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Blind Source Separation of Fetal ECG

M.Sc. Project Report by:

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1 Abstract

This work aims to perform a real-time separation of fetal electrocardiogram (FECG) signals from ECG signals recorded from pregnant women. The proposed method employs a two-phase training approach, first pre-training the model with simulated data and then fine-tuning it with real-world data. The method is based on a Residual Network (ResNet) architecture, which is designed to handle deep neural networks, and supervised and self-supervised learning. Results show that the proposed method is successful in separating FECG signals on real-world data with high accuracy and precision. The model is able to predict the time positions and reconstruct the PQRST morphology of the FECG signals, resulting in significant advancements for fetal heart monitoring.

2 Introduction

An electrocardiogram (ECG) is a non-invasive test that records the electrical activity of the heart to assess its health and detect any abnormalities [1]. It is also used to monitor fetal heart activity during pregnancy to prevent neonatal morbidity and mortality [2][3]. During the test, electrodes are placed on the mother's thorax and abdomen, and an ECG machine records the reflected ultrasonic sound waves produced by the transmission of high frequency sound waves through the maternal abdomen.

Compared to regular fetal heartbeat monitoring, fetal ECG (FECG) monitoring provides more detailed and accurate information about the fetal heart rhythm. An ECG records the electrical activity of the fetal heart, which allows healthcare providers to identify more subtle changes in the fetal heart rhythm. This can be especially important during labor and delivery, as changes in the fetal heart rate can indicate potential problems such as fetal distress or placental dysfunction. FECG monitoring can also detect abnormalities that may not be detectable with regular heartbeat monitoring. For example, ECG can detect fetal tachycardia (rapid heart rate) or fetal bradycardia (slow heart rate), which may not be detectable with regular heartbeat monitoring. These abnormalities can indicate potential problems that need to be addressed in order to ensure the health and safety of both the mother and the baby. In addition to providing more detailed and accurate information about the fetal heart rhythm, FECG monitoring can also help identify potential problems during labor and delivery. By continuously monitoring the fetal heart rhythm, healthcare providers can identify potential problems early on and take appropriate action to address them. This can include adjusting the position of the mother, administering medication, or considering a cesarean delivery if necessary. Overall, FECG monitoring is a valuable tool that can provide healthcare providers with important information about the well-being of a fetus during labor and delivery. By using ECG in conjunction with other methods of fetal monitoring, healthcare providers can ensure the health and safety of both the mother and the baby.

However, although ECG tests are convenient and easy to perform [2], analyzing FECG signals can be difficult because they are mixed with maternal ECG (MECG) signals and other sources of noise, such as respiratory noise, muscle artifacts, electrode motion, or baseline wander. Furthermore, the distinct morphological differences between these signals, such as the smaller amplitude and wider cardiac cycle of FECG, can make it difficult to discern the FECG in the presence of the larger and narrower cardiac cycle MECG, making it challenging to accurately analyze the raw FECG signals. Therefore, an effective process for extracting FECG signals is important and in demand.

Blind Source Separation (BSS) is a technique used to separate and identify individual sources of a signal that have been mixed together. It is used in a variety of fields, including audio and speech processing, biomedical engineering, and image analysis. BSS can be achieved through various methods, such as independent component analysis or non-negative matrix factorization, and it is often paired with machine learning algorithms like neural networks to optimize the separation and detection of the individual signals. The goal of BSS is to separate the mixed signals into their individual components, allowing for more accurate analysis and understanding of the original signals.

BSS is commonly used in the analysis of ECG signals. BSS can be used to separate the FECG signal from the MECG signal and other sources of noise, such as electronic equipment or body movements. By separating and isolating the FECG signal, it is possible to identify the fetal heartbeat and use it to synchronize medical imaging techniques like cardiac MRI more accurately.

