DESIGN OF A BRAIN COMPUTER INTERFACE SYSTEM BASED ON ELECTROENCEPHALOGRAM(EEG)

Ozan Gunaydin, Mehmed Ozkan

Institute of Biomedical Engineering , Bogazici University
Kandilli Kampus, 34684, Istanbul, Turkey
phone: + (90) 532-2103403, fax: + (90) 216-5163479, email: ozan.gunaydin@boun.edu.tr
web: www.bme.boun.edu.tr

ABSTRACT

A Brain Computer Interface (BCI) is a communication device between the brain and an external device, usually a computer to repair or assist human motor-sensory functions. In this project, both acquisition hardware and software of a two-channel EEG brain computer interface based on motor imagery related mu and beta rhythms was designed. In order to discriminate left and right hand movement imagery, three different feature extraction methods were developed using: Discrete Wavelet Transform, Power Spectrum Analysis and Band Pass FIR filters. These features were used as inputs to a two layer feed forward back propagation neural network for classification. Designed system was trained and simulated with the data provided in BCI Competition II. With the direction of the results, a low power system with the TI MSP430 microcontroller using FIR filters and a neural network was implemented.

1. GENERAL INFORMATION

Electroencephalography (EEG) is the recording of electrical activity along the scalp produced by the firing of neurons within the brain [1]. Detection of patterns in spontaneous EEG is a complicated task. EEG signals are detected from the scalp and contain noise as a result of electrical interference and movement of electrodes. Signal can also be corrupted by eye blinks and other muscular activities [2].

EEG based BCI systems are usually implemented by signal acquisition, filtering, analysis and classification of specific features or patterns in the spontaneous or event related EEG activity. In this study, after the investigation of the components in EEG, motor imagery related mu and beta rhythms were selected for the information sources of the system. After the selection of information source; EEG hardware instrumentation techniques, feature extraction and Classification methods were studied and the method of implementation was determined. Finally, the designed classification method was tested and discussed with the data provided in BCI Competition II [3]. With the direction of the results, a low power two channel Brain computer interface was implemented with TI MSP430 Microcontroller.

In order to extract different frequency bands in EEG activity, spectral analysis must be employed first. Conventionally, Fourier transