Simulation of EEG-Based Apparatus Control for Quadriplegic Patients

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Abstract. The use of electroencephalogram (EEG) waves in the field of Brain Computer Interfaces (BCI) has recently attracted a lot of interest, with varied applications ranging from entertainment to medicine emerging, showing that EEG waves are suitable for controlling appliances through a microcontroller. This study presents an offline strategy for the extraction of digital control signals from brain EEG waves using MATLAB/SIMULINK. The principle is applied as follows: (i) the extraction of $\alpha$- and $\beta$-bands from the original brain EEG wave; (ii) detection of the peaks of both bands; and (iii) calculation of the power density of both bands to classify the mental mode and to generate appropriate control signals. Simulation results including signal processing tracking for various EEG waves are demonstrated that verify the effectiveness of the proposed strategy in terms of using brain EEG waves for apparatus control.

1. Introduction
Quadriplegic and paralyzed people, as well as those with hand amputations cannot operate traditional electrical appliances using manual controls; currently, they thus often require assistance from others for regular activities. The percentage of this type of user in the population is increasing due to the growing number of health issues in an aging population and increases in the number of accident survivors [1]. Electroencephalogram wave (EEGs) are generated by brain activation waves, being electrical signals that arise from changes in brain activity. EEG detection is relatively non-invasive compared to most devices used to read brainwaves[2], making designing a Brain Computer Interface (BCI) for use in controlling home appliances to help patients with quadriplegia and similar impairments is thus eminently feasible. Designing such a system requires signal acquisition, signal pre-processing, and feature extraction and classification to be applied to the control of the system. Several investigational calculations of brain activity have been completed using human control orders, and based on detected cerebral activity, operator and control instructions for various projects have been developed [3]. BCI systems rely on machine learning algorithms that classify user brain signals to trigger the desired action [4]. BCIs can thus offer a means of control and communication to most disabled people based on identifying and classifying their Brain EEG waves using features such as event related potentials (ERPs) [5].
One of the challenges in current BCI research, is feature extraction, as Brain EEG waves have random time-varying effects that are challenging in terms of classification where the goal is to identify the Brain EEG wave type as accurately as possible. Techniques for feature extraction that identify the unique properties of Brain EEG waves are under development, as while EEG investigation was previously limited to graphical examination, this limited the application of numerical analysis or standardisation. Other techniques have thus now been proposed to calculate data from Brain EEG waves [6], and several BCI algorithms and techniques have developed [7]. Brain EEG waves are now filtered and noise and artifacts such as heartbeats, eye blinks, and other confounding effects are removed. Suitable pre-processing strategies for this include Principle Component Analysis (PCA) and Common Spatial Patterns (CSP), [8].

EEG waveforms can be characterised as Alpha, Beta, Theta, and Delta waves. The electrical activity of the brain is subject to voltage variations between 20 and 150 μA, peak to peak, and frequency variation of 0.5 to 60 Hz. The electrodes used to collect these readings are generally in the 10 to 20 system standard structure, which is modified universally. After filtering and amplification of Brain EEG waves, these can be transformed into a numerical layout by ADC and sent for extra pre-processing [9]. In [10] the author proposed and implemented an adaptive control to make a velocity wheel subject to speed commands, adjusting to the variations of roughness and load between surface and the wheels, while in [1], the author used simple control commands to control a system using head tilts or voice commands, implementing an energy saving microcontroller which made the system more reliable, with no need for a separate computer, creating a low cost, low energy design of small size. However, in [11] the author implemented a Fuzzy Neural network algorithm for brain actuated control, with direct control commands input to the system, while in [12] the author used another technique to control the system via thought based on capturing signals from the brain and eyes and processing these to manage control system based on a wireless brain sensor.

The current work presents an offline strategy for the extraction of binary control signals from brain EEG waves using MATPLAB/SIMULINK. The principle of the proposed strategy is as follows: (i) extraction of the α-band and the β-band from the original signal; (ii) detecting the peaks of both bands; (iii) calculating the power density of both bands to classify the thinking mode; and (iv) generating decision signals to send the microcontroller for load automation control.

2. EEG processing stages

2.1 EEG Measurement
EEG sensors have electrodes that can be placed on the scalp, that then send signals by wire or wirelessly (by Bluetooth) based on micro electrical activity to a computer; these travel through four main steps, as shown in Figure 1 [13]. Brain EEG waves, as electrical signals, are subject to noise, interference, and artefacts. With the help of MATLAB, these issues can be simply tackled by applying signal filtration, such as eliminating low frequencies. MATLAB's signal processing applications can thus be used to make brain EEG waves clearer and easier to analyse [14]. For this work, EEG data was collected from a reliable dataset (Physio bank) well known globally for signals that are filtered and without noise; the sampling frequency is 160 Hz. The features of the signals were extracted in MATLAB with fast Fourier transform (FFT) analysis in order to calculate the comparative spectral power density (PSD) for the α band (8–13Hz) and β band (13–30 Hz), extracted from the raw brain EEG [15].
2.2 Pre-processing BPF

The second stage of signal use is pre-processing, which can be done using either an M-file to identify the sub-bands of the brain EEG wave or by using the SIMULINK block model in MATLAB to design a band pass filter in two parts: a low pass filter that can distinguish the band from the main signal and high pass filter which can separate the β band from the main signal.

2.3 Feature Extraction

In this work, the method used for feature extraction was a two band pass filter, one to extract the α band (8-13 Hz) and the second to extract the β (13-30 Hz), via Fast Fourier Transform (FFT). This is a mathematical methodology that applies power spectral density (PSD), a feature of advanced EEGs, which can selectively identify the EEG waves. FFT are used to analyse PSD based on a sequence of autocorrelation created using various nonparametric techniques. Welch’s method is one of such approach, which allows the information sequence to be used to window information, creating changed periodograms [16]. The \( x(n) \) data sequence and \( t_0 \) are the starting point for the \( t_n \) sequence, while \( L \) is the length of a 2M representative info segment, expressed as follows:

\[
X_i = X(n + t_0)
\]

where \( n=0,1,2,...,M-1 \) and \( i = 0,1,2,...,L-1 \).

The periodograms’ output provides the following equation:

\[
\tilde{P}_{xx}^{(i)}(f) = \frac{1}{M^2} \sum_{n=0}^{M-1} x_i(n) \omega(n) e^{-j2\pi fn M - 1} n = 0 \]

(2)

In terms of function windowing, the standardisation factor \( U \) provides the power, selected as shown below:

\[
U = \frac{1}{M} \sum_{n=0}^{M-1} \omega^2(n)
\]

(3)

The window function is \( w(n) \), and the average of them modified periodograms gives the power spectrum as follows:
\[ P_{xx}^W = \frac{1}{L} \sum_{l=0}^{L-1} P_{xx}(f) \] (4)

2.4 Classifier
Support vector machines were introduced by Vapnik, with his model being further developed between 1995 and 1998 [16]. SVM is a process that separates two type of classes by sketching a hyper plane with the classes placed on each side of the plane. The hyper plane is the extrication of these two classes, and generally, non-linear SVM classifiers are used to separate features in extracted signals. SVM processes and trains the signal, allowing the classification of various data types [17] A new classification mechanism was adopted in [18] for the signal, based on higher power values as converted to a logic system, which helps to control the higher levels of the signal sent to the microcontroller.

3. Performance analysis using SIMULINK
3.1 Offline strategy
This work presents an offline strategy for managing binary digital control signals from brain EEG waves using MATLAB/SIMULINK as in the block diagram shown in Figure 2.

Figure 2. Block diagram of the proposed offline strategy for processing EEG.

Figure 2 outlines the system and how the brain EEG waves are processed, being first collected from the main source then uploaded to the work space and read in SIMULINK as EEG raw data. The next step is the extraction of the \( \alpha \) band and \( \beta \) band, performed by passing the data through a low pass filter (LPF) to extract the \( \alpha \) band and a high pass filter (HPF) to extract the \( \beta \) band. The next stage is to determine the peaks in order to calculate the power for each band and to classify the relevant mental decision. After that binary digital signals are generated for the microcontroller to implement load automation control. These steps are explained in more detail, with graphs, in the simulation results and discussion section.

3.2 EEGLAB
EEGLAB is a useful toolbox in MATLAB for processing raw EEG data, as shown in figure 3. This open source platform allows several useful modes of visualisation of averaged and single trial data, artifact rejection, event related statistics, and time-frequency analysis, and the accompanying MATLAB toolbox for processing EEG data continuous events includes tools for independent component analysis (ICA) [19].
Figure 3 Brain EEG wave as used in the SIMULINK model.

