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Can Heart Sound Denoising be Beneficial in Phonocardiogram Classification Tasks?

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***Abstract*— The purpose of computer-aided diagnosis (CAD) systems is to improve the detection of diseases in a shorter time and with reduced subjectivity. A robust system frequently requires a noise-free input signal. For CADs which use heart sounds, this problem is critical as heart sounds are often low amplitude and affected by some unavoidable sources of noise such as movement artifacts and physiological sounds. Removing noises by using denoising algorithms can be beneficial in improving the diagnostics accuracy of CADs. In this study, four denoising algorithms were investigated. Each algorithm has been carefully adapted to fit the requirements of the phonocardiograph signal. The effect of the denoising algorithms was objectively compared based on the improvement it introduces in the classification performance of the heart sound dataset. According to the findings, using denoising methods directly before classification decreased the algorithm's classification performance because a murmur was also treated as noise and suppressed by the denoising process. However, when denoising using Wiener estimation-based spectral subtraction was used as a preprocessing step to improve the segmentation algorithm, it increased the system's classification performance with a sensitivity of 96.0%, a specificity of 74.0%, and an overall score of 85.0%. As a result, to improve performance, denoising can be added as a preprocessing step into heart sound classifiers that are based on heart sound segmentation.**

Keywords: denoising, phonocardiogram spectral subtraction, wiener estimation, wavelet thresholding, heart sound segmentation, heart sound classification.

I. INTRODUCTION

A heart synchronously pumps blood throughout the body. Its valves open and close due to the pressure difference inside the heart chambers. The associated mechanical vibrations and opening and closure of the valves give rise to the heart sounds. These sounds can be heard and recorded from the chest of the subject via a stethoscope. The graphical representation of the recorded sound wave is referred to as phonocardiograph (PCG) [1]. A heart sound consists of four fundamental heart sounds(FHS): referred to as the first heart sound (S1), the second heart sound (S2), systolic interval, and diastolic interval. Under normal conditions, the interval between S1 and S2 and vice versa should be quiet. But if there is damage to the valves, there will be a turbulent blood flow which is called a murmur [2]. Due to its low amplitude, a heart sound recording is naturally susceptible to noise such as ambient noise and other physiological noises [3]. An example of clean, noisy, and murmur categories of heart sound is shown in Figure 1.

There are primarily eight significant parameters to focus on while evaluating the presence of murmur in PCG signals

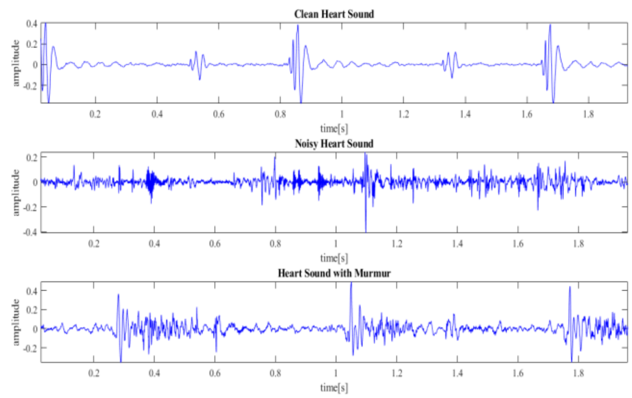

Figure1. Visualization of clean, noisy, and murmur recording of heart sounds

[4]. These are sound intensity, frequency content, timing, duration, shape, systolic and diastolic intervals, ratio of the first heart sound amplitude to second heart sound amplitude (S1/S2), and ratio of diastolic to systolic duration (D/S). Successful quantification of the aforementioned parameters is nearly impossible in noisy recordings. A noise reduction mechanism will play a vital role in such scenarios. The heart sound is the most routinely acquired physiological signal in clinical practice due to its ease of acquisition. It provides crucial information about cardiac health. However, the accuracy of manual auscultation diagnosis was reported to be low [5]. This is due to the human auditory system's inherent limitation to do accurate auscultation. The listening process is highly subjective which requires extensive experience to master [6]. This frequently leads clinicians to rely on more expensive imaging devices for cardiac screening, such as echocardiography.

To counter the subjectivity and the high percentage of diagnostic errors, computer-aided diagnostic (CAD) systems that detect the presence of murmurs can provide paramount importance [7],[8]. For the successful implementation of such systems, the quality of the input signal should be high. To achieve the required quality, auscultation is usually performed in the quietest possible settings. However, there are always inevitable noise sources that have the potential to degrade diagnostic accuracy. Instrument noise, thermal noise, movement artifact, physiological noises from lungs and stomach, are the most common types of noises which cannot be avoided [9].

