Blind Source Separation of Fetal ECG

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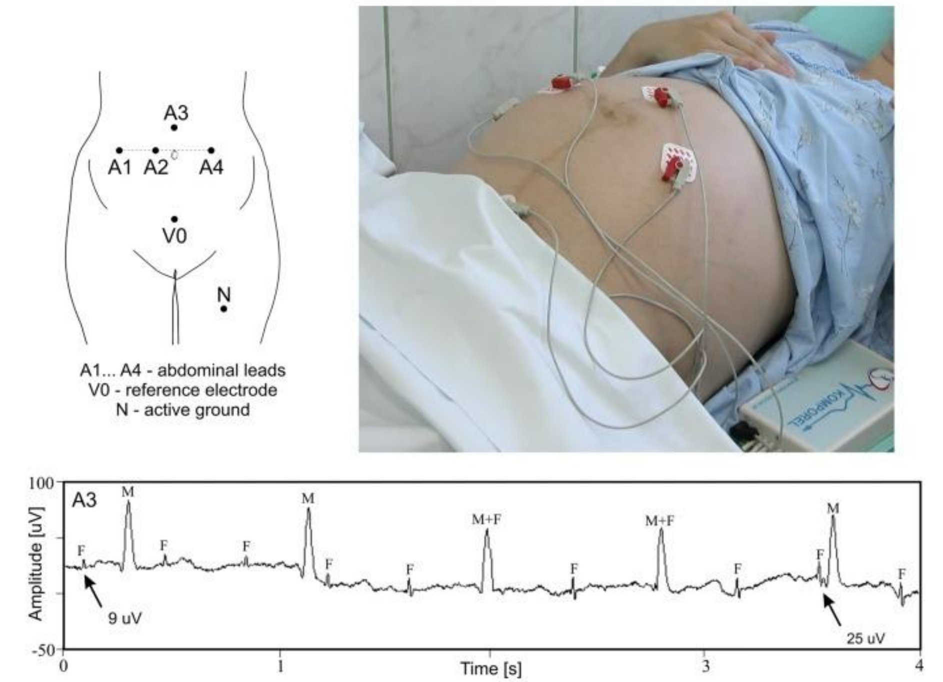
Fig. 2



Agenda

Objective

Separation of fetal ECG (FECG) signals from ECG signals recorded from pregnant women's abdomen.

Introduction

Introduction

ECG

- Non-invasive test
- Records heart's electrical activity
- Assesses heart health and detects any abnormalities

Fetal ECG Monitoring

- Tracks fetal heart activity during pregnancy
- Electrodes placed on mother's abdomen
- Provides more detailed and accurate information compared to other methods
    - accurate assessment of fetal heart rate, rhythm, and variability
- Typically used during high-risk pregnancies or during labor and delivery
    - detects potential problems

Introduction

Challenges in FECG Monitoring

- Mixed with Maternal ECG signals and other noise sources
- Distinct morphological differences between FECG and Maternal ECG (MECG) signals:
  - FECG's smaller amplitude and wider cardiac cycle are the major morphology differences
  - Difficult to discern FECG in presence of larger and narrower cardiac cycle MECG

- Accurately analyzing raw FECG signals becomes a challenge due to these difficulties.

- Therefore, it is necessary to develop a method that can separate the FECG signals effectively

Introduction

FECG Separation for Cardiac MRI

- A good separation of FECG signals improves the isolation of fetal cardiac features
- Can be used to accurately predict heartbeat's timing
- This assists medical imaging techniques like cardiac MRI
- Helps to synchronize the MRI sample with the fetal heartbeat

Introduction

Techniques for extracting FECG signals

- There are several techniques in the literature for extracting FECG signals
- Within them are:
  - Wavelet Transform
  - Matched Filtering
  - Correlation Techniques
  - Blind Source Separation (BSS)
- Among them, **BSS tends to perform better** than most of the other signal processing techniques

Introduction

BSS

- Used to separate mixed signals into their individual components
- Can be achieved through various methods, such as:
    - Independent Component Analysis (ICA)
    - non-negative matrix factorization (NMF)
    - machine learning algorithms like neural networks
- Implementing by NN can help to learn the mapping between mixed signals and individual source signals

BSS in Recent Studies

- Recent works, however, still struggle to achieve accurate, high-quality BSS for FECG separation
- As a result some fetal cardiac conditions remain undetected until birth
- These conditions require further analysis after birth using tools like echocardiography or MRI

Our Method

Our Method

Proposed Method:

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

Our Method

Proposed Method:
Simulated data pre-training before real-world data training

Motivation for the Proposed Method:

- As seen, achieving accurate and high-quality BSS for extracting FECG signals is challenging.
- A major factor for this challenge is the **limited availability of real-world ECG data from pregnant women.**
- The amount of available data is limited due to several reasons, including:
  - ethical considerations
  - low quality of real data
  - high diversity of real data
- As a result, obtaining diverse and representative training data is difficult
- This limits the performance of machine learning models and their prediction accuracy.

