Classification of the Source of 1D Doppler Ultrasound Activity in Fetal Monitoring

Johann Vargas-Calixto[1*], Rachel Beanland[2*], Reza Sameni[1,3], Nasim Katebi[1], Shanice Reynolds[1], Suchitra Chandrasekaran[1], Peter Rohloff[4], Sunil Sazawal[5,6], Saikat Deb[5,6], Sayan Das[5], Gari D. Clifford[1,3†], and Faezeh Marzbanrad[2†]

[1] Emory University, Atlanta, GA, USA, [2] Monash University, Melbourne, Australia
[3] Georgia Institute of Technology, Atlanta, GA, USA
[4] Maya Health Alliance, Tecpán, Guatemala and Brigham and Women's Hospital, Boston, MA, USA
[5] Center for Public Health Kinetics, New Delhi, India
[6] Swami Vivekanand Subharti University, Meerut, India, * Co-first authors, † Co-senior authors

Abstract

Background: *Cardiotocography and obstetric ultrasound imaging are the standard for fetal monitoring during pregnancy and labor. These technologies are often expensive and, with very few exceptions, can only be used by highly trained personnel. Medical care during gestation differs in low- to middle-income countries (LMIC) from high-income countries. Our research has previously demonstrated that a low-cost 1D Doppler ultrasound (DUS) can be used during pregnancy to assess maternal and fetal health. However, differentiation between DUS signals from the fetal heart (FH) and umbilical cord (UC) can be challenging for untrained users.* ***Methods***: *We trained a random forest classifier to detect whether 1D DUS recordings originated from FH activity or UC blood flow. This classifier was trained using the relative energy in each 10 Hz interval of the power spectrum derived from a balanced set of recordings. We used leave-one-out cross-validation to test our results.* ***Results***: *We achieved an area under the curve of 0.93 and an accuracy of 82.6% for identifying FH activity, and 84.7% for UC blood flow.* ***Conclusions***: *It is possible to differentiate the source of the 1D Doppler ultrasound signal. Depending on the source, different clinical parameters can be analyzed, enabling more targeted assessments of maternal and fetal health.*

1. Introduction

Mothers and fetuses are commonly monitored during pregnancy using technologies such as cardiotocography and obstetric ultrasound imaging. Despite being the clinical standard that has been in use for multiple decades, they are only available to a fraction of the world. Current monitoring technologies are expensive, have limited specificity, require constant maintenance, and can only be operated by highly trained personnel [1]. In consequence, the clinical standard in high-income settings is not readily available in low- to middle-income countries (LMIC).

LMIC account for 95% of maternal deaths worldwide, and approximately 98% of neonatal deaths and stillbirths [2]. Maternal and fetal mortality is preventable in most cases, provided early identification of pregnancy complications and adequate treatment. Maternal hypertension, preeclampsia, and fetal growth restriction (FGR) are the main contributors to maternal and fetal morbidity and mortality. Furthermore, the protocols available to screen these complications in LMIC are less precise than those used in high-income countries. For example, in the absence of ultrasound imaging, fetal growth is assessed by manually measuring the symphysis fundal height [3].

In our previous research, we introduced a smartphone-based medical system to improve maternal and fetal monitoring in LMIC [4]. This system comprises a one-dimensional (1D) Doppler ultrasound (DUS) to record cardiac and uterine activity, and a blood pressure cuff to monitor maternal pressure. Our system has been successfully used by traditional birth attendants in Guatemala, as it requires minimal training to operate. Moreover, we have evaluated fetal development [5] and maternal hypertension [6] using prenatal 1D DUS signals.

One-dimensional DUS signals can capture rich information about the activity of the fetal heart (FH) and circulation in important blood vessels, such as the umbilical arteries. For example, 1D DUS is useful for detecting the opening and closing of FH valves, which is important for evaluating congenital heart disease [7]. Alternatively, 1D DUS can be used to evaluate fetal vascular resistance in the umbilical cord (UC) [8]. Extracting the right physiological

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parameters requires knowing the source of the DUS signal.