Cardiac MRI is an important tool for evaluating complex congenital heart diseases and determining treatment paths for patients. FECGs have greatly improved the way these conditions are treated by allowing for early preparation for complex malformations and, under certain circumstances, the contemplation of miscarriage. However, there are some conditions that remain undetected until birth and may require further analysis with tools like echocardiography or MRI. To synchronize the MRI sample with the fetal heartbeat, it is necessary to accurately predict the time points at which the heartbeat occurs. To improve the quality of fetal ECG detection, various signal processing techniques, including adaptive filters, single value decomposition (SVD) and wavelet transformations, have been employed since the 1960s.

Eventually, our goal is to optimize and perform a real-time separation and detection of FECGs for fetal cardiac monitoring.

3 Related Work

There are several techniques in the literature for extracting FECG signals, including correlation techniques, matched filtering, wavelet transform, and BSS.

An example of a classical signal processing approach is described in Lima Herrera et al. [4], which proposes the use of wavelet decomposition and an adaptive filter with the least mean square algorithm for noise cancellation to extract FECG signals. Another study by Ghaffari et al. [5] proposed a new method for selecting the best channel for detecting fetal QRS complexes from FECG signals, using a combination of geometric features and wavelet-based techniques.

Among the techniques above, BSS tends to perform better than most of the other signal processing techniques [6]. In one study [2], the Joint BSS (JBSS) algorithm was evaluated for its effectiveness in separating the mixed signals, and it was found that the JBSS-CUM4 algorithm performed well for FECG extraction. In Zhongliang et al. [7] a comparison between artificial neural networks (ANN), BSS and adaptive filtering for separating FECG and MECG was conducted. The results showed that BSS techniques based on empirical mode decomposition (EMD) were the most effective in extracting FECG. Ramli et al. [8] also examined BSS techniques, specifically the Degenerate Unmixing Estimation Technique (DUET) algorithm, for extracting FECG in situations where the number of sources is greater than the number of mixtures, such as in the case of twins or triplets' pregnancies.

Other studies employ Independent Component Analysis (ICA), a subtype of BSS techniques, to separate mixed signals. ICA is a computational method for decomposing a multivariate signal into its additive subcomponents. The authors in [9] studied the use of the FastICA algorithm with maternal R-peak suppression for FECG signal extraction, and [10] reported on an improved FastICA method that incorporated an over relaxation factor into Newton's iterative algorithm to process the initial weight vector randomly. This improved FastICA was able to separate the source component by selecting the best maternal MECG and removing it using singular value decomposition (SVD).

Deep learning approaches to FECG extraction were also useful for understanding the various preprocessing techniques and datasets used in the field and provided useful information when planning the current network. One example of a deep learning method is [11] by Fang-Wen et al., which uses the simulated PhysioNet [12] dataset to detect FECG peaks. However, this work only uses simulated data and does not perform a full BSS as intended in the current project.

Other works in this field focus on fetal heart disease classification or the use of generative models, which are not applicable to the current problem.

4 Methods

4.1 Simulated data pre-training before real-world data training

4.1.1 Motivation

One of the major challenges in training a machine learning model for FECG separation is the limited availability of real-world ECG data from pregnant women. Due to a variety of reasons, there is a relatively small pool of such data available for researchers to study and use in developing new diagnostic and predictive tools. This lack of data limits our ability to identify potential fetal cardiac risk factors or warning signs of adverse events, and our understanding of fetal cardiac health and our ability to predict and prevent complications.

The availability of real-world ECG data for pregnant women is limited for a number of reasons. One reason is ethical considerations, as ECG data is often collected during medical procedures and the privacy and confidentiality of patients must be protected. This is especially important for pregnant women, who may be more sensitive to the risks associated with data collection and sharing. Another reason is data quality, which can be low due to the noise present in the data and the physiological changes that occur during pregnancy. Additionally, data diversity can be a challenge, as ECG data can vary significantly from one individual to another, making it difficult to collect a representative sample of data from pregnant women. These issues can make it difficult for machine learning researchers to obtain high-quality, diverse, and representative training data for the purpose of studying ECG data from pregnant women, which can limit the performance of machine learning models and the accuracy of their predictions.

