Detecting Patent Ductus Arteriosus in Neonatal Phonocardiograms

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Abstract

During fetal development, ductus arteriosus allows blood ejected by the right ventricle to bypass the lung. The persistence of this ductus after birth however is considered pathological and is termed patent ductus arteriosus (PDA). Using phonocardiograms (PCGs) acquired from a digital stethoscope, the objective is to explore discriminatory features and statistically analyse them. In this research, we obtained 48 PCG recordings from 41 neonates. 17 recordings (15 neonates) had PDA, 8 recordings (7 neonates) had other heart structure abnormalities identified during echocardiography and were excluded in this study, and 23 recordings (21 neonates) had no heart structure abnormalities based on clinical assessment. Recordings were denoised using non-negative matrix co-factorization. Denoised phonocardiograms were then segmented into S1, systolic, S2, and diastolic periods. Temporal (durations and maximum values), statistical (variance, skewness, and kurtosis), and power (total power, and 25-100 Hz, 25-45 Hz, 45-80 Hz, 100-200 Hz, and 200-400 Hz band powers) were obtained for each heart segment and relative ratios between segments calculated. Statistical tests were then performed to identify significant features for discriminating PCG recordings.

1. Introduction

Accurate and timely assessment of neonatal health is of paramount importance, particularly when it comes to detecting life-threatening conditions such as cardiorespiratory diseases [1]. The traditional method of using a stethoscope to record chest sounds has been a mainstay in neonatal care, but recent advancements have introduced digital stethoscopes with tailored Artificial Intelligence (AI) for newborns [2–5]. While these innovations hold promise, the neonatal intensive care environment presents unique challenges, including heightened levels of ambient noise compared to adult and pediatric wards. These challenges have, in turn, resulted in suboptimal chest sound recordings and inaccurate assessments of critical parameters such as heart rate and breathing rate [6].

The sources of noise interference in neonatal phonocardiograms (PCGs) are multifaceted, encompassing external and background noise [7], cross-interference between heart and lung sounds, as well as internal sounds like bowel movements, gastric reflux, and air swallow. Additionally, the noise introduced by respiratory support equipment further complicates matters. To ensure accurate assessment and diagnosis, it becomes imperative to address and mitigate these sources of interference, effectively separating heart and lung sounds from extraneous noise [8].

The persistence of the duct beyond the 72-hour mark is considered pathological and falls within the spectrum of CHD, characterized as Patent Ductus Arteriosus (PDA) [9–13]. Detecting PDA and other CHDs, particularly within the first three days post-birth, holds paramount importance as it enables efficient allocation of limited echocardiography resources and minimizes the risk of missing PDA-related CHDs. Despite being a cost-effective and reliable screening tool, auscultation's subjective nature, dependent on the assessor's auditory acuity and expertise, poses challenges. AI can bridge this gap by providing an objective interpretation of heart sounds, complementing traditional auscultation methods [14].

In the pursuit of achieving clarity and precision in neonatal PCGs, researchers and clinicians have explored various denoising and sound separation methods, which can broadly be categorized into multichannel and single-channel approaches.

In contrast, limited attention has been directed towards automated PCG classification in the pediatric population, and even fewer studies have delved into the challenge of interpreting PCGs in newborns. Some noteworthy contributions include a statistical analysis of various features aimed at the automated detection of PDA murmur [15]. Overall, this study aimed to select features of importance for PDA detection using neonatal PCGs.

2. Methods

2.1. Data Collection

41 neonatal PCG recordings were obtained from Monash Children's Hospital. Among these, 17 recordings (from 15 neonates) were identified as having PDA, a condition of particular interest in this study. Additionally, 8 recordings (from 8 neonates) exhibited structural abnormalities in the heart, as confirmed by echocardiography, but unrelated to PDA. These recordings were excluded from the analysis. The remaining 23 recordings (from 21 neonates) displayed no heart structure abnormalities based on clinical assessments and were considered part of the healthy control group.

2.2. Data Preprocessing

To prepare the PCG recordings for analysis, a series of preprocessing steps were employed. These included denoising using the non-negative matrix factorization (NMF) technique, which effectively removed extraneous noise sources such as lung sounds, respiratory support interference, and other environmental noises [16, 17]. This denoising process was crucial for isolating the relevant heart sounds for further analysis. Figure 1 shows the sample outcome result of the NMF method sound separation [17].

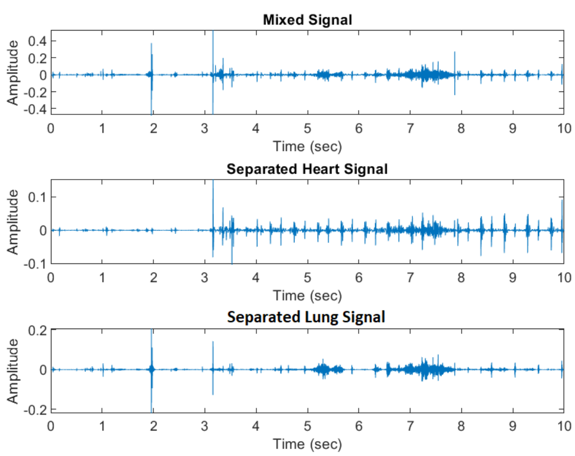

Figure 1. Example of NMF Sound Separation

2.3. Signal Segmentation

The denoised PCG recordings were then segmented into four distinct cardiac periods (Figure 2): S1, representing the first heart sound; systolic, covering the period from S1 to S2; S2, representing the second heart sound; and diastolic, encompassing the period after S2. This segmentation allowed for the extraction of specific features from each of these cardiac phases based on our previous work [18].

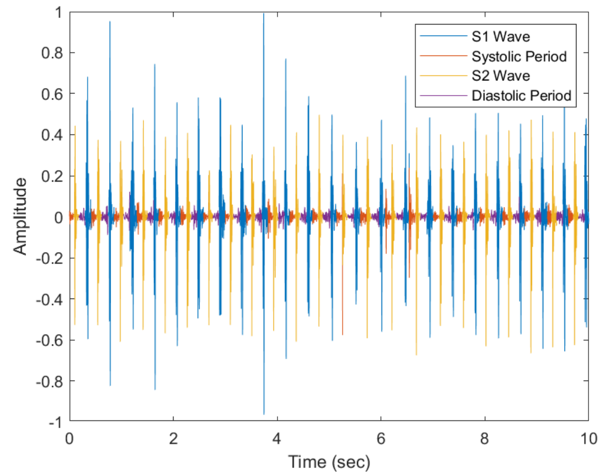

Figure 2. Example of Heart Sound Segmentation

2.4. Feature Extraction

Based on Gomez *et. al.* [19] 67 features were obtained from S1, systolic, S2, and diastolic periods. Various features were extracted from each of the segmented cardiac periods based on:

- Temporal Features: These included measures such as durations and maximum values for each of the four cardiac periods. These temporal attributes captured the time-related characteristics of the heart sounds.
- Statistical Features: Statistical properties like variance, skewness, and kurtosis were computed for each cardiac period. These statistics provided insight into the distribution and shape of the heart sound signals during different phases of the cardiac cycle.
- Power Features: Power spectral analysis was performed to quantify the frequency content of the heart sounds. Total power, as well as power in specific frequency bands (25-100 Hz, 25-45 Hz, 45-80 Hz, 100-200Hz, and 200-400Hz), were calculated for each cardiac period. These power features offered insights into the spectral characteristics of the heart sounds [18].

2.5. Feature selection

In total, 1087 features were extracted. Additionally, the p-values resulting from statistical tests the t-test and Mann-Whitney tests, with respect to normality tests, were utilized to assess the significance of features in distinguishing between PDA and healthy heart sounds. The Bonferroni method was used to adjust the p-value (Confidence Interval 95%). MATLAB and Python software were used for the analysis of the data. Table 1 describes each feature extracted for further analysis.

Table 1. Features Extracted from the Heartbeat Cycle

Feature	Description
cwt_morlet_feature	Features based on continuous wavelet transform using Morlet mother wavelet
mfcc_features	Features based on Mel Frequency Cepstral Coefficients (MFCCs)
power_ratio_max_Dia	Ratio of maximum power to total power in the diastolic region
audio_lpc10_9_S2	Linear predictive coefficients for S2 sound
bobillo_feature	Set of heartbeat segment features represented in a 4-way tensor which is decomposed and compressed to get the most discriminating parameters.
sd_IntDia	Standard deviation of diastolic interval timing
m_mean_SYS	Mean value in the systolic period
audio_lsf6_4_Sys	Line spectral frequencies for systolic interval
n_broken_s2	Number of discontinuities on the derivative of the signal in the S2 wave
mean_IntDia	Mean value of diastolic interval timing

Table 2. Top 10 Most Statistically Significant Features Mean Values for PDa and No PDA (p-value<0.02)

Feature	PDA	No PDA
cwt_morlet_features_219	$-2.48e^{-1}$	$-5.46e^{-1}$
mfcc_features_96	$-2.26e^{3}$	$-2.54e^{3}$
cwt_morlet_features_179	$-3.66e^{-1}$	$-5.23e^{-1}$
cwt_morlet_features_218	$-4.26e^{-1}$	$-6.02e^{-1}$
mfcc_features_253	$-1.12e^{1}$	$-1.32e^{1}$
power_ratio_max_Dia	$2.77e^{-1}$	$2.38e^{-1}$
audio_lpc10_9_S2	$1.94e^{-1}$	$2.51e^{-1}$
bobillo_features_16	$9.00e^{-2}$	$6.12e^{-1}$
cwt_morlet_features_220	$4.60e^{-2}$	$4.17e^{-1}$
mfcc_features_200	$1.45e^{1}$	$1.63e^{1}$

3. Results

Table 2 shows the t-test and its non-parametric counterpart, Mann-Whitney, were used for ranking the statistical significance of each feature based on their p-value. Among 1087 features only 30 features were in the confidence interval of 95%, which was concluded as statistically significant. The top 10 features' details are reported in Table 2.

Features of cwt_morlet_features_219, mfcc_features_96, and cwt_morlet_features_179 are the most significant. Figure 3 shows the pattern of significance in selected features.

4. Discussion and Conclusion

In our study, we performed the NMF method in the context of neonatal chest sound separation, particularly for the detection of PDA. We utilized a large set of features from time and frequency domains to assess the level of their relevance for the considered tasks. Many of these features have been previously used for heart sound assessment [20, 21]; others have been introduced here. The extracted features describe the data within four different segments of a cardiac cycle. From the results, the majority of the most important features tend to describe the temporal and power content from cwt_morlet_features_219 and mffc_feature_232. The small sample size is a limitation aspect of this study.

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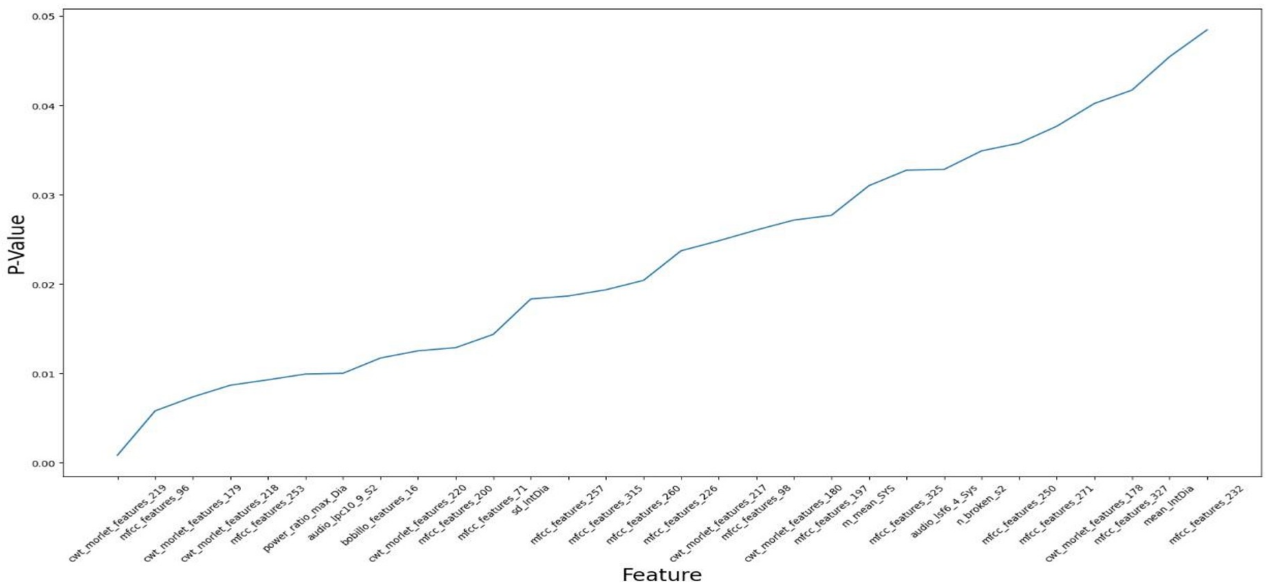

Figure 3. Significance Pattern in Selected Features

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