Our Method

Proposed Method:
Simulated data pre-training before real-world data training

Concept:

- To address this challenge we propose using a synthetic dataset of pregnant women's ECG signals
- This dataset is created using a designated simulator
- It will be used to pre-train our model before training on real ECG data.
- Hence, the training process will be divided into two phases:

  1. <u>Model pre-training on synthetic data:</u>
     - The model will initially learn how to extract FECG signals based on this data
     - Synthetic data can be generate as much as needed
     - Thus, the issue of limited data can be mitigated
  2. <u>Model fine-tune training real-world ECG data</u>
     - Continue to train this pre-trained model on real-world ECG data
     - This improves its ability to extract fetal ECG signals from real-world data.

Our Method

Learning Paradigms

Our Method

Learning Paradigms

Learning Paradigms:

Pre-training phase: Supervised learning

- In this phase, the model is trained on synthetic data
- Data is generated by combining MECG and FECG signals
- It allows us to use supervised learning, as we have labels for both MECG and FECG signals

Fine-tune training phase: Self-supervised learning

- In pregnant women's ECG tests, one electrode is sometimes placed on the mother's chest
- This produces a thoracic ECG (TECG) signal
- Meaning, we can obtain the mother's real ECG signal in addition to the mixed signal
- Thus, we can learn in a self-supervised manner its label

Our Method

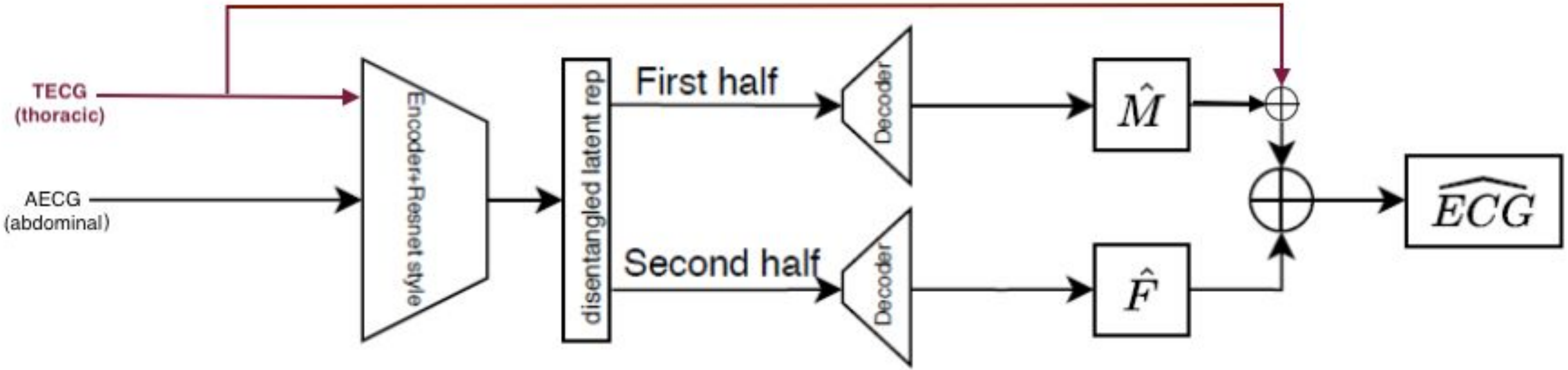
Network Architecture

Our Method

Network Architecture

Network Architecture:

- Our network is based on ResNet architecture
- Inpunעnt Signals
  - abdominal ECG (AECG) & thoracic ECG (TECG)
  - divided into windows of 1024 samples
  - fed into the ResNet encoder

