

Development of a wireless intracranial neuromonitoring device for drug-resistant epilepsy: impact of global versus local reference

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Abstract

1 Introduction

Around 600,000 people in the UK have epilepsy and around a third of these are diagnosed with drug resistant epilepsy (DRE). This condition leads to patients facing increased life challenges, reduced social outcomes and experiencing more trauma and mental illness [1]. Surgery can help many people, usually by removing parts of the brain that are associated with seizures. However, in order to locate these parts and assess their safe resectability, invasive brain activity recording is often required, currently achieved by inserting electrodes through small holes in the skull. There are two main drawbacks to the current method: first, the patient's brain is left open during the monitoring period, resulting in limiting the duration of the monitoring to about 3 weeks and potentially limiting data collection and compromising surgical procedures; and second, the patient is confined to a hospital bed, which causes the patient pain, and may even make it impossible for them to use the toilet, which can be particularly difficult to tolerate in pediatric patients. Therefore, the development of a new miniature wireless implantable device that could improve the patient experience and increase monitoring and diagnostic rates is extremely important for the well-being of patients. A team at Imperial College London is developing such a device [2]. This device does not provide a globally referenced EEG signal. Based on this, the aim of this study is to assess the effects of global and local referencing in intracranial EEG electrode recordings.

With the development of machine learning, researchers have been able to effectively detect epilepsy from EEG signals based on global references. Specifically, the main models include, support vector machines (SVMs) [3][4][5], decision trees and random forests [6], k-nearest neighbour (k-NN) [3][4], and naïve Bayes [3] classifiers. Overall, all of the above models are very effective in epilepsy recognition. Based on this, this study focuses on proposing the conversion of EEG signals from global to local references in order to explore the feasibility of using local reference signals in the process of epilepsy recognition by machine learning.

The aim of this project is to evaluate the impact of global versus local reference on epilepsy detection algorithms for EEG signals, and to develop a MATLAB-based detection algorithm for local referencing to provide algorithmic support for a miniaturised, wireless, implantable device for intracranial monitoring of patients with drug-resistant epilepsy (DRE).

2 Intracranial EEG dataset

This intracranial electroencephalogram (EEG) dataset [7], from St. Anne's University Hospital and Mayo Clinic, contains 155,182 and 193,118 data segments, respectively. Each dataset contains data segments from physiologic activity, pathologic/epileptic activity, artificial disturbances, and power line noise. The data was acquired at a sampling rate of 32 kHz. Then, the data was down sampled to 5 kHz.

3 Proposed method

3.1 Pre-processing

In order to reduce noise in the data, highlight features associated with epileptic activity, and provide better inputs for subsequent machine learning algorithms, a series of preprocessing steps are performed on the iEEG signal.

Filtering: High frequency noise is removed from the signal by passing it through a low-pass filter

Down sampling: the raw signal is oversampled at 5kHz and is down sampled to reduce the computational burden and make the data easier to process.

Removing baseline drift: Baseline drift is a change in the long-term trend in the signal that can be caused by electrode shift or device drift. Baseline drift is removed by methods such as high-pass filters or polynomial fitting.

Normalization: Normalize the signal so that signals from different channels or different time periods have similar scales, which helps train the model to learn features more effectively.

3.2 Feature extraction

Extract features from the preprocessed signals that are used to train the machine learning model. This includes time domain features (e.g., mean, standard deviation), frequency domain features (e.g., energy, spectrum), and entropy.

3.3 Classification

In this experiment, machine learning models of SVM and Random Forest are used for epilepsy recognition.

The number of positive samples (seizures) and negative samples (non-seizure activity) in the training data was similar to avoid overfitting the model to one category.

4 Results and discussion

4.1 Feature selection

4.2 Classification accuracy

4.3 Confusion matrix

5 Conclusion and future works

Reference

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