FH and UC sourced DUS signals have the pulse rate of fetal heartbeats. This pulse rate is evident when listening to the recorded signal. Audibly differentiating the source of the recording is not straightforward because both signals have the same pulse rate. Unfortunately, as 1D DUS signals are not the standard for fetal and maternal monitoring, the automatic identification of the source of 1D DUS signals is yet to be investigated.

The objective of this preliminary study was to assess whether it is possible to train a classifier to differentiate between FH activity and UC blood flow from 1D DUS recordings. To achieve this, we trained a random forest (RF) classifier using the power spectral density (PSD) of the DUS recordings. In the future, such a classifier could benefit the users of our system by informing them in real time the source of the 1D DUS signal being recorded.

2. Methods

2.1. Data Description

The data used in this study were acquired by traditional birth attendants in Pemba, Tanzania. The study was approved by the IRB of Emory University (STUDY00005252). The recordings were obtained during monthly check-up visits, where the birth attendants recorded 1D DUS signals, maternal pressure, and maternal weight. We included in the analysis women between 18 and 49 years of age which enrolled in the study prior to the first 19 weeks of gestation, and singleton pregnancies.

The DUS signals were acquired using the Contec Baby Sound-A Pocket Fetal Doppler device (Contec Medical, Qinhuangdao Hebei, PRC). This device produce an audible DUS signal which was recoded into a Samsung smartphone at a sampling frequency of 11,025 Hz.

2.2. Signal Processing

We limited our analysis to recordings that were labeled as good quality by a custom signal-quality index [9].

Author R.B. was trained to differentiate FH from UC sounds in 1D DUS signals by a trained ultrasonographer. R.B. listened and manually labeled a balanced set of DUS recordings in segments of 3.75 s. In the field, our system provides signal-quality feedback to users using 3.75 s windows. Thus, we aimed to use the same segments to classify the DUS source. Due to the challenges of manual labeling, we only included a small subset of the dataset in this preliminary study. In total, there were labeled recordings from 16 different participants: eight participants had FH sounds and eight participants had UC sounds. Although one participant may have sounds from both structures, we only included one type of source per participant to accentuate the inter-participant variability across classes.

We extracted 12 to 14 segments of 3.75 s (41,343 samples) in length from each participant; a total of 100 segments per class. These segments may be consecutive but they do not overlap. Next, we standardized each segment by its mean and standard deviation.

The PSD of 1D DUS recordings has been shown to be predictive of fetal and placental pathology [8]. Thus, we computed the PSD of each segment using the *pwelch* function in MATLAB (R2024b). PSD was estimated using a frequency resolution of 10 Hz, 50% overlap, and up to a maximum frequency of 2 kHz. We obtained 201 PSD estimates in the 0–2 kHz range from each DUS segment.

2.3. DUS Source Classification

We used the PSD estimates as classification features to train a random forest (RF) classifier. To obtain test results, we used the leave-one-participant-out cross-validation (LOOCV) approach. The test predictions were aggregated across all participants to obtain the overall performance of the classifier. The number of classification features was defined by the sequential forward feature selection (SFFS) algorithm. Below, we describe the classification steps performed in each training iteration.

1. *Majority sub-sampling*: Using LOOCV in a balanced data set resulted in class imbalance during training. To mitigate the effects of class imbalance in the classification scores, we sub-sampled the majority class. First, we observed N_{min}, the number of training segments available in the minority class. Then, we randomly sampled without replacement N_{min} training segments from the majority class. We used the resulting balanced set of segments to train the RF classifier.

2. *Feature selection*: We used the built-in *sequentialfs* algorithm in MATLAB to select the best subset of features. The SFFS algorithm adds classification features one-by-one, selecting at each step the feature that reduces the loss function the most. Once the loss function fails to decres, the algorithm stops. In this study, we used the binomial deviation loss function calculated from the out-of-bag predictions of the RF classifier.

3. *Classification*: The RF classifier consisted of 100 classification trees and was trained using the balanced training set and the optimal subset of features defined by SFFS.

