**Machine Learning for Electrode Motion artefact removal in ECG signals**

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# **Project Specification**

Table 1 indicates the relevant sub-field that are employed in this project.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | Control | X | Embedded Systems |  | High Frequency Electronics |  | Microelectronics |
|  | Electric Power | X | Software | X | Connected Health |  | MEMS |
|  | Cyber-Security |  | Wireless Communications | X | Signal/Image Processing | X | Intelligent Systems |
|  | Digital Design |  | Sensor Networks | X | Data Analytics | X | Electronics |

Table 1 Shows the sub-fields that are relevant to this MSc project

The electrocardiogram (ECG) is a non-invasive method to measure the electrical activity of the heart and can be used to diagnose heart disease. According to the World Health Organisation (WHO), chronic heart disease was the number one cause of death from 2000 – 2019. Long term ECG monitoring is currently the gold standard for diagnosing cardiovascular diseases (CVDs), however obtaining reliable long-term measurements of the ECG signal is challenging because patients are required to collect their ECG signal remotely on a wearable device. Wearable devices are inherently contaminated with noise which can supress the essential pathological biomarkers and, in some cases, render the ECG completely unusable. ECG signals can be contaminated by many types of noise including: 1) Baseline Wander, 2) Powerline Interference, 3) Electromyographic and 4) Electrode Motion artefacts. Most of these noise sources can be reduced through the use of time and frequency domain digital filters. However, the frequency spectrum of electrode motion noise overlaps with the frequency spectrum of a typical ECG signal making it very difficult to remove in the time and frequency domain. The objective of this project is to explore if AI/ machine learning can be used to learn the characteristics of, and correct for, electrode motion induced noise on ECG signals.

**Objectives**

1. Conduct a literature review on ECG motion artefact removal algorithms to identify the different approaches that exist, and the challenges involved in developing effective methods and assessing their performance.
2. Using available online sources (e.g. Physionet1) compile an ECG dataset which can be used to investigate and assess ECG motion artifact removal algorithms.
3. Develop a model for generating synthetic motion artefacts in clean ECG signals and use it to create a reference dataset for ground truth comparisons.
4. Investigate machine learning approaches to reducing electrode motion noise on ECG signals.
5. Develop and implement a candidate approach using Python or Matlab and validate its performance on the datasets from (2) and (3).
6. Compare the performance of the developed algorithm against alternative baseline algorithms from the literature.

**MEng Extension**

1. Explore advanced deep learning concepts (e.g., transfer learning, data augmentation) to enhance the performance of models and/or develop and evaluate alternative machine approaches for motion artefact removal.
2. Provide a rigorous assessment of all approaches developed with regard to real-time/embedded system implementation constraints.

**Learning Outcomes**

At the end of the project the student will be able to demonstrate:

1. A good understanding of ECG denoising algorithms.
2. A working knowledge of machine learning/ deep learning models and associated development tools
3. Enhanced programming skills in Python or Matlab, particularly with regard to algorithm development and signal processing.

# **Introduction**

There are 4 major sources of noise in ECG signals, these are 1) Baseline Wander (BW), 2) Powerline Interference (PL), 3) Muscle Artefact (MA) and 4) **Electrode Motion (EM)**. BW and PL have a relatively unique frequency content and thus are easily removed by simple digital filters (Eg notch, low-pass). MA and EM noise are more challenging to remove as they can have a wide frequency content that overlaps with that of the ECG signal, specifically the PQRST complex. Adaptive filters are primarily used for these type of noise sources, however these require a reference noise signal which needs to be estimated, providing a potential source of error.

Electrode motion noise in Electrocardiogram (ECG) signals refers to the interference caused by the movement of electrodes attached to the skin. When electrodes move, even slightly, they can pick up additional electrical activity not related to the heart's electrical signals. This extra activity is seen as noise in the ECG signal, which can distort the true reading. It's particularly problematic during physical activity or if the electrode doesn't adhere well to the skin. This noise appears as irregular spikes or a fuzzy baseline in the ECG trace, making it challenging to accurately interpret the heart's electrical activity. Managing electrode motion noise is crucial for ensuring reliable ECG readings, especially in scenarios requiring patient movement or long-term monitoring.

Electrode Motion is difficult to remove from an ECG signal for several reasons. Firstly, the signal attenuated by electrode motion can be very similar to the ECG signal itself, this similarity can make it difficult to remove through the use of digital filters which use both time and frequency domain characteristics to separate the two signals. The variability of EM noise also adds to the difficulty to remove the noise, this comes from the wide range of movements a subject can undergo such as running, walking, jumping or any other from of activity. Each activity will return a different characteristic shape of noise. Electrode placement can also vary the shape of the noise signal. Finally, individual differences such as skin type, amount of hair and other factors influencing the electrode-skin contact will affect the amount of EM noise added during movement, it is important that algorithms can deal with this problem effectively.

## **High-Pass Finite Impulse Response (FIR) Filter.**

Described by the following discrete difference equation:

(1)

Where is the coefficient of the filter, M-1 is the order of the filter, M is the length of the filter, x(n) is the input signal and y(n) is the filtered signal.

## **High-Pass Infinite Impulse Response (IIR) Filter.**

Described by the following discrete difference equation:

(2)

Where and are the coefficients of the filter, N is the order of the filter, x(n) is the input signal and y(n) is the filtered signal.

## **Moving Average (MA) Filter.**

Described by the following discrete difference equation:

(3)

(4)

Where denotes the noisy ECG signal, denotes the estimated noise, is the ECG signal after denoising, M is the filter length.

## **Moving Median Filter**

Same as MA but uses median instead of average.

## **Wavelet Transform Denoising**

A diagram of a flowchart

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Figure 1 Demonstration of 3-level discrete wavelet transform decomposition.

## **Empirical Mode Decomposition**

Described by :

(5)

Where represents the intrinsic mode function and represents the residual signal.

## **Adaptive Filter**

A diagram of a computer algorithm

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Figure 2 Block diagram of adaptive filter.

## Using available online sources (e.g. Physionet1) compile an ECG dataset which can be used to investigate and assess ECG motion artifact removal algorithms.

## Develop a model for generating synthetic motion artefacts in clean ECG signals and use it to create a reference dataset for ground truth comparisons.

## Investigate machine learning approaches to reducing electrode motion noise on ECG signals.

## Develop and implement a candidate approach using Python or Matlab and validate its performance on the datasets from (2) and (3).

## Compare the performance of the developed algorithm against alternative baseline algorithms from the literature.

# Project Timeline.

**Current Position**

# Current State of Project

A screenshot of a computer

Description automatically generatedAll work on this project is being tracked and version controlled using Github. A repository has been created [X] that stores all code and documentation for the project, this enables effective tracking of databases, models and reports. Sourcetree has been used as a graphical user interface (GUI) for Git which enables both developers and reviewers to easily look at changes throughout the project life cycle. All commitments to code and reports have been described in the corresponding repository commit, this is shown in the figure below:

As of 09/01/24, The project contains a mixture of MATLAB and Python code. MATLAB has been used to generate the reference database on which the model will be trained, this is due to MATLABs enhanced ability for signal processing problems where noise is being modelled and added to clean ECG signals. MATLABs ability to work with matrices makes this relatively simple. Python is used to develop machine learning models, using the reference database. To date, only a reference deep learning model has been added to the repository. Python has numerous frameworks specifically designed for implementing AI models (Pytorch, Tensorflow) and so has been selected as an appropriate language to use.

## Database Creation

The following outlines the procedure followed to obtain the database used for both training and validation of the machine learning models developed in this project.

# Plan for future work

# Problems encountered

# Problems that could arise

# **References**

[1] **https://archive.physionet.org/physiobank/database/macecgdb/**

[X] [ben120-web/MSc-Project: This repository will contain the codebase used to develop various models to remove electrode motion noise from ECG signals using learning models. (github.com)](https://github.com/ben120-web/MSc-Project)