A Brain Computer Interface Controlled, 3-D Printed Prosthetic Hand

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Completed under the supervision of

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18 August 2019

A thesis submitted in partial fulfilment of the requirements for the degree of Bachelor of Engineering in Electrical Engineering at The University of Newcastle, Australia.

# Abstract

# Acknowledgements

# List of Contributions

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# Literature Review

To facilitate an online Brain Computer Interface control system, it is widely accepted that three main functional blocks are required. These blocks are:

1. Data Acquisition and Preprocessing,
2. Feature Extraction, and
3. Classification.

Each of these blocks can consist of different approaches and procedures. A literature review, in conjunction with MATLAB simulations, was conducted to predict the relative performance of each potential system. This enabled a reduction in the number of potential solutions, and the eventual derivation of an optimal system.

1. Data Acquisition and Preprocessing
2. Feature Extraction

To reduce the computational intensity required to classify the EEG event, a feature extraction algorithm is applied to the acquired signal. Proposed algorithms include a Short Time Fourier Transform approach (STFT), an Adaptive Autoregressive Model (AAR), and a Discrete Wavelet Transform (DWT) approach. Additionally, a hybrid approach consisting of an amalgamation of Multivariate Empirical Mode Decomposition (MEMD) and STFT is considered. It is noted that the articles sited use different testing data and methodologies, thus a valid absolute performance comparison cannot be made without evaluating these approaches against the same dataset. Additionally, the quoted performance of the feature extraction algorithm is dependent on the performance of the classification technique employed by the study, again reducing the validity of an absolute performance comparison.

1. Adaptive Autoregressive Model (AAR)

An Adaptive Autoregressive Model (AAR) is a variation on an Autoregressive Model (AR), which allows the parameters of the model to adjust over time. This feature is beneficial when applied to an EEG signal, as the signal is non-stationary <REFERENCE NEEDED>. An AAR model of order is described by:

, and

Where is the n-th sample of the EEG observation, is the zero-mean-Gaussian noise with variance , and are the time-varying AR coefficients. Thus, a sample is predicted by the past samples, with new information introduced through the model through the innovation function , which in the above example is a normal distribution < <https://ieeexplore-ieee-org.ezproxy.newcastle.edu.au/document/6740323>>.

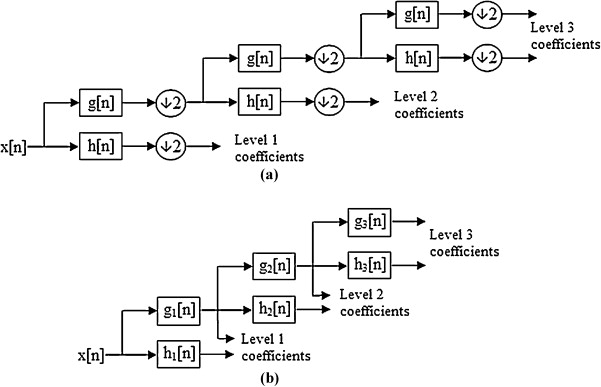
Such a model utilises only time-domain parameters, thus utilising the high temporal resolution offered by EEG data acquisition systems at the peril of ignoring the prominent frequency-domain characteristics induced by ERPs. Low order models () are not computationally intensive, however accuracy increases with model order. However, prior works indicate that AAR approaches may result in low accuracy, with Rodríguez-Bermúdez & García-Laencina, 2012 reporting a 62.2% accuracy <<https://link.springer.com/article/10.1007/s10916-012-9893-4>>.

1. Discrete Wavelet Transform (DWT)

The Discrete Wavelet Transform (DWT) is a time-frequency approach, thus utilising both the temporal resolution of EEG signals, and the frequency characteristics of ERPs. This approach involves passing the signal through a multi-stage filter bank, consisting of highpass and lowpass filters. The highpass filtered signal produces the “detail coefficients” at that level of the filter bank, while the lowpass filtered signal produces the “estimate coefficients”. The lowpass filtered signal is then passed to the next level of the filter bank, as shown in <FIGURE>.

Since the frequency content of the signal has been bandlimited to one half of its original bandwidth, by Nyquist’s theorem, the signal can be subsampled by a factor of 2, reducing the number of samples at each step, thus reducing computation time. In turn, this doubles the frequency resolution. Thus, DWT approaches offer high spectral resolution over the low frequency content. This characteristic is beneficial when extracting features from EEG data for motor imagery, since these signals occur in the low frequency spectrum, however a higher resolution will increase the computation time compared to analysing the STFT over a similar bandwidth.

When paired with a Long-Term Short-Term Memory (LTSTM) classifier, Jie Zhou et al. achieved an accuracy of 91.43% on the Graz 2003 Brain Computer Interface Competition III dataset. Thus, the DWT method may be suitable for online motor imagery feature extraction.



< <https://www.sciencedirect.com/science/article/pii/S2314717214000075>>