This paper performs a systematic comparison of four algorithms for PCG denoising. With proper parameters suitable for PCG, these algorithms are objectively compared on the improvement they introduce on the classification accuracy in detecting the presence of murmur on an open heart sound dataset. The rest of the paper is organized as follows. Section II presents related work. Section III deliberates the methodology and a brief introduction to all the algorithms used in this study. In section IV, the results and discussion part are presented. Finally, section V presents concluding remarks.

II. Related Work

The straightforward approach to achieve a clean heart sound signal is to discard the noisy part of a signal based on a predefined signal quality metric. Springer et. al. [10] proposed such a technique by using ten signal quality metrics to perform signal quality classification that can differentiate poor quality from diagnostically useful recordings. They reported their approach works with 87% accuracy on manually annotated data. This may be appropriate for real-time recording situations in which we have the option of conducting the recording several times. However, due to PCG's intrinsic sensitivity to noise, rejecting any recording that contains noise might be expensive.

The bandpass filter was the other commonly used approach to eliminate both high and low-frequency noises [11],[12]. The regularly applied cutoff frequencies in PCG denoising range from 20Hz to 1.5KHz depending on the application. However, the presence of considerable spectral overlap between noise and heart sounds makes it difficult to select an optimal cutoff frequency [13].

Spectral subtraction with its variants was another filtering methodology that was often used for PCG denoising [14],[15]. To estimate the noise, it takes advantage of the fact that the heart sound signal has an off-and-on nature where the noise is predominantly present in the off part of the signal. Different noise estimation techniques have been investigated [16],[17],and [18]. For spectral subtraction to work very well, the noise must be stationary with a Gaussian distribution. However, this assumption is not always true. Hence, researchers have proposed short frame sizes to achieve this stationarity property. The spectral overlap between noise and fundamental heart sounds makes spectral subtraction an interesting approach. However, care should be taken as murmurs also occupy the same ‘off’ part of the signal where noise is predominantly detected.

Wavelet transform was another technique often used to denoise PCG signals [19], [20], and [21]. It has been reported that fundamental heart sound signals produce bigger wavelet coefficients than noisy components. Hence coefficient thresholding has proven to effectively eliminate the noisy parts signals. Heart sound signal amplitude is very small hence the choice of a good threshold is also a delicate problem.

All algorithms proposed in the literature report some level of improvement in signal quality after processing. To effectively compare the performance of these denoising algorithms, an objective evaluation on a similar clinical dataset is needed to be conducted. In this paper, the effect of these algorithms on the heart sound classification performance was compared to classify normal/abnormal heart sounds.

III. Methodology

The overall system had five blocks as indicated in Figure 2. To demonstrate the effect of the selected denoising algorithms on the classification accuracy of heart sounds, two experiments were conducted. The experiments were based on the heart sound classification algorithm proposed by Potes et al. [22]. A brief description Potes et al. approach and each of the blocks used in this system is presented next.

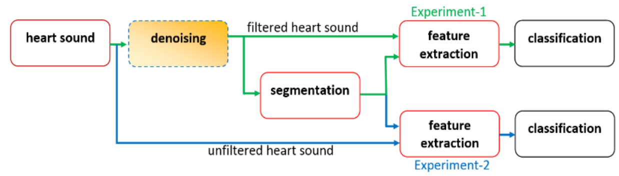

Figure 2. The block diagram of the proposed methodology employed to compare the effect of denoising on heart sound classification.

A. Description of the heart sound classifier algorithm used in this paper

Potes et al.[22] , the winner of the 2016 Physionet CinC challenge [23], proposed a murmur detection algorithm from heart sound recordings by first locating the FHS. Each PCG was first downsampled to 1KHz. The heart sound data was then bandpass filtered between 25Hz and 400Hz. After that spikes were removed. FHSs were then extracted using Springer et al. [24] segmentation algorithm which is publicly available online on the Physionet repository. An ensemble of two classifiers was then used in their proposed technique. The first one was AdaBoost-abstain classifier which was trained on time-domain features, frequency-domain features, and mel-cepstral coefficients (MFCC) features. Features were computed from each FHS of the segmented heart sounds.

The second classifier was based on convolutional neural networks (CNN). For this, each heart sound was decomposed into four frequency bands (25-45Hz, 45-80Hz, 80-200Hz, and 200-400Hz). Each band was then segmented into FHS. The proposed CNN had three layers and an output layer that predicted the final class.

