Artificial neural network based automatic detection of motor evoked potentials.

# Abstract

**Introduction:** Motor evoked potentials (MEP) can be detected using various methods that determine signal changepoints. The current detection methods perform well given a high signal to noise ratio. However performance can diminish with artefact such as those arising due poor signal quality and external electrical potentials. Part of the problem is likely because the methods ignore the morphology of a signal making it impossible to differential noise from MEPs. The lack of the knowledge of the signal morphology also limits the applications, such as identification of abnormality, of the detection methods. **Methods:** Here, we investigated a new detection method able to learn MEP morphology using artificial neural networks. To build an end-to-end MEP model, we trained a neural network model with architecture based on combined CNN and LSTM, using sample MEP data recorded from able-bodied individuals. The MEP detection capability of the classifier was compared with that of a changepoint based detection method. **Results**: The result shows that ….. **Conclusion**: …..

# Introduction

* What is MEP
* Characteristics of MEP  
  {Morphology, polarity, latency, amplitude and time width}

Figure X. MEP morphologies.

* What is MEP used for
* Why would you autodetect MEP
* What is the current method of autodetecting MEP
* How do we want to innovate MEP detection here.  
  Following the recent success of deep learning an obvious question is what tasks, either currently performed manually or automatically, could be improved with deep artificial neural network. Here, we investigate the utility of deep learning for automated detection of MEPs.

# Methods

Neural network Architecture  
Given the different temporal characteristics and morphologies of MEP, a generalised detector must be capable recognising the wave regardless of its, 1) latency, 2) polarity, 3) morphology, 4) amplitude, and 5) time width. This is a task suited to a convolutional neural networks (CNNs) due to their translation, scale and rotation invariance properties. This implies that, e.g. if an MEP wave and its time-shifted version are each fed to a CNN, both will equally be recognised. Another type of layer that may be applicable is Long Short-Term Memory (LSTM). LSTMs are well-suited to capture dependent sequential information such as morphology, and their temporal dynamics over several time steps.  
  
Various architectures were investigated including a U-net-like setup that downsamples and then upsamples input feature along the time axis with the opposite effect along the feature axis. To investigate an architecture, the data available for training was split into a training set and a validation set. The ratio of the split was 80%:20% respectively. These dataset were used to train each architecture with sufficient epochs to cause overfitting. Using this method it was confirmed that 1D CNN layers connected to an LSTM layer lead to sufficient network learning of the dataset features. Various configurations of these two layers were further investigated. The chosen architecture based primarily on the network capacity and capability to overfit the training dataset is shown Figure Y.

[ ]  
Figure Y. Neural network architecture.

Final training and testing  
The architecture shown in Figure Y was trained for the final time by re-combining the training set and the validation set. The network was training until it overfitted the dataset with a callback on model checkpoint used to capture the best model. The best model was used to perform inference on the testing dataset.

## Deployment and comparison with changepoint detection method

The final classifier model was deployed for an end-user using EPRecorder. This is to showcase the practicality of the developed model. Custom made scripts were used to export the model to MATLAB environment. In MATLAB, the forward pass for 1D CNN, LSTM, Dense, and other necessary layers were custom written to allow frictionless deployment within the environment. The deployment allowed automated delineation of MEPs on that loaded in EPRecorder

For comparison, a changepoint MEP detection method was also implemented in EPRecorder. The changepoint algorithm works as follows. The area per sample and peak-to-peak of the pre-stimulus (baseline) of all included epochs are computed as features. For each of the features, a 95% confidence interval are constructed and scaled. The first and the last changepoints of the epochs are determined within post-stimulus signal. The first changepoint is taken as the possible start of a response while the last changepoint is taken as the possible stop of the response. The epoch signal between the start and stop is the possible response region. For each epoch, the are per sample and peak-to-peak of the possible response region. A response is detected for an epoch if the following criteria are satisfied: a) the area per sample and peak-to-peak of the possible response region of the epoch is greater than the upper-limit of a scaled 95% confidence interval which was computed using the pre-stimulus data, b) the peak-to-peak amplitude is greater than 0.05 mV.

Spinally evoked MEP data acquired from people with spinal cord injury (SCI) loaded were used to compare the performance of the developed model and the changepoint MEP detection method.

# Results and discussions

* Training and testing
* Comparison with the changepoint detection method

# Conclusions

# Research

* With Convolutional neural network the following issues can be resolved.
  + The wave should be detected regardless of it's temporal placement/offset.
  + Polar opposite waves should both be recognised as waves.
  + The wave should be detected regardless of it's time width. (But does convolution solve this one?)