4.1.2 Concept

This brought us to the concept of using a synthetic dataset of pregnant women's ECG signals, created with a designated simulator, to pre-train our model. The idea is to divide the training process into two phases. In the first phase, we will train the model on the synthetic data, so it learns how to extract fetal ECG signals from a synthetic mixed ECG signal. Since we can generate as much synthetic data as needed, we will not have the issue of a lack of data in this phase. In the second phase, we will fine-tune the pre-trained model by continuing to train it on real-world ECG data. This will allow the model to apply the knowledge it gained from the larger synthetic dataset to improve its ability to extract fetal ECG signals from real-world data, which is our ultimate goal. We will discuss further about these two different phases in the *Model Training* section.

4.2 Learning Paradigms

4.2.1 Pre-training phase: supervised learning

During the first phase of training the model on synthetic data, the simulator generates a mixed ECG signal by combining both the maternal and fetal ECG signals. This means we have labels for both the maternal and fetal ECG signals, allowing us to use supervised learning.

4.2.2 Fine-tune training phase: self-supervised learning

In ECG tests on pregnant women, one electrode is typically placed on the mother's chest, producing a thoracic ECG (TECG) signal. In other words, from every real-world ECG signal we can obtain the labeled signal for the mother's ECG, in addition to the mixed ECG signal. From a learning perspective, we can utilize self-supervised learning during the second phase of training the model on real-world ECG.

4.3 Network Architecture

The Network is based on the Residual Network (ResNet) architecture. ResNet is a convolutional neural network (CNN) architecture that was designed to address the problem of vanishing gradients, which is a common issue in very deep neural networks. Its architecture is based on the idea of skip connections, which allows the network to learn an identity function. This is achieved by adding the input of a layer to the output of a higher layer, which allows the gradients to flow more easily back to the earlier layers. This makes it possible to train very deep networks, as the gradients can propagate more easily through the network.

As depicted in figure [1], the input signals of our network are the abdominal ECG (AECG) and the thoracic ECG (TECG) signals. Both signals have been resized to 1024 samples and are fed into the

ResNet encoder, which is composed of 14 ResNet basic blocks, each of which is composed of two layers of Conv1D-BatchNorm-Relu. The encoder is responsible for learning and extracting deep features of both maternal and fetal ECG signals from the input signals. It extracts 2048 features (channels) and encodes them as a latent variable vector, which is divided into two parts using disentanglement techniques to represent the maternal and fetal features separately. The maternal features are encoded in the first half of the vector, and the fetal features are encoded in the second half. The maternal and fetal feature representations are then fed into two ResNet Decoders, which are symmetrical to the encoder and are made up of 14 ResNet basic blocks using two ConvTranspose1D-BatchNorm-Relu layers. These decoders reconstruct the maternal and fetal ECG signals, separately. The output of the maternal ECG decoder is then added to the TECG input signal, as the ResNet-based architecture is expected to learn the delta between TECG and the maternal part in AECG. The combined signal and the output of the fetal ECG decoder are the final reconstructed maternal and fetal ECG signals, which are also the outputs of the network.

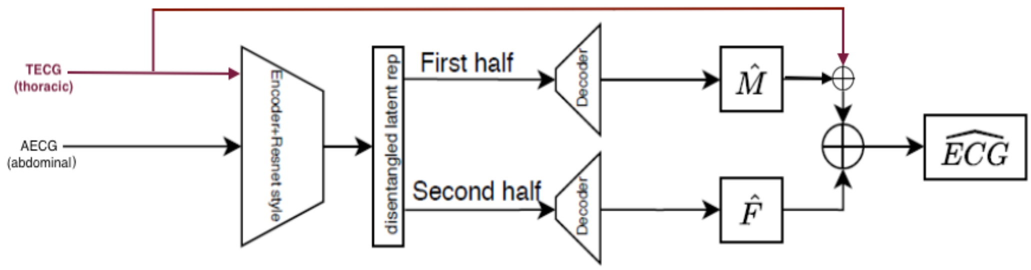

Figure 1 - Block Diagram of the network architecture

4.4 Model Training

4.4.1 Model pre-training on simulated data

When working with simulated data, both the MECG and FECG labels are available. These labels are combined to create the AECG signal, which is the first input for the model. The second input for the model, TECG, should be slightly different from the MECG label that is provided by the simulator because in reality, AECG and TECG signals recorded separately, by different electrodes, and may be affected by different noises, caused by various types of noise, such as electronic equipment and body movements. If the model only learned to perform subtraction between AECG and TECG, it would not be useful for the second phase of the training process on real-world data. To create the simulated TECG signal, we add noise to the MECG label or shift it by a period or two, or both.

The pre-training phase involved dividing the simulated dataset into three sets: a training set (60%), a validation set (20%), and a test set (20%). In the first step, the model is fit using the training set to adjust its parameters, primarily the weights of connections between neurons in the network. The model then produces MECG and FECG outputs, which are compared to their labels using an L1 loss function. Based on the comparison results, backpropagation is applied to adjust the model's parameters. In the second step, the model's fit is validated using the validation set to provide an unbiased evaluation of the model's performance on the training set while adjusting hyperparameters. In the final step, the model's fit is tested using the test set to provide an unbiased evaluation of the model's performance on the training set.

4.4.2 Model fine-tune training on real-world data

During the first phase of the training process, the parameters of the best model were saved for use later during the fine-tune training on the real-world data. The best model was chosen based on the average correlation between the model's outputs and their corresponding labels.

In the second phase of the training process, the pre-trained model will be fine-tune trained to fit a specific pair of real-world ECG signals, AECG and TECG, taken from a particular pregnant woman. During this phase, we will keep all the parameters of the pre-trained model representing the weights of the FECG decoder fixed, while we will adjust the remaining parameters of the model based solely on the comparison between the final reconstructed MECG signal and the TECG input signal, using an L1 loss function. This process is self-supervised, as explicit labels are not available.

5 <u>Data</u>

5.1 Simulated Data

After a deep and throughout research, the Fetal ECG Synthetic (FECGSyn) [12] database was chosen to be the simulated data for our model. This database is created by using the FECG simulator by Behar et al. [13] The simulator basically simulates a 3D pregnant woman. In this model the maternal-fetal heart are punctual dipoles with different magnitudes and spatial positions so that maternal-fetal-noise signals can be treated as singular component. These individual sources propagate their signals towards observational point (electrodes) that are placed on the 3D model in different 34 positions(channels) on her abdomen. The signals are created according to the parameters shown in figure [2].

	Parameters	Definition	Range/type
	fs	sampling frequency [Hz]	—
NS	$ntype$	type of noise	MA, EM, BW (Moody et al., 1984)
	SNR_{fm}	signal to noise ratio of the FECG relative to maternal interference	—
	SNR_{mn}	signal to noise ratio of the MECG relative to noise	—
HR	mhr	maternal heart rate [bpm]	70-140 bpm
	fhr	foetal heart rate [bpm]	120-160 bpm (von Steinburg et al., 2012)
	$macc$	maternal acceleration/deceleration [bpm]	—
	$facc$	foetal acceleration/deceleration [bpm]	—
	$macctype/facctype$	maternal/foetal acceleration/deceleration type	'none', 'nsr', 'tanh', 'mexhat', 'gauss'
TR	$ftraj$	foetal heart trajectory to model foetal movement	'none', 'linear', 'spline', 'helix'
RS	$mres$	maternal respiration frequency	$0.2 - 0.3$ Hz
	$fres$	foetal respiration frequency	$0.8 - 0.95$ Hz (Dornan et al., 1984)
GE	$mheart$	maternal heart position in polar coordinates	—
	$fheart$	foetal heart position in polar coordinates	—
	$elpos$	electrode position in polar coordinates	—
	$mvcg$	maternal vectorcardiogram number	1-9
	$fvcg$	foetal vectorcardiogram number	1-9
EB	$mectb$	ectopic beat for the maternal ECG	boolean
	$fectb$	ectopic beat for the foetal ECG	boolean

Figure 2 - Parameters of the FECG

The dataset consists of 10 simulated pregnancies, with 6 different physiological events simulated for each pregnancy. For each event, there are 5 Signal-to-Noise Ratio (SNR) levels of additive noise. Each combination of event and noise level has 5 repetitions. Each signal has a duration of 5 minutes and a sampling rate of 250 Hz with 16-bit resolution. The dataset includes 3 signals (FECG, MECG, and Noise) that are provided separately.

In order to get a standardized input size, the simulated data was divided into windows of size 1024.

5.2 Real-World Data

The Non-Invasive Fetal ECG Arrhythmia (NIFEA) [14] database was chosen to be the real-world data for out model. This database provides 12 fetal arrhythmias recordings and 14 normal rhythm recordings performed using the Non-Invasive Fetal ECG (NI-FECG) [15] technique. For each recording, a set of four or five abdominal channels and one chest maternal channel were recorded. The sampling frequency was 500 Hz or 1 kHz.

In order to get a standardized input size, the real-world data was also divided into windows of size 1024.

6 Results

6.1 Simulated ECG Data

Our model succeeds in an optimal and precise way to separate Simulated ECG Data. The model wasn't able to reconstruct only 6% of the overall datasets. The supervised setting helped to extract the critical features presents in both FECG and MECG. As shown in figures [3] and [4], the model succeeds in both predicting the time positions, that it is the most important aspect of the project, and the PQRST morphology. It still has some difficulties in predicting peaks that are placed at the beginning of the signal and to be more precise with the signals' amplitudes.

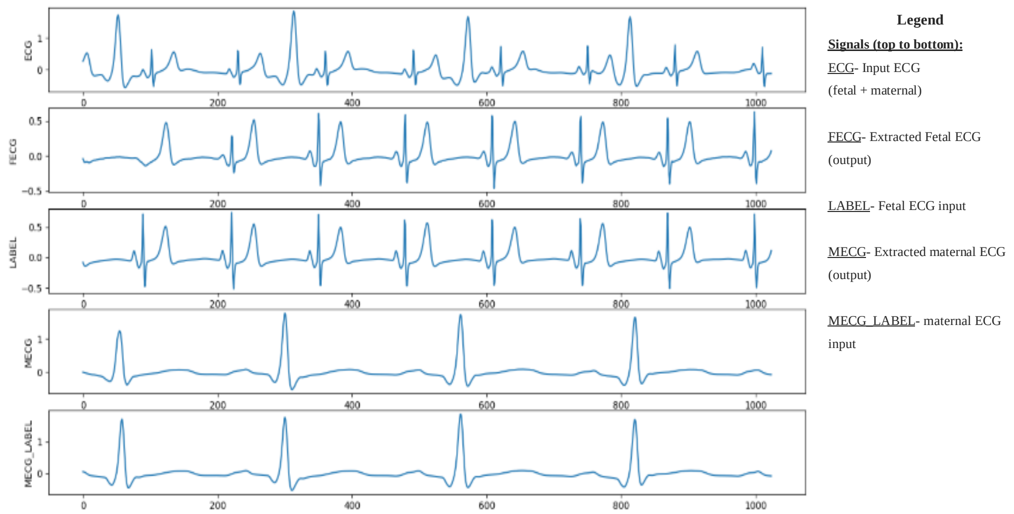

Figure 3 – An example of FECG and MECG extracted from synthetic signals; We can see a very high correlation between the model output signals, the extracted *FECG* and *MECG* (2nd and 4th rows, respectively), and their respective label signals (3rd and 5th rows). As said, the model has some difficulties in predicting peaks that are placed at the beginning of the signal and to be more precise with the signals' amplitudes.

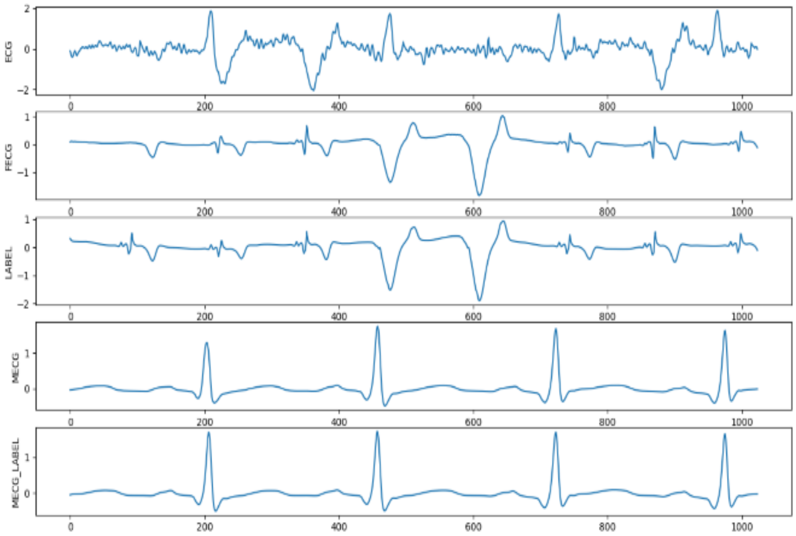

Figure 4 - Another example of FECG and MECG extracted from synthetic signals; Although the input signal *ECG* in this example is more noised than the one in figure 3, we can still see a very high correlation between the model output signals and their respective label signals.

6.2 Real-World ECG Data

Our model succeeds in an optimal and precise way to separate mixed ECG signals from the NIFEA database.

As shown in figures [5] and [6], one key success of the model is its ability to accurately predict the time positions of the fetal ECG (FECG) signals, which is a crucial aspect of the project. In addition, the model was able to effectively process FECG signals with small amplitudes and not treat them as noise, which can be a common issue in these types of analyses. Furthermore, the model was able to reconstruct the majority of the PQRST morphology features of the FECG signals, which provide important information about the function of the fetal heart.

By being able to accurately predict the time positions and reconstruct the PQRST morphology of the FECG signals, the model is able to provide valuable insights into the fetal heart's activity and potentially identify any abnormalities or issues. This is a critical aspect of the project, as it has the potential to improve our understanding of fetal heart health and inform the development of diagnostic and treatment approaches.

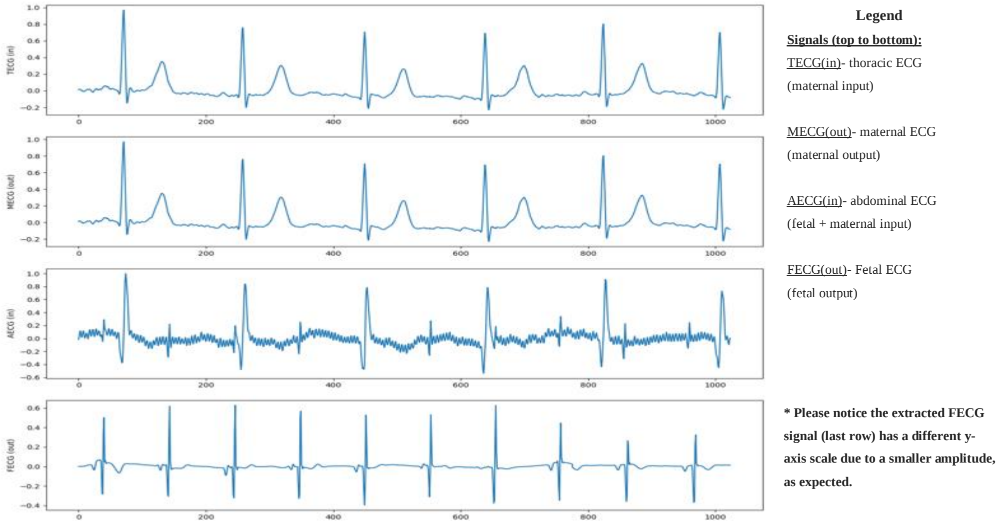

Figure 5 – An example of FECG and MECG extracted from <u>real-world</u> signals; By comparing *AECG(in)* and *FECG(out)* signals (last two rows), we can see that our model succeeded to reconstruct time positions and the majority of the PQRST morphology features of the FECG signal.

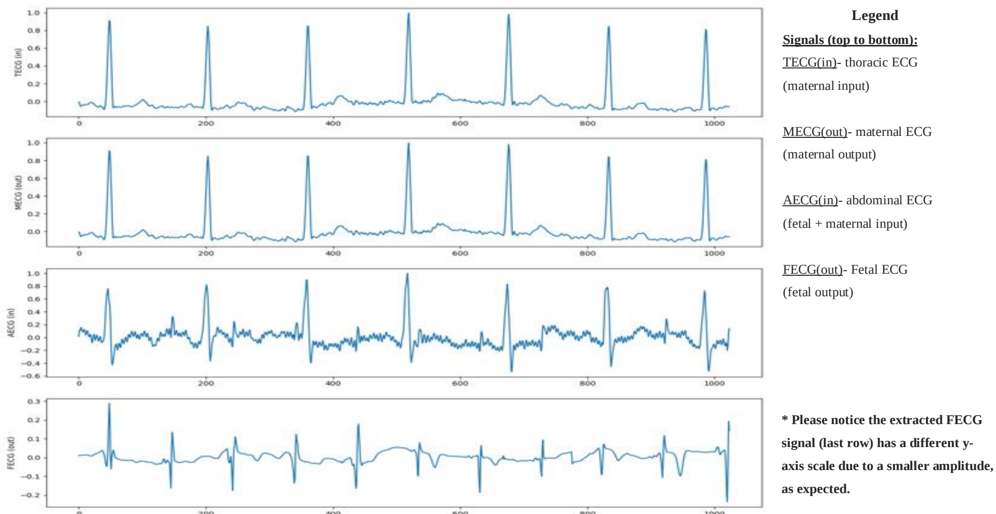

Figure 6 – Another example of FECG and MECG extracted from <u>real-world</u> signals; By comparing *AECG(in)* and *FECG(out)* signals, we can see that in addition to a successful reconstruction of time positions and PQRST morphology, as in figure 5, our model was also able to process a FECG signal with relatively small amplitudes, rather than treating it as a noise. And vice versa, meaning, no noises from the input signal were added to the extracted FECG signal.

7 Conclusions

In this project, we have proposed a novel deep learning-based approach to separate FECG signals from MECG signals. Our proposed approach consists of a self-supervised two-step training process, where we first pre-train the model on simulated data and then fine-tune it on real-world data. The pre-training phase involved dividing the simulated dataset into three sets: a training set, a validation set, and a test set. The model is fit using the training set, and backpropagation is applied to adjust the model's parameters. The model's fit is validated using the validation set and tested using the test set.

We then fine-tune the pre-trained model on real-world data to fit a specific pair of AECG and TECG signals taken from a particular pregnant woman. During this phase, we keep all the parameters of the pre-trained model representing the weights of the FECG decoder fixed, while we adjust the remaining parameters of the model based solely on the comparison between the final reconstructed MECG signal and the TECG input signal, using an L1 loss function.

Our results show that our proposed approach is effective in separating FECG signals from MECG signals in both simulated and real-world ECG data. The model is able to accurately predict the time positions of the FECG signals, which is crucial for fetal monitoring.

In conclusion, our proposed approach has the potential to improve fetal monitoring and aid in the diagnosis of fetal abnormalities. Future work can focus on developing an "end-to-end" system that can perform real-time separation and detection of FECG signals by refining the pre-trained model live on a pair of AECG and TECG signals acquired from a pregnant woman, rather than performing fine-tuning after recording the signals.

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