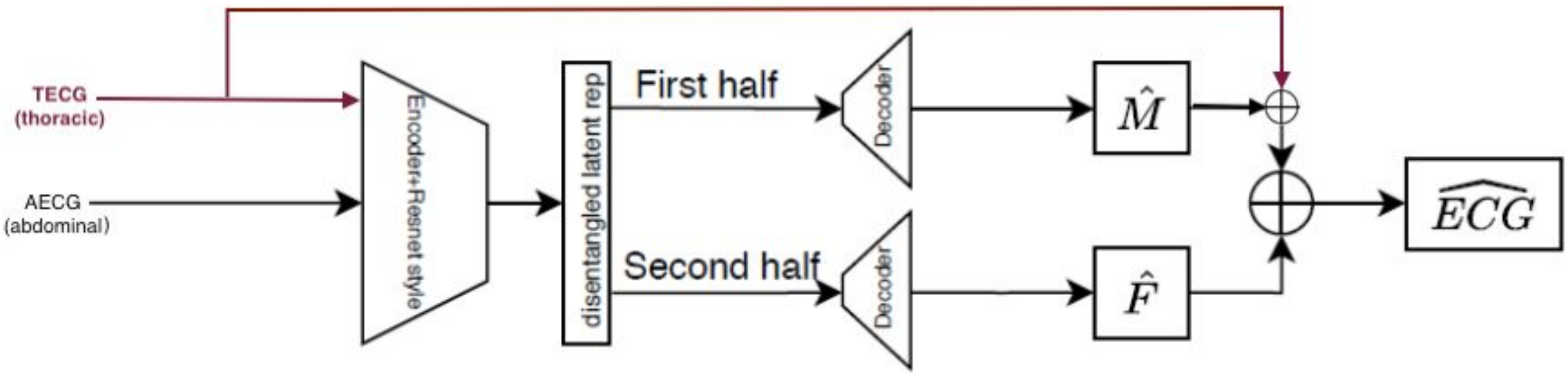


Our Method

Network Architecture

Network Architecture:

- ResNet Encoder
  - composed of 14 ResNet basic blocks
  - extracts deep features from both maternal and fetal ECG signals
  - resulting in a 2048-channel latent variable vector
- Disentangled Representation
  - used to separate maternal and fetal features
  - maternal features in the first half of the vector
  - fetal features in the second half

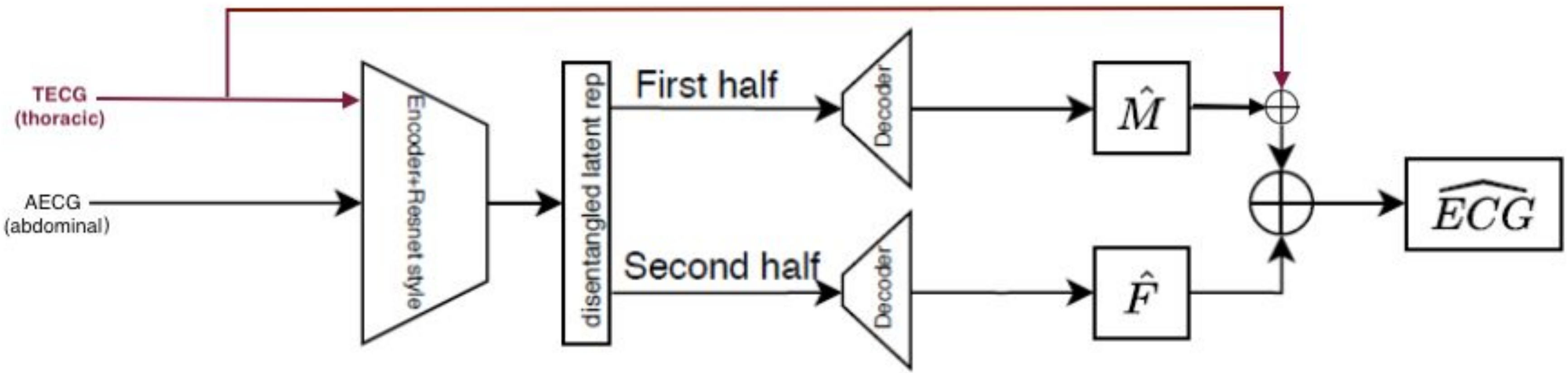


Our Method

Network Architecture

Network Architecture:

- Two ResNet Decoders (Maternal & Fetal)
  - fed with the separated maternal and fetal features
  - each composed of 14 ResNet basic blocks
  - reconstruct maternal and fetal ECG signals separately
- The output of the maternal decoder is added to the TECG input signal
- This allows the ResNet-based network to learn the difference between TECG and the maternal part in AECG



Our Method

Model Training

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Model Training

First Training Phase: Model Pre-Training on Simulated Data

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Model Training

First Training Phase: Model Pre-Training on Simulated Data

Simulated AECG Input Signal

- Since data is simulated, MECG and FECG labels are available
- Simulated AECG signal is created by combining them

Simulated TECG Input Signal

- Should be slightly different from the MECG label provided by the simulator
- This is necessary to ensure the model handles differences between the maternal part of AECG and TECG
- This is also necessary to prevent the model from being limited to learning only subtraction between input signals
- Thus, simulated TECG signal is created by one of the following:
  - adding noise to the MECG label
  - shifting it by a period or two

Our Method

Model Training

First Training Phase: Model Pre-Training on Simulated Data

Training Process

- While model is trained, it produces MECG and FECG outputs
- Both are compared to their labels using an L1 loss function
- Model is validated using validation set to:
  - adjust hyperparameters
  - provide unbiased evaluation of performance on training set
- Model is tested using test set to provide unbiased evaluation of performance on training set

Saving Best Model

- During this phase, parameters of the best model saved for using later at the second phase:
  - there, the best model will be used to fine-tune the training on **real-world** data
- best model chosen based on average correlation between outputs and corresponding labels

Our Method

Model Training

Second Training Phase: Model Fine-Tune Training on Real-World Data

Our Method

Model Training

Second Training Phase: Model Fine-Tune Training on Real-World Data

Training Process

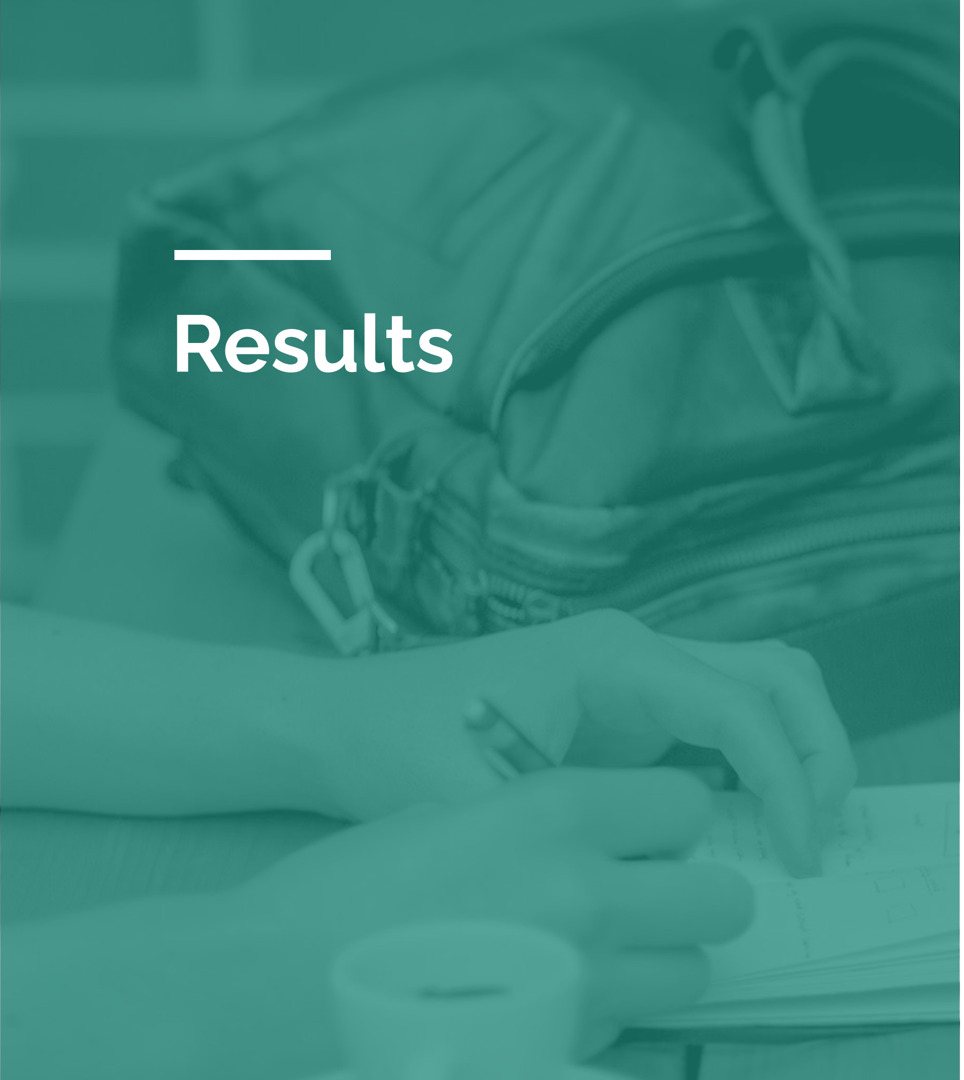
- Now, we take the best model from the first phase
- We continue training it to fit a specific pair of real-world ECG signals, AECG and TECG
- This pair was taken from a particular pregnant woman

Parameters’ Adjustment During Model Training

- “Freeze” the parameters of the FECG Decoder
  - By keeping their values fixed, as taken from the best model from the first phase
- Update remaining parameters using only maternal part:
  - by comparing the final reconstructed MECG signal to the TECG signal
  - done using an L1 loss function
- This process is self-supervised, as explicit labels are not available

Results

Results



Results were separated for:

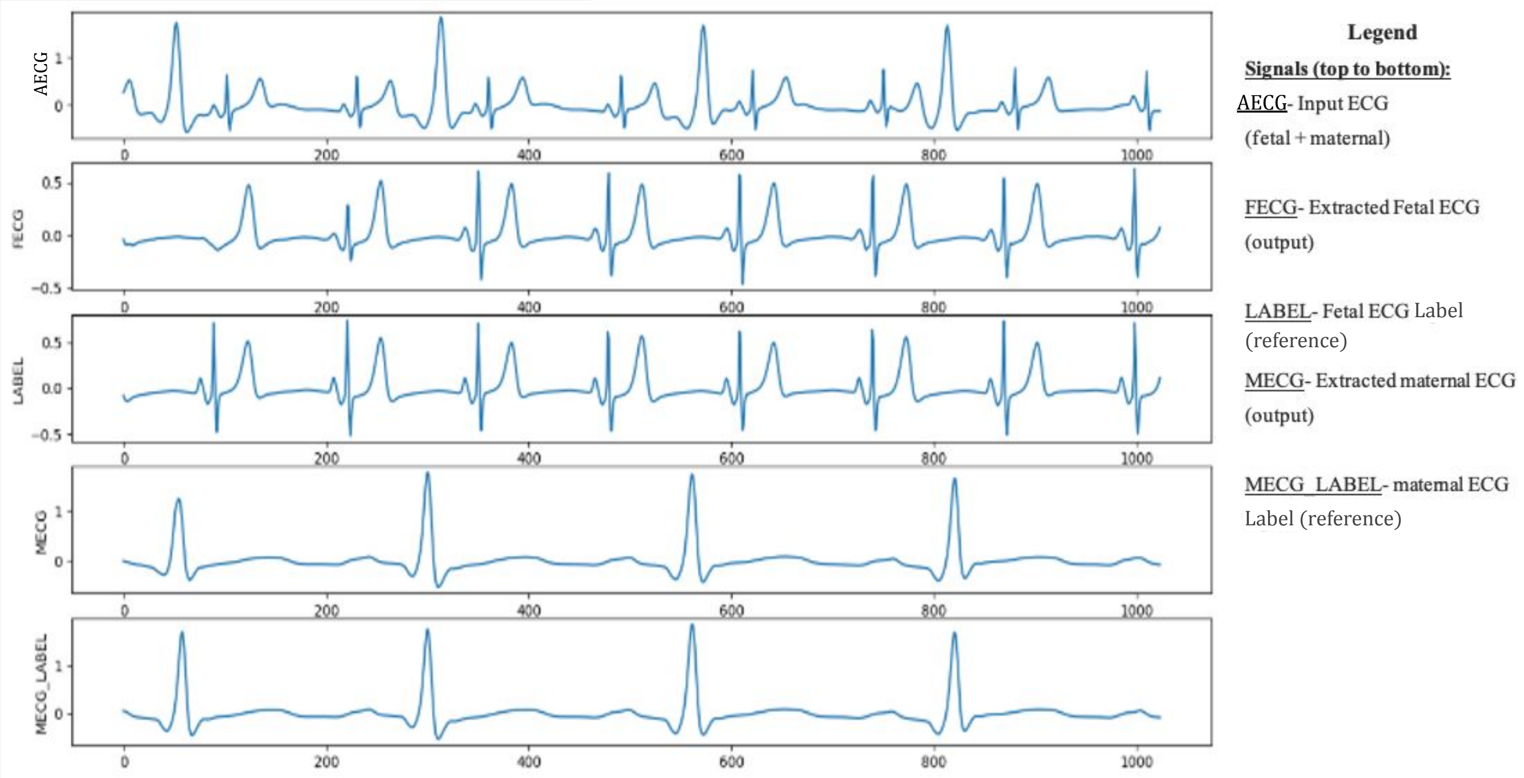
1. Inference results on Simulated Data
2. Inference results on Real-World ECG Data

