**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 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.

# **Overview of objectives.**

This section will provide more detail on the project objectives. It will describe both the scientific and technical procedure that will investigated and explain how it is relevant to each objective.

**A literature review was conducted to investigate current algorithms/techniques used to reduce electrode motion (EM) from ECG signals.**

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 can struggle to

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.

# **Methodology**

# **Results**

# **Conclusion**

# **References**

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