4. *Model evaluation*: At each training iteration, the RF classifier was used to generate predictions on the segments of the test participant. We recorded the classification scores to assess the area under the receiver-operating characteristics curve (AUROC). The classification labels were recorded using a standard threshold of 0.5. These labels were used to calculate the total confusion matrix and model accuracy.

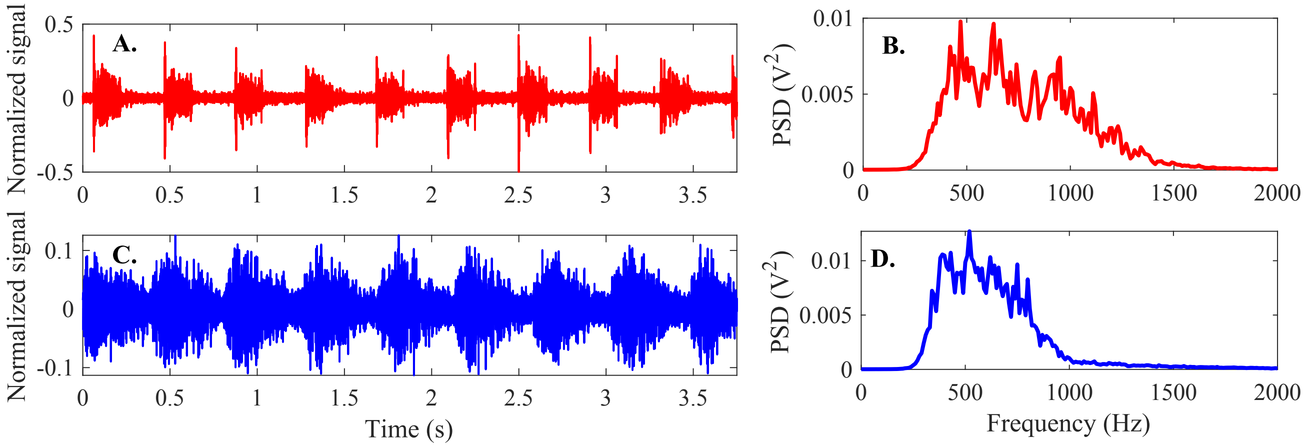

Figure 1. Examples of 1D DUS signal and their PSD of (A, B) fetal heart and (C, D) umbilical cord sounds.

3. Results

3.1. Power Spectrum of DUS Recordings

Fig. 1 shows the 1D DUS signal and PSD of one FH (A and B) and one UC (C and D) recording. Both signals show bursts of activity at each heartbeat. These plots show that both signals have similar periodicity, which makes it difficult to differentiate them by only listening to them.

Fig. 2 shows the average PSD of all segments recorded from FH and UC sounds. In average, the FH PSD had most of its amplitude in frequencies below 500 Hz, and then it decayed at higher frequencies. In contrast, the UC PSD increased at higher frequencies than the FH PSD, and had most of its content between 400–900 Hz. These morphological PSD differences may be useful for classification.

3.2. Classification Results

At iteration, the SFFS algorithm selected only 3 to 7 features (μ = 4.94, σ = 1.29) out of the 201 available. Fig. 3 shows the number of times that the power of each frequency was used in training. The power at 50 Hz was the most robust feature, it was used by all classifiers. The remaining features were selected from bands around 200–400 Hz and 1,000–1,200 Hz.

The classifiers correctly classifier 82 FH segments and 85 UC segments. Averaging the intra-participant predictions, 82.6% (σ = 27.7%) of FH segments and 84.7% (σ = 20.1%) of UC segments were correctly classified. Finally, we obtained an AUROC = 0.93 using the aggregated prediction scores.