The signals were thus transferred from the database to EEGLab [20], and the specified channel selected; this was the same for all ten subjects (F4); after that, the signal was converted from the frequency domain to the time domain, with the band determined at that point. Next, the relevant state was identified, classified as either relaxed (α) or thinking (β) for each subject. This signal could not be transferred to the microcontroller after analysis, however, so extracting the relevant data according to the mathematical algorithms in the EEGLab was necessary to determine the highest power between the α or β bands.

4. Simulation Result and Discussion

Brain EEG waves for ten different subjects were analysed in a new SIMULINK block model in MATLAB in which the mathematical algorithm was modified in order to obtain the power of each signal with respect to the α band and β band. Results for the ten subjects are shown in Table 1, while Appendix A offers the full MATLAB/SIMULINK model.

Table 1. Power (α and β), classified modes, and control states.

| Signals | Power (α) $V^2/Hz$ | Power (β) $V^2/Hz$ | Classifier | Control Signal |
|---------|--------------------|--------------------|------------|----------------|
| Sub-01  | 23.16              | 22.31              | Relax      | 0              |
| Sub-02  | 21.84              | 21.5               | Relax      | 0              |
| Sub-03  | 23.98              | 22.6               | Relax      | 0              |
| Sub-04  | 22                 | 22.49              | Mental     | 1              |
| Sub-05  | 23.4               | 22.32              | Relax      | 0              |
| Sub-06  | 22.82              | 22.26              | Relax      | 0              |
| Sub-07  | 22.25              | 21.69              | Relax      | 0              |
| Sub-08  | 25.18              | 22.4               | Relax      | 0              |
Table 1 shows the brain states for each subject clearly, confirming that subject 04 has the most active mental state among all subjects; for the other subjects, the α power is higher, indicating a Relaxed state. This comparison was done by calculating the power of the α band and β band in each case in order to select the band with the highest power as a binary control signal for each subject. To further evaluate the proposed model result after calculating the power of the α and β band in SIMULINK, a series of signal tracking algorithms for two subjects were developed in order to support the methodology of the presented work and to track the signal in the proposed SIMULINK application as shown below. This involved uploading the signal into MATLAB then sending the brain EEG wave to the microcontroller, as shown in figures 4 and 5. The results give an overview of signal tracking for subjects three and four.
**Figure 4** Signals tracking for subject three.

Figures 4 and 5 shows the signal tracking for subjects three and four. To avoid redundancy, only the results from Figure 4 are discussed here, however. Figure 4-A shows the raw Brain EEG wave from the database (Physio-Bank) for subject three; figure 4-B shows the extraction of the α band using an LPF; figure 4-C shows the extraction of the β Band using an HPF. Figure 4-D shows the power for the α band and β band, and at this stage the power of the α band and β band must be calculated; to facilitate this, the signal must enter the RMS for peak detection to measure the power of the α and β bands. Figure 4-E shows the digital control signal sent to the microcontroller at the final stage of the process, which could allow control of a home appliance. Figure 5 illustrates the same procedures for subject four. Table 2 shows the data statistics for the α band and β band power for subjects three and four.

**Table 2.** Data statistics for α-Band and β-Band power in subjects three and four.

| Subjects | Max | Min | Mean | Range | STD  |
|----------|-----|-----|------|-------|------|
| Sub-3(α) | 112 | 66  | 97.2 | 47    | 18.8 |
| Sub-3(β) | 116 | 66  | 95   | 50    | 20   |
| Sub-4(α) | 112 | 65  | 97.2 | 47    | 18.83|
| Sub-4(β) | 116 | 66  | 95   | 50    | 20.9 |

Analysis of the Maximum, Mean and Range power for both subjects shows the same values in the α band and β band, while the Minimum and Standard deviations vary, in the α-ban for the minimum power and in β band for the standard deviation.
5. Conclusion
Testing of a SIMULINK model in SIMULINK/MATLAB shows effective result for the offline strategy of signal filtration, feature extraction and classification of brain EEG waves proposed in this paper. This supports this as a new strategy for classifying brain EEG waves according to whether the user’s mental state is Thinking or Relaxed, a binary classification suitable for controlling home appliances using a microcontroller. In the future work, this will be used to establish a new strategy that will be validated in EEGlab, based on the designed SIMULINK model in MATLAB and using a frequency domain strategy.

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7. Reference
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Appendix A: The developed MATLAB/SIMULINK model.