$e(i) = x(i) - \mathbf{w}^T(i)\mathbf{v}_2(i) \tag{1}$$

$$\mathbf{w}(i+1) = (1-\alpha)\mathbf{w}(i) + \mu\frac{\mathbf{v}_2(i)e(i)}{\|\mathbf{v}_2(i)\|^2} \tag{2}$$

where $x(i)$ is the signal acquired by the HM, $\mathbf{w}(i)$ denotes the coefficients of the NLMS filter, $\mathbf{v}_2(i)$ is the noise measured by the BNM, α is the leakage coefficient, $(\cdot)^T$ denotes matrix transpose, $\|\cdot\|$ stands for the vector Euclidean norm, and μ is the step size determining the size at which the filter coefficients are updated. Usually α is a very small number and μ can be tuned following [5].

In the NLMS algorithm (1)-(2), the filter coefficients are updated sample-by-sample. In this section, we develop an iterative Wiener filter based noise cancelation algorithm which processes the heart signals in batch. The filter coefficients $\mathbf{w}$ are given by

$$\mathbf{w} = (\mathbf{R}_{v_2} + \beta\lambda_M(\mathbf{R}_{v_2})\mathbf{I})^{-1}\mathbf{r}_{xv_2} \tag{3}$$

$$\beta = r_x - 2\mathbf{w}^T\mathbf{r}_{xv_2} + \mathbf{w}^T\mathbf{R}_{v_2}\mathbf{w} \tag{4}$$

where $\mathbf{R}_{v_2}$ is the estimated covariance matrix of $\mathbf{v}_2(i)$, $\mathbf{r}_{xv_2}$ is the estimated cross-correlation vector between $\mathbf{v}_2(i)$ and $x(i)$, r_x is the estimated power of $x(i)$, $\lambda_M(\cdot)$ stands for the largest eigenvalue of a matrix, $(\cdot)^{-1}$ denotes matrix inversion, and $\mathbf{I}$ is an identity matrix. The diagonal loading factor β in (3) is the estimation error of the Wiener filter as shown in (4), and is calculated iteratively by (3) and (4).

We test the performance of the NLMS and the proposed iterative Wiener filter based noise cancelation algorithms with practical hospital/clinic noise. Heartbeat measurements of 15-second duration are taken from the second author. A FireFace UCX collects data at 44.1 kHz sampling frequency, which is re-sampled down to 2 kHz (heart murmurs are below 1 kHz [9]). For both algorithms, the filter length is set to 512 samples. For the NLMS filter (2), the leakage coefficient $\alpha = 0.001$ is used and μ is set to 0.1. For the proposed algorithm, the iteration between (3) and (4) terminates when the difference between β in two consecutive iterations is less than 10^{-4}.

The spectrograms of the BNM, unfiltered HM, and the HM signal filtered by the NLMS algorithm are displayed side-by-side in Fig. 3, while the spectrogram of the HM signal filtered by the proposed algorithm is shown in Fig. 4. We can see from both figures that the BNM mainly acquires the background noise, as the heart sound signal is absent from the BNM spectrogram. The background noise is also acquired by the HM, particularly at the frequency bands around 200-300 Hz and 400-500 Hz.

We can see from Fig. 3 that the noise energy at 500 Hz and the band between 200 Hz and 300 Hz is slightly suppressed by the NLMS algorithm. Interestingly, it can be seen from Fig. 4 that the noise energy at 400 Hz and 200-300 Hz is further suppressed by the proposed iterative Wiener filter based algorithm compared with the NLMS algorithm. However, by carefully comparing Fig. 3 and Fig. 4, we can see that the proposed algorithm introduces low frequency noise.

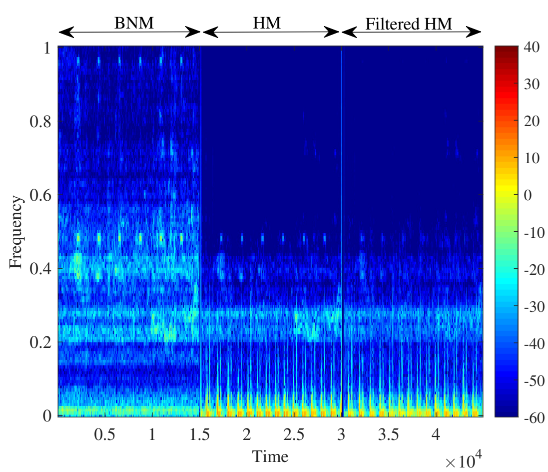

Fig. 3. Spectrogram of BNM, unfiltered and filtered (NLMS) HM signals.

