**Artificial Intelligence for Electrode Motion Removal in ECG signals.**

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**Abstract**

The aim of this thesis is to explore the application of artificial intelligence (AI) for the removal of electrode motion artifacts from ECG signals. A comprehensive reference database was developed, consisting of both clean and noisy ECG signals. The clean ECG signals were generated using three ordinary differential equations to accurately model the heart's electrical activity. Noisy signals were synthesized by extracting noise from the MIT-BIH Noise Stress Test Database (NSTDB) and using an autoregressive model to predict new noise shapes, while maintaining the same statistical properties. Each noise instance was then scaled to various Signal-to-Noise Ratio (SNR) levels and superimposed on the clean signals to create a diverse set of corrupted ECG signals.

We developed and evaluated multiple machine and deep learning models to address the problem of noise removal. These models included Support Vector Machines (SVM), Random Forests, Principal Component Analysis (PCA) with K-Nearest Neighbours (KNN), Generative Adversarial Networks (GANs), Autoencoders, Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) units. A custom loss function was designed to enhance the performance of these models.

The performance of each algorithm was rigorously validated using both synthetic and real ECG databases. Key performance metrics such as Root Mean Squared Error (RMSE), correlation coefficient, SNR improvement, and Wavelet Energy Based Diagnostic Distortion (WEDD) were employed to assess the efficacy of the noise removal techniques. Additionally, the results of the proposed AI-based methods were compared against traditional time-frequency based approaches to establish their relative advantages.

This study demonstrates the potential of advanced AI models in improving the quality of ECG signal processing by effectively mitigating the impact of electrode motion artifacts. The findings suggest that these AI techniques can offer significant improvements over conventional methods, paving the way for more accurate and reliable ECG analysis in clinical settings.

**Acknowledgments**

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**Chapter 1: Introduction**

The Electrocardiogram (ECG) is a vital tool in modern medicine, offering a non-invasive and direct method for monitoring the electrical activity of the heart. By recording the heart’s electrical signals through electrodes placed on the skin, the ECG provides essential insights into the rhythmic patterns and conditions affecting the heart’s function. This capability makes the ECG indispensable for diagnosing various cardiac abnormalities, such as arrhythmia’s, heart disease, and myocardial infarction.

An ECG signal represents the sum of electrical potentials generated by the heart muscle during each cardiac cycle. The signal is characterized by a series of waves and complexes, most notably the p wave, QRS complex, and T wave, each corresponding to specific phases of the heart’s electrical cycle. The P wave indicates atrial depolarization, the QRS complex represents the ventricular depolarization, and the T wave is associates with ventricular repolarization. Analysing these components allows healthcare professionals to assess the timing of cardiac events, the presence of abnormal rhythms, and the heath of the heart muscle.

Monitoring ECG signals is crucial for several reasons:

* **Early detection**: Continuous or periodic ECG monitoring can help detect early signs of heart disease, even before symptoms appear.
* **Diagnosis**: ECG readings are essential for diagnosing various cardiac conditions, including arrhythmia’s, ischemic heart disease, and congenital heart defects.
* **Treatment monitoring**: For patients undergoing treatment for heart conditions, ECG monitoring provides valuable feedback on the effectiveness of interventions, such as medications, pacemaker function, and recovery after cardiac procedures.
* **Prognosis**: ECG findings can inform prognosis, helping predict the likelihood of cardiac events such as sudden cardiac death or recurrence of heart attacks.

**Figure 1** below shows the typical waveform of a beat within an ECG signal.

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Figure 1 Standard waveforms associated with an ECG beat.

Despite its importance, the accuracy of ECG monitoring can be compromised by various sources of noise that can significantly affect the quality of the signal. 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)** [1]. BW and PL have a relatively unique frequency content and thus are easily removed by simple digital filters [2]. Simple notch and low-pass filters can be used to remove these kinds of noise. 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 [3]. 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 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. **Figure 2** shows an example of an ECG signal corrupt with EM noise, it is evident that no clinical A graph showing a graph

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Figure 2 ECG signal corrupt with electrode motion noise.

EM 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 with 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 form 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.

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* Summary of Findings
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* Future Work

**References**

**[1]** Ben Jabeur, T., Bashier, E., Sandhu, Q., Bwalya, K. J., & Joshua, A. (2024). Noise and Artifacts Elimination in ECG Signals Using Wavelet, Variational Mode Decomposition and Nonlocal Means Algorithm. arXiv. The paper discusses the elimination of various noise types in ECG signals, including Baseline Wander (BW), Powerline Interference (PL), Muscle Artifact (MA), and Electrode Motion (EM) artifacts.

[2] Sörnmo, L., & Laguna, P. (2005). **"Bioelectrical Signal Processing in Cardiac and Neurological Applications"**

**[3]** Dai, X., & Bai, Y. (2021). Denoising ECG by Adaptive Filter with Empirical Mode Decomposition. *IEEE Access*, 9, 71659-71668. doi: 10.1109/ACCESS.2021.3080795.

**Appendices**

* Additional Data
* Code Listings
* Supplementary Material