Fetal Heart Sound Split Detection and Classification in Phonocardiographic Signals

Kristóf Müller[1], Bálint Áron Üveges[1], Márton Áron Goda[1]

[1] Pázmány Péter Catholic University Faculty of Information Technology and Bionics, Budapest, Hungary

Abstract

Fetal cardiovascular monitoring is essential in assessing high-risk gestations during the third trimester. With available technologies and signal processing methods, several congenital heart diseases can be detected prenatally, and adequate treatment can be prepared in advance. Phonocardiography is one such method, with the advantage of being inexpensive and convenient compared to other commercially available solutions. In this paper, an easily adaptable process is introduced to classify fetal S_1 as regular or split heart sounds. The process also includes a simple heart sound segmentation, based on the Teager-Kaiser energy operator and a moving average filter. Multiple signal features were evaluated, including time domain, frequency domain, and time-frequency information. The feature-space was constructed by principal component analysis with different feature compositions and classified using k-means clustering. Classification accuracy was evaluated on a clinical recording where 1874 heart sounds had been detected. The recording was labelled by an expert with 892 regular and 762 split S_1 and 220 non-decidable or noisy segments, which served as the ground truth. The highest overall accuracy achieved with individual features was 90.7%. A possible improvement upon this design using multiple classification stages based on additional features is also described.

1. Introduction

1.1. Motivation

Monitoring the development of the fetal heart during gestation is crucial to diagnose congenital heart diseases (CHD). With earlier detection of anomalies, possible treatment can be planned in advance enabling a better long-term clinical outcome. The state-of-the-art CHD diagnosis methods make use of an ultrasound (US) technique called echocardiography. However, this approach requires a trained professional to perform the measurement, and the device itself is more expensive than instruments with other modalities. Fetal-phonocardiography (fPCG) is often used to measure fetal heart rate (FHR) but the recorded signal carries enough information to detect some CHDs and recently became a popular research topic. In fPCG signals extraneous noises called *murmurs* and heart sound splitting could indicate certain CHDs, for example valve stenosis or Ebstein's anomaly. An example for regular heart sounds and heart sounds with split S_1 can be seen in Figure 1 and 2 respectively. Data acquisition is possible at the 24th week of gestation, when the fetal heartbeat becomes strong enough to be detected. For split heartsounds most published datasets and methods focus postnatal recordings, meaning it is still important to acquire more data and knowledge about fetal cases.

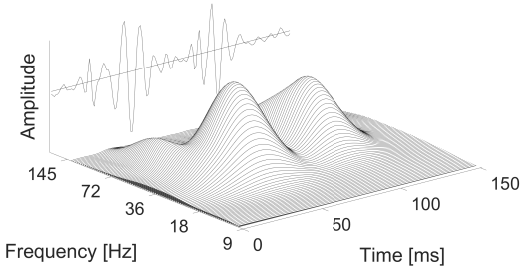

Figure 1: Two fetal heart sounds with regular S_1 and their time-frequency representation

1.2. Literature overview

The split detection can be divided into two smaller tasks, detecting and segmenting the heart sounds and their classification. For accurate segmentation an electrocardiogram (ECG) recorded simultaneously with the PCG could be used, like in the process described by Wang *et al.* [1]. Where an averaged S_1 signal obtained by utilizing QRS detection on the ECG signal. This technique is not feasible in fetal PCG since it requires multiple sensors and a higher

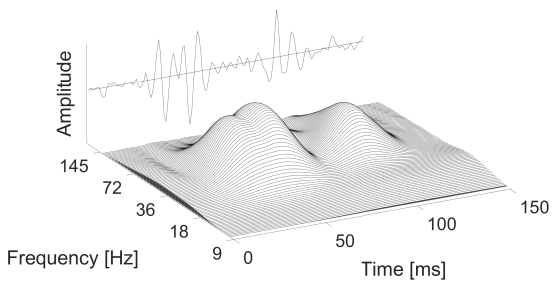

Figure 2: Two fetal heart sounds with split S_1 and their time-frequency representation

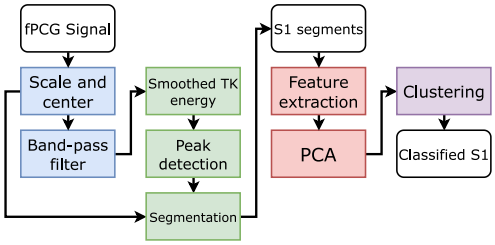

Figure 3: The process overview

technical proficiency from the end user. Additionally the electrical signal from the maternal heart could overpower the smaller fetal signal, and suppressing it could prove difficult. But recently, devices with simultaneous phono- and electrocardiogram recording capabilities became available [2] and these could be applied for fetal recordings in the future. Other heart sound detection methods where only the PCG data is used also had promising results [3]. Here Sava *et al.* used a MP based method combined with cross-correlation for accurate heart sound detection. In recent years, a significant development in PCG abnormality detection approaches was the PhysioNet Challenge in 2016 [4], where the different teams were tasked with classifying abnormal PCG signals. For this challenge Goda and Hajas developed a classification method based on a segmented PCG signal and a combination of time, frequency and wavelet-envelope features with singular value decomposition (SVD) and a support vector machine (SVM) classification [5].