The final classification decision was based on a predefined decision rule which was tuned to maximize the challenge score on the provided open heart sound dataset. They evaluated the performance on the train-test split as well as on a blind test set provided by the competition organizers. As the blind test set is not publicly available, the performance improvement introduced by our approach was evaluated on the in-house train-test split. Their implementation source code is publicly available online on the Physionet repository [23].

B. Heart sound data set

The heart sound dataset was from the 2016 Physionet Challenge [23] consisting of recordings from five independent databases. The dataset contained 3240 recordings spanning from 5 to 120 seconds in duration from both normal and abnormal subjects. The recordings were sampled at 2kHz and saved as a .wav file. The training and validation set were mutually exclusive, that is, no recording from the same subject was used in both the training and validation set. The recordings were done in uncontrolled environments hence they are corrupted by different types of noises such as motion artifacts, talking, breathing, and gastrointestinal sounds. Detail explanation of how the dataset was created can be found in Liu et al. [25].

C. Heart sound denoising techniques

Due to its low amplitude, heart sound is normally susceptible to noise. Hence, extracting features and other diagnostic information will be very difficult in the presence of noise. For instance, correctly locating the FHS including S1, S2, systole, and diastole will be difficult in the presence of noise. Therefore, it is necessary to eliminate noise from the heart sounds before the segmentation process is done. The following section presents the denoising algorithms used in this paper.

1) Denoising by wavelet thresholding

The elimination of noise components by thresholding the wavelet coefficients is based on the premise that the signal energy is concentrated predominantly in a limited number of wavelet dimensions in a noisy signal [26]. Compared to other coefficients (especially noise), the energy of these coefficients has higher values, which have their energy spread over a large number of wavelet coefficients. Thresholding the lower coefficients of the wavelet to zero can reduce the noise components of the signal [26].

Noise in a signal can be suppressed by using level-dependent wavelet thresholding techniques that were widely used in the literature [27],[28], and [29]. Level dependent threshold (τ) can be represented by :

$$\tau = \sigma_j(\sqrt{2\log N_j}) \quad (1)$$

$$\sigma_j = \frac{MAD(D_j)}{0.6745} \quad (2)$$

where MAD is the median absolute deviation of the detailed coefficients for each level (D_j) and N_j is the length of the noisy signal for each level.

The procedure of level-dependent wavelet threshold techniques is illustrated by the following steps [26]:

- Using a Hamming window of frame size 25 milliseconds, divide the noisy heart sound signal into several segments.
- Using the discrete wavelet transform (DWT), compute the wavelet coefficients of the noisy heart sound signal.
- Apply a hard or a soft level-dependent threshold to the noisy heart sound signal's detailed coefficients. Hard (T_{hard}) and soft (T_{soft}) thresholds can be expressed by the equations (3) and (4). Soft thresholding was used for this paper.

$$T_{hard}(D_j) = \begin{cases} D_j & , |D_j| > \tau \\ 0 & , |D_j| \leq \tau \end{cases} \quad (3)$$

$$T_{soft}(D_j) = \begin{cases} \text{sign}(D_j) * (|D_j| - \tau), & |D_j| > \tau \\ 0 & , |D_j| \leq \tau \end{cases} \quad (4)$$

- By applying the inverse DWT to the thresholded wavelet coefficients, reconstruct the improved heart sound signal.

2) Spectral Subtraction

Spectral subtraction achieves denoising by subtracting the estimated power spectrum of the noise from the power spectrum of the noisy heart sound signal, without prior knowledge of the power spectral density of the clean and noise signals. For heart sounds, spectral subtraction suppresses background noise by assuming the noise is stationary or changing slowly during the relatively silent segments (systole and diastole) and activity periods (S1 and S2) [30]. The procedure of spectral subtraction is summarized by the following steps.

The main scheme of this technique is the average noise and signal spectrum are estimated from the given heart sound recording. The mandatory assumption for spectral subtraction to work is that noise is stationary and additive. The recorded signal $r(t)$ is the sum of the desired signal $d(t)$ and noise signal $n(t)$ as shown in (5).

$$r(t) = d(t) + n(t) \quad (5)$$

The expected noise spectrum is unknown in this case. But PCG signal contains fundamental heart sounds S1 and S2 with the pauses in between, systole and diastole respectively. In a normal heart sound signal, the systole and diastole intervals are supposed to be silent hence these parts are used to estimate the noise spectrum.