Results

Simulated ECG Data

Results

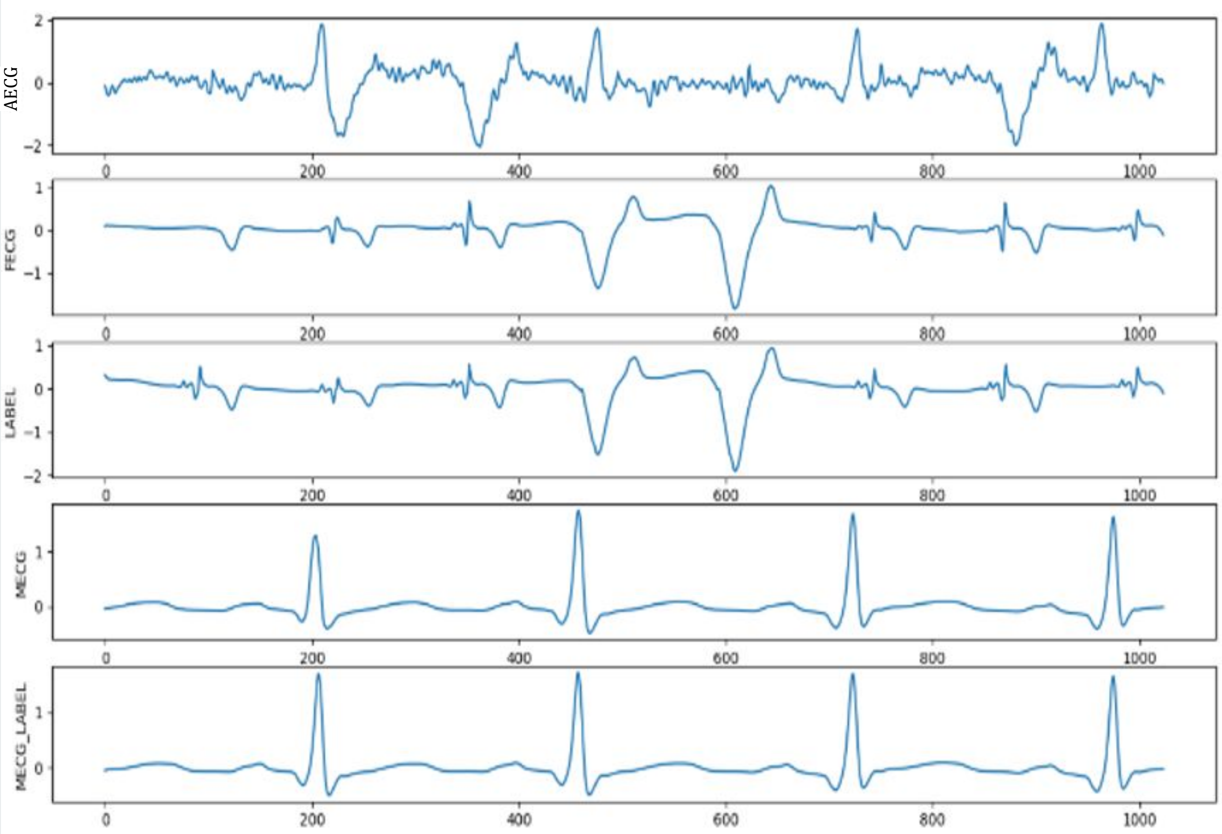
Simulated ECG Data



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). The model has some difficulties to be precise the signals' amplitudes.