Fig. 5 shows the power spectral density (PSD) plots of unfiltered HM signal and the signal filtered by the two noise cancelation algorithms. There is visual evidence of noise attenuation displayed in Fig. 5. The proposed algorithm attenuates the background noise in the 200-300 Hz band (which contains heart murmur sounds [9]) better than the NLMS algorithm. The results in Figs. 3-5 suggest that a sub-band filter could be designed to further improve the noise cancelation performance.

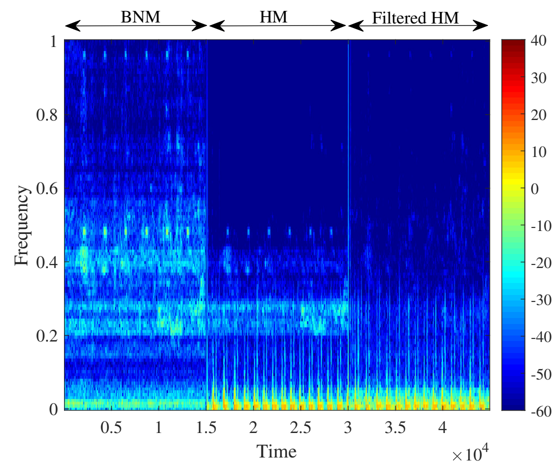

Fig. 4. Spectrogram of BNM, unfiltered and filtered (proposed iterative Wiener filter) HM signals.

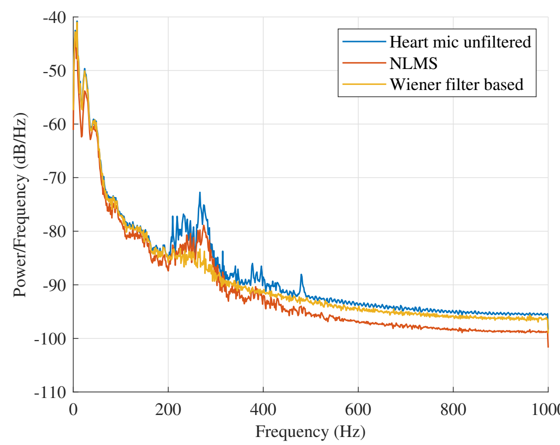

Fig. 5. PSD of unfiltered and filtered HM signals.

We also test the performance of the NLMS algorithm in other external noises and internal noise (e.g. breathing), and find that as the BNM faces away from chest, it is better at suppressing external noise than internal noise [5].

IV. MACHINE LEARNING BASED CVD CLASSIFICATION

Murmur sounds from the coronary arteries blockage affect the basic characteristics of PCG signals, which provides the opportunity to detect these changes using machine learning techniques. In this section, we develop a CNN based CVD classifier using both the PCG and ECG signals. The architecture of the neural network is similar to [3] with the main difference that the ECG signal is added to the input of the neural network to improve classification. As shown in the MATLAB layer graph in Fig. 6, this multi-input deep neural network consists of five inputs, four of which are used for the PCG signal filtered at different non-overlapping frequency bands, and the remaining one is for the ECG signal. The four frequency bands of the PCG signals are 25-45 Hz, 45-80 Hz, 80-200 Hz, and 200-400 Hz, which are chosen according to the spectral properties of heart sounds and PCG recording artifacts

[9]. The ECG signal is bandpass filtered to the band of 2-60 Hz. ECG and PCG signals are segmented into sequences of 2500 samples for the input of the neural network.

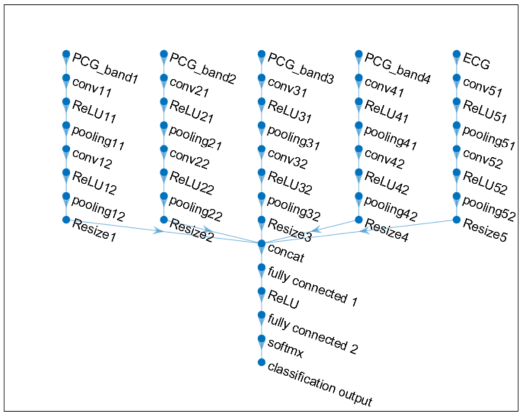

Fig. 6. Architecture of the proposed CNN based CVD classifier.