To achieve the stationarity property, the heart sound signal was framed with sizes of 25ms. For each frame, i, Fourier Frequency domain representation was given by (6) and (7).

$$R_i(\omega) = D_i(\omega) + N_i(\omega) \text{frame}_i \in \{\text{PCG} + \text{Noise frames}\} \quad (6)$$

$$R_i(\omega) = \quad 0 \quad N_i(\omega) \text{frame}_i \in \{\text{Noise only frame s}\} \quad (7)$$

An activity detection algorithm based on energy, dynamic range, and statistical properties was used to distinguish between these two frame types [31]. The average magnitude of the noise spectrum, $\mu(\omega)$ is then given by (8).

$$\mu(\omega) = E\{|N_i(\omega)|\} \quad (8)$$

Assuming that noise characteristics in PCG signals change slowly and hence averaging over noise-only frames gives the expected noise spectrum (9).

$$\hat{\mu}(\omega) = \frac{1}{\#\text{ of noise only frames}} \sum_{\text{noise only frames}} |R_i(\omega)| \quad (9)$$

The estimated clean desired signal, $\widehat{D}(\omega)$, is then given by spectral subtraction as in (10).

$$\widehat{D}(\omega) = R_i(\omega) - \hat{\mu}(\omega) \quad (10)$$

The estimate of clean PCG spectrum for each frame, $\widehat{D}_i(\omega)$, from a corrupted recording frame, $R_i(\omega)$, and the estimated noise spectrum, $\hat{\mu}(\omega)$, can be rewritten as shown in (11).

$$\widehat{D}_i(\omega) = G_i(\omega) R_i(\omega) \quad (11)$$

where, $G(\omega)$, is the gain function and is computed by (12).

$$G_i(\omega) = f(R_i(\omega), \hat{\mu}(\omega)) \quad (12)$$

Different techniques are applied to compute the gain function. The gain functions of the three spectral subtraction used in this paper are displayed in Table 1 :

TABLE 1: SPECTRAL SUBTRACTION GAIN FUNCTIONS

Gain Function	Formula
Magnitude Subtraction	$G_i(\omega) = \left[1 - \frac{\hat{\mu}(\omega)}{\lvert R_i(\omega)\rvert}\right]$
Power Subtraction	$G_i(\omega) = \sqrt{1 - \frac{\hat{\mu}_i^2(\omega)}{\lvert R_i(\omega)\rvert^2}}$
Wiener Estimation	$G_i(\omega) = 1 - \frac{\hat{\mu}_i^2(\omega)}{\lvert R_i(\omega)\rvert^2}$

D. Heart Sound Segmentation

In automated heart sound analysis, segmentation is an essential step. The main goal of segmentation is to precisely locate the fundamental sounds of the heart, including S1, S2, systole, and diastole. This helps to determine the murmur in both the systolic and the diastolic sections effectively. We used the state-of-the-art open-source heart sound segmentation algorithms from Springer et al. [24] for this paper. The Hidden Markov Model (HMM) was used explicitly for its noise tolerance. The algorithm was tested for 102 306 heartbeats. Algorithms have shown good performance with an F1 score of 98.5% for S1 and systole sections and a 97.2% for S2 localization and diastole intervals.

E. Feature extraction

A total of 124 features that combined time domain, frequency domain, and MFCC features were computed as described in section III. A and Potes et al.[22]. The features were computed based on S1, S2, systolic and diastolic segments.

F. Classification

The classification algorithm is an ensemble of AdaBoost and CNN as explained in section III. A Potes et al.[22]. Features extracted from the FHS of the PCG were used as input in the proposed AdaBoost classifier. A proposed CNN was also trained using PCGs cardiac cycles decomposed into four frequency bands for each FHS.

IV. Results and Discussion

To test the effect of denoising on the classification of heart sounds, two experiments were conducted. The scoring was done by computing the weighted sensitivities and specificities of the algorithms as shown in Table 2 and the overall score is the average of the two as indicated in (15) [25]. The description and the results of these experiments are presented in the following sections.