Results

Simulated ECG Data



Legend

Signals (top to bottom):

AECG- Input ECG (fetal + maternal)

FECG- Extracted Fetal ECG (output)

LABEL- Fetal ECG Label (reference)

MECG- Extracted maternal ECG (output)

MECG_LABEL- maternal ECG Label (reference)

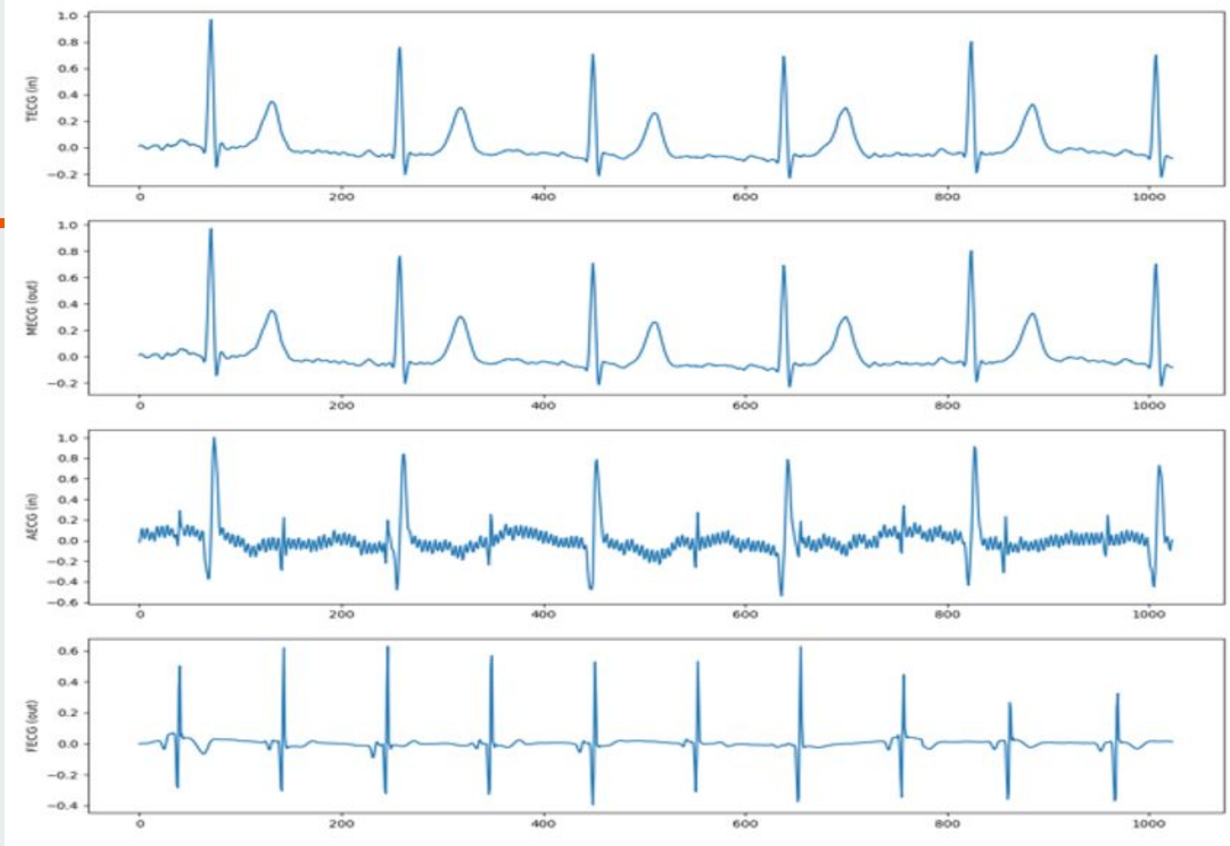
Another example of FECG and MECG extracted from synthetic signals; Although the input signal *ECG* in this example is more noisy than the one before, we can still see a very high correlation between the model output signals and their respective label signals.