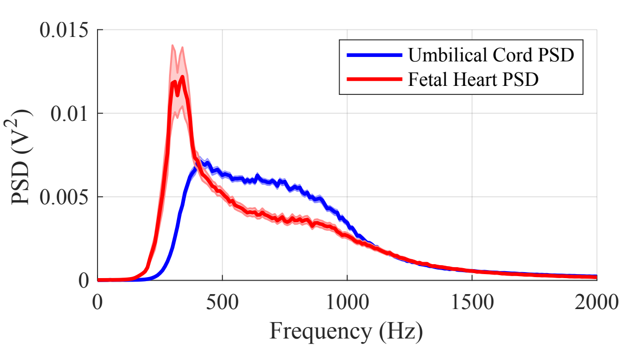

Figure 2. PSD (mean ± standard error) of all segments of umbilical cord (blue) and fetal heart (red) sounds.

4. Discussion

The objective of this study was to evaluate whether the PSD of 1D DUS recordings could be used to distinguish between fetal cardiac and umbilical sources. Our results showed that these signals have distinct PSD morphologies when recorded from the FH or UC. Furthermore, an RF classifier was able to discriminate between both sources with an average detection rate of more than 80% and an AUROC of 0.93. These results strongly support the use of such signals to provide real-time feedback to users.

During gestation and labor, maternal and fetal monitoring is important to screen possible complications and provide the best care possible. Although the current standard is to use ultrasound imaging to fetal cardiac and umbilical assessments, this technology is expensive and requires highly trained operators; the current clinical standard is out of reach for most settings in LMIC. Using 1D DUS has shown promise in the detection of FGR, fetal anemia, abnormal vascular resistance, and maternal hypertension. However, there is still a need for well-trained users that can differentiate 1D DUS signals from different fetal cardiac, umbilical, placental and maternal sources. Our results show that it is possible to use the PSD of these record-

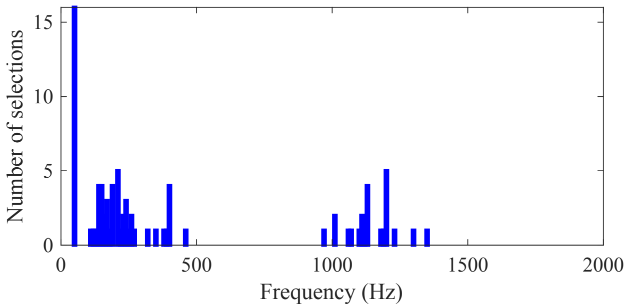

Figure 3. Number of times that the power of each frequency was used in classification. The power at 50 Hz was the most used feature. Note that all devices ran off batteries and there were no devices powered by mains electricity connected to the subjects.

ings to identify their source and to do so using only 3.75 s of signal at a time. Therefore, it is feasible to implement this approach in our current system and provide real-time feedback to users. However, the size of RF classifiers depend on the size of the training set. Thus, we need to explore other classifiers that are more compact to be included in our smartphone application.

The present is a preliminary study to assess the potential of this approach. We are aware that using such a limited number of participants may raise doubts about the generalizability of our results. We took measures to address this issue . First, we used LOOCV to avoid intra-participant correlations between the training and test segments. Next, we avoided including signals from both sources per participant. Finally, we used an SFFS algorithm to reduce the number of features used by the classifier and avoid overfitting.

We are currently working to increase the number of participants included in this approach and the number of sites. We have data available that were collected from three different countries. After reviewing the labels, we will include them in a larger classifier. Then, we will test the performance of this larger classifier and its cross-setting generalizability. Also, we will assess the classifier performance using other 1D DUS monitors to make sure that our algorithm does not depend on a single device. Finally, we aim to include data from other sources such as maternal spiral arteries and placenta. We believe that with such improvements the model could be implemented in our system and used in LMIC.

5. Conclusions

We have presented an RF classifier that uses the PSD of 1D DUS recordings to identify their source. This model correctly detected over 80% of segments (AUROC = 0.93). Thus, there is potential in this approach to provide real-time feedback to users of 1D DUS technologies in LMIC.

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Address for correspondence:

Johann Vargas-Calixto

101 Woodruff Circle, Suite 4100, Atlanta, GA 30322

cavarga@emory.edu