TABLE 2: Mechanism of evaluating the classification results [25]

		signal quality	percentage of recordings	model prediction		
				abnormal	unsure	normal
reference label	abnormal	good	wa1	Aa1	Aq1	An1
		poor	wa2	Aa2	Aq2	An2
	normal	good	wn1	Na1	Nq1	Nn1
		poor	wn2	Na2	Nq2	Nn2

The modified sensitivity (13) and specificity (14) are then given by:

$$\mathrm{Se} = \frac{\mathrm{wa1*Aa1}}{\mathrm{Aa1+Aq1+An1}} + \frac{\mathrm{wa2*(Aa2+Aq2)}}{\mathrm{Aa1+Aq1+An1}} \tag{13}$$

$$\mathrm{Sp} = \frac{\mathrm{wn1*Nn1}}{\mathrm{Na2+Nq2+Nn2}} + \frac{\mathrm{wn2*(Nn2+Nq2)}}{\mathrm{Na2+Nq2+Nn2}} \tag{14}$$

where in the training set wa1=0.8602, wa2=0.1398, wn1=0.9252 and wn2=0.0748 and in the validation set wa1=0.7888, wa2=0.2119, wn1=0.9467 and wn2=0.0533 [25].

The overall score is then given by (15):

$$\text{overall score} = \frac{\mathrm{Se+Sp}}{2} \tag{15}$$

A. Experiment I

In the first experiment, the heart sound data were denoised, and segmentation was done on the denoised data to extract S1, S2, systole, and diastole intervals. Features from each segment were computed on the denoised data. The extracted features were fed to the classifier. The results of this experiment are shown in Table 3.

TABLE 3: Results of experiment I

Denoising Algorithm	Se	Sp	overall score
Without denoising [22]	**0.967**	0.687	**0.827**
Magnitude based spectral subtraction	0.788	0.793	0.791
Power base spectral subtraction	0.808	0.813	0.811
Wiener based spectral substraction	0.755	**0.847**	0.801
Wavelet denoising	0.788	0.793	0.791

As can be seen in Table 3, the sensitivity of the classification system has reduced. An improvement in specificity has been observed. However, the overall classification score was reduced. The application of the denoising algorithms has eliminated murmur along with the noise in the signal. This is the reason why the introduction of the denoising block has reduced the performance of the system. Denoised heart sounds with murmur will appear to be normal in this scenario and can be classified as normal. This is why the specificity has increased.

B. Experiment II

In the second experiment, the heart sound data were denoised, and segmentation was done on the denoised data to extract S1, S2, systole, and diastole intervals. However, the features were computed on the original non-denoised data, this was then followed by classification. The results of the second experiment are shown in Table 4.

TABLE 4: Results of experiment II

Denoising Algorithm	Se	Sp	overall score
Without denoising [22]	**0.967**	0.687	0.827
Magnitude based spectral subtraction	0.952	0.717	0.834
Power base spectral subtraction	0.954	0.723	0.839
Wiener based spectral substraction	0.960	**0.740**	**0.850**
Wavelet denoising	0.953	0.727	0.840

Table 4 indicates the effect of the introduction of the denoising system to improve the performance of the segmentation but not the feature extraction. We can see that there was still a small decrease in the sensitivity of the system with a significant improvement in the specificity. The overall accuracy has also an improvement. The denoising algorithm improves the accurate localization of the FHS, which will in turn made a proper feature computation for each segment. As the feature extraction was done on the original data, all the information contained in the heart sound including the murmur was maintained. This improved the overall performance of the system very well.

V. Conclusion

Heartbeat recordings might reveal vital information about a person's cardiac health. However, the auscultation process is always subjective and prone to error mainly because of the auditory limitation of the human ear and the susceptibility of the heart sounds to ambient noise. Automatic diagnosis systems can play an important role to limit the subjectivity and errors in auscultation. However, achieving the needed diagnostic accuracy of such systems necessitates the highest possible signal quality. Incorporating denoising algorithms can improve the overall system accuracy

In this paper, four denoising algorithms were objectively compared to select an optimal method for heart sound denoising. It was observed that direct application of the denoising algorithms did not improve the classification performance as murmur was also treated as noise and was consequently removed. On the other hand, the classification of the system was improved by applying the denoising system as a preprocessing step to improve the segmentation algorithm only and performing the feature extraction on the original untouched signal. In doing so the localization of the fundamental heart sound was more accurate which improved the feature extraction and hence improved the classification performance. Wiener estimation-based spectral subtraction had improved the specificity of the state-of-the-art classification algorithm from 68.7% to 74%. The sensitivity was 96.0%, and an overall score of 85.0% was achieved. One significant limitation of the paper is that it did not examine all of the alternative denoising methods; in particular, it did not evaluate nonlinear and nonstationary approaches, which could be considered as future work.

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