Results

Real-World ECG Data

Results

Real-World ECG Data



Legend

Signals (top to bottom):

TECG(in)- thoracic ECG (maternal input)

MECG(out)- maternal ECG (maternal output)

AECG(in)- abdominal ECG (fetal + maternal input)

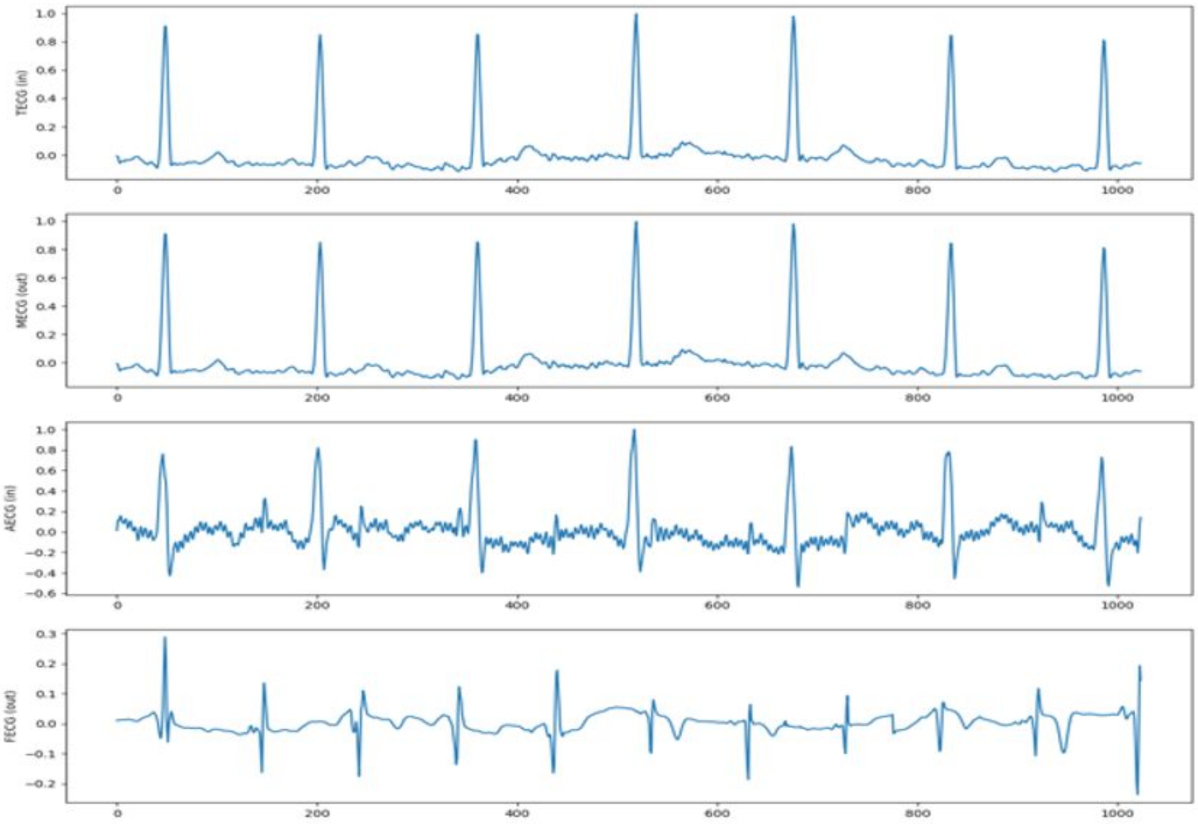
FECG(out)- Fetal ECG (fetal output)

*** Please notice the extracted FECG signal (last row) has a different y-axis scale due to a smaller amplitude, as expected.**

An example of FECG and MECG extracted from real-world 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.

Results

Real-World ECG Data



Legend

<u>Signals (top to bottom):</u>

<u>TECG(in)</u>- thoracic ECG (maternal input)

<u>MECG(out)</u>- maternal ECG (maternal output)

<u>AECG(in)</u>- abdominal ECG (fetal + maternal input)

<u>FECG(out)</u>- Fetal ECG (fetal output)

*** Please notice the extracted FECG signal (last row) has a different y-axis scale due to a smaller amplitude, as expected.**

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 before, 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.

Conclusions

Conclusions

- This project proposes a deep learning-based approach to separate FECG signals from MECG signals
- Consists of a two-step self-supervised training process
- Results show the model is effective in separating FECG signals from MECG signals for real ECG data
- It succeeded in FECG reconstruction of most cardiac features
- Among them, an accurate prediction of heartbeat's time positions
- Which is the most important aspect of our project

Further Steps

Further Steps

- One potential future direction for this work is to develop an "end-to-end" system
- Such system can perform real-time separation of FECG signals
- It would refine the pre-trained model during the process of recording the fetal ECG signal
- Instead of a posteriori, after the recording is complete
- As a result, the process will be more efficient and streamlined

Questions?

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