Each of the five input signal sequences is passed through a CNN network of two convolutional layers. The first convolutional layer consists of 8 parallel finite impulse response (FIR) filters of length 5, where each filter is followed by a rectified linear unit (ReLU) and a max-pooling of 2. The second convolutional layer has 4 parallel FIR filters with length 5, each followed by a ReLU and a max-pooling of 2. The output of the five CNNs is concatenated and fed into a multi-layer perceptron (MLP) network, which has an input layer, a hidden layer with 20 neurons, and an output layer. Softmax is adopted as the activation function at the output layer.

The whole neural network has 249922 learnable parameters. These parameters are trained by the data set A in the public database created for the 2016 PhysioNet/CIC challenge [4]. Data set A contains 409 PCG recordings made at nine different recording positions and orientations from 121 patients. The PCG recordings were labeled through echocardiographic examination of patients at the Massachusetts General Hospital, Boston, MA, USA. As these recordings were performed either in an uncontrolled environment at the hospital or during in-home visits, they were corrupted by various sources of noise such as talking, dogs barking, and children playing.

All but except 4 PCGs were recorded simultaneously with ECG signals. We observed through visual inspection that some of the ECG recordings are of low quality due to unknown reasons. Among the 405 recordings with both PCG and ECG, 324 randomly chosen recordings (80%) are used to train the proposed neural network, and the remaining 81 recordings (20%) are reserved for verification. To avoid over-fitting of the neural network to long recordings, maximal of 10 heart cycles from each recording are adopted for training. For verification, the classification results on each heart cycle are averaged to obtain a score $s \in (0, 1)$, which is compared with a threshold parameter p to obtain the final decision of each patient ($s \geq p$ leads to a positive diagnosis).

The adaptive moment estimation (ADAM) algorithm is used for stochastic optimization in training the neural network with the following configurations: number of epochs is 400; batch size is 1024; learning rate is 7×10^{-4}; the training data is shuffled before every training epoch.

TABLE I
CVD CLASSIFICATION ACCURACY OBTAINED FROM TWO DIFFERENT NEURAL NETWORKS

Method	Sensitivity	Specificity	Accuracy
ECG and PCG ($p = 0.4$)	94.92%	45.45%	81.48%
PCG only ($p = 0.4$)	94.92%	43.48%	80.49%
ECG and PCG ($p = 0.5$)	91.53%	54.55%	81.48%
PCG only ($p = 0.5$)	91.53%	43.48%	78.05%
ECG and PCG ($p = 0.6$)	84.75%	63.64%	79.01%
PCG only ($p = 0.6$)	86.44%	56.52%	78.05%

Table I shows the performance comparison between the proposed classification algorithm which uses both the ECG and PCG signals and the classifier only using the PCG signal [3]. The proposed neural network achieves a similar sensitivity compared with the PCG only classifier, but a higher classification specificity and accuracy. In particular, there is a remarkable improvement of specificity for all the three p values tested, indicating the benefit of incorporating the ECG signals, even though some of them are of low quality. We expect that with higher quality ECG recording, the classification results will improve. The confusion charts of the two methods at $p = 0.5$ are shown in Fig. 7, where '1' and '-1' stand for CVD and non-CVD, respectively.

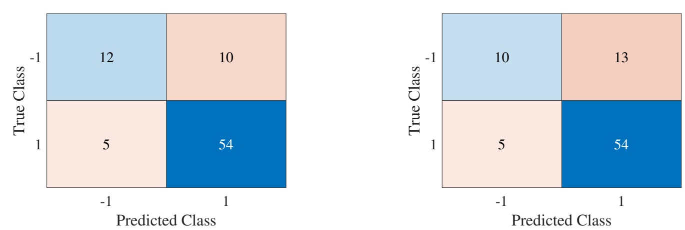

Fig. 7. Confusion charts: ECG and PCG (left); PCG only (right).

The proposed neural network in Fig. 6 can be expanded to take input signals from multiple stethoscopes. Note that with the expansion of network, a larger number of labeled ECG and PCG recordings are required to train a larger number of learnable parameters. We are in the process of data collection using Ticking Heart's wearable vest in Fig. 1. It is expected that with multichannel PCG and ECG signals of high integrity, the diagnosis accuracy can be further increased.

V. CONCLUSIONS

In this paper, we have presented a multi-channel PCG and ECG device for CVD pre-screening and monitoring. An iterative Wiener filter based noise cancelation algorithm has been proposed to suppress the PCG background noise. We have developed a CNN based classifier for CVD detection using both the ECG and PCG signals, which shows higher classification accuracy compared with using only the PCG signal.

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