2. Methods and materials

Our process consisted of four main stages, being preprocessing, heart sound segmentation, feature extraction and clustering. A schematic for this can be seen in Figure 3, the different stages marked with colors. In the preprocessing stage the DC offset was removed, and the signal was rescaled to the interval of [-1,1]. Then an infinite impulse response (IIR) band-pass filter with a central frequency of

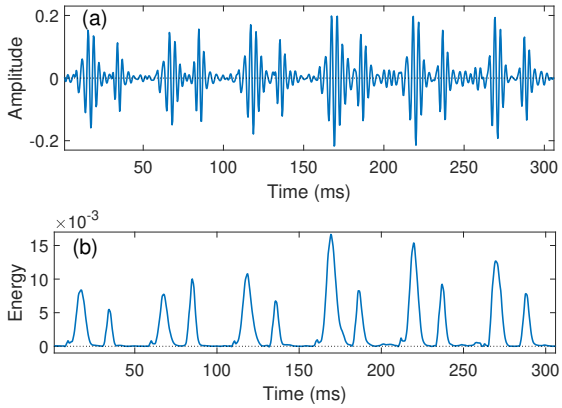

Figure 4: The energy of the signal. (a) Filtered signal (b) Smoothed TK energy

30 Hz and a Q-factor of 3 was applied to remove some of the noise present in the signal and to enhance the prevalence of the S_1 sounds. This filtered signal (seen in Figure 4a) was only used for heart sound detection, the later stages used the segments from the original signal in order to circumvent any unwanted artifacts introduced by this filtering.

2.1. Heart Sound segmentation

Since our focus was to examine the S_1 sounds, the detection and segmentation steps were optimized for those sounds only. No other parts were included in the classification. A simple detection algorithm was implemented based on the discrete Teager-Kaiser (TK) energy operator [6] of the signal. In the presented process the discrete TK energy operator was extended with a smoothing moving mean filter with a 60 ms window, an example result of this extension can be seen in Figure 4b. Peaks in the smoothed energy corresponded with impulses in the signal, and a local maximum search was done to locate these peaks. To reduce the amount of false positive detections, physiology-based parameters were introduced. Firstly, the minimal beat-to-beat time for the minimal difference between the detections, which was set to 270 ms, giving an upper bound of 222 bpm for the heart rate. The mean periodicity of the peaks was then calculated and used as a coarse estimate for fetal heart rate. This was done to remove statistical outliers with other periodicities. Finally the local maximum energy values were compared and the statistical outliers removed, similarly to the previous step. In both cases an outlier was defined as a value with more than three scaled median absolute deviations from the median value. The remaining local maxima were considered S_1 events and a time-window with a constant size was extracted from the original signal around these timepoints.

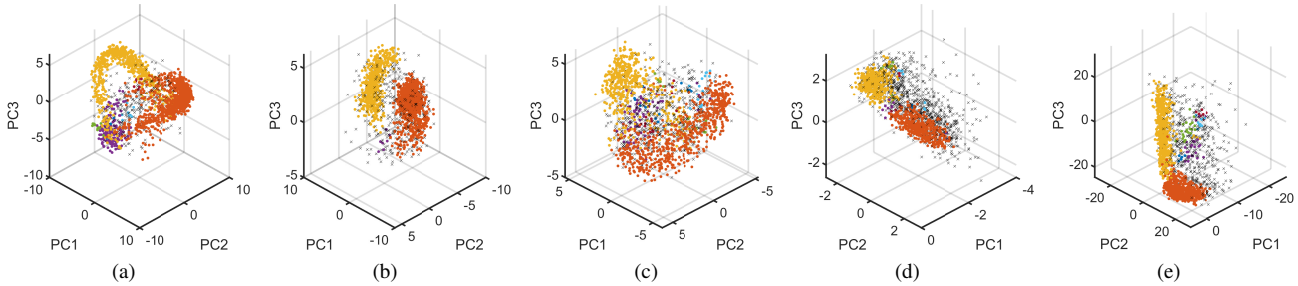

Figure 5: The exploratory clustering phase with first 3 principal components shown. Orange represents the supposed regular, yellow the supposed split, and black the rejected datapoints. Other colors are smaller unknown clusters (a) Raw signal, (b) Hilbert envelope, (c) Instantaneous phase, (d) Fourier spectrum, (e) CWT

2.2. Examined features

The features for each segment had three types: time domain, frequency domain and time-frequency domain. The time domain features included the raw signal, the envelope, and the instantaneous phase. The latter two were calculated with the help of Hilbert transformation [7]. Frequency domain information was obtained from the Fourier transform of the signal. The magnitude of the resulting complex coefficients gave the spectrum of the segment. This feature was included because previously it was successfully used for the characterization of split heart sounds [5]. The final type of features was the continuous wavelet-transform (CWT) [8] of the segment taken with the Morlet wavelet family, since they give a good basis for general signals. The resulting coefficient matrix was flattened to a vector so that the further processing steps could be the same as with the other features. The next step in the processing was a principal component analysis (PCA) to extract prominent differences and to reduce the dimensionality of the data. The loadings for each feature was calculated with the SVD method.

2.3. Exploratory clustering

To choose the most appropriate classification method and to validate the split classification abilities of a certain feature, an exploratory clustering phase was performed, where the size, number, and the separability of the clusters were observed. This was done with a general density based clustering method (DBSCAN) on each feature representation individually. In order to compensate for the *curse of dimensionality*, the standard Euclidean metric was modified in the distance calculation. This distance metric is defined as:

$$d(\mathbf{a},\mathbf{b}) = \sqrt{\sum_{n=1}^{N}(a_n - b_n)^2\, w(n)}, \qquad (1)$$

where $\mathbf{a}$ and $\mathbf{b}$ are both N dimensional vectors with a_n and b_n being their n$^{\text{th}}$ coordinates. This d function satisfies all properties for a metric function if and only if $w \not\equiv 0$. In our case the weight function was defined as:

$$w(n) = e^{\frac{-n}{\lambda}}, \qquad (2)$$

where the parameter λ is used as a *leniency* term for the higher dimensions. Meaning a higher λ value represents a less strict weight function. In the presented case, a λ value of 3 was chosen, the DBSCAN parameters were optimized for the given feature space. The result of this clustering can be seen in Figure 5.

3. Results

Evaluation of the different feature representations was done on a manually labeled dataset, consisting of three classes: normal, split, and undecidable. The dataset contained in total 1874 segments, from which were 892 regular, 762 split, 220 undecidable segments. These segments were extracted from a 20 minute long fPCG recording, from a particular subject, where S_1 split was observed, using the previously described (2.1) segmentation algorithm, which was validated with different, shorter recordings with labelled heart sounds. This segmentation method was chosen to build the dataset, since a satisfactory public dataset could not be found at the time of development, and so that a full implementation could be modelled. For classification, k-means clustering was used since the exploratory segmentation revealed that there were two main clusters in all representations and these clusters were linearly separable, as seen in Figure 5. The accuracy calculation was done in the following way:

$$Se = \frac{Ss}{Ss + Rs},\ Sp = \frac{Rr}{Rr + Sr},\ Acc = \frac{Se + Sp}{2} \qquad (3)$$

These terms are defined in Table 1. The features were examined first on their classification capabilities, these can

Labeling		Clustering	
		Regular	Split
Manual	Regular	Rr	Sr
	Split	Rs	Ss

Table 1: Definition of the terms used in accuracy calculation

be seen in Table 2. Then with the same dataset their runtime performance was measured in the online version of MATLAB [9], this result can be seen in Table 3.

4. Conclusion

In this paper we proposed an automatic method to detect split S_1 sounds from an fPCG recording. We showed that a simple heart sound segmentation method could prove to be satisfactory if the signal contains enough elements and the most prevalent feature is the examined phenomenon. As a possible improvement, we can implement multiple classification stages with different features. For example by using the specificity of the Hilbert envelope to improve the Fourier spectrum the overall accuracy increased to 0.912. Currently, the process as described here, is not yet capable of automatic diagnosis or as a pre-screening tool, but could prove useful in aiding medical experts in their decisions. In the future we would like to improve our dataset with more subjects and other pathological cases, enabling more significant results. The process could be further refined with a more sophisticated segmentation method and including other features.

Feature	Se	Sp	Acc
Raw signal	0.908	0.777	0.843
Hilbert envelope	0.745	**0.956**	0.851
Instantaneous phase	0.888	0.771	0.829
Fourier spectrum	**0.953**	0.861	**0.907**
CWT	0.860	0.892	0.876

Table 2: Accuracy measures for each feature representation. Best results marked in bold

Feature	Average running time	
Raw signal	1.86 s	(baseline, x)
Hilbert envelope	2.00 s	(1.08x)
Instantaneous phase	2.15 s	(1.16x)
Fourier spectrum	**0.46 s**	**(0.25x)**
CWT	39.44 s	(21.17x)

Table 3: Average time taken in seconds for feature extraction for our dataset. Best result marked in bold

Acknowledgements

The work was supported by the TKP2021-NVA-27 grant, funded by the Ministry of Innovation and Technology with support from the National Research Development and Innovation Fund under the TKP2021 program.

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Address for correspondence:

Kristóf Müller
Room 204, Práter street 50/A, 1083 Budapest, Hungary
muller.kristof@itk.ppke.hu
Bálint Áron Üveges
Room 240, Práter street 50/A, 1083 Budapest, Hungary
uveges.balint.aron@itk.ppke.hu
Márton Áron Goda
Room 204, Práter street 50/A, 1083 Budapest, Hungary
goda.marton.aron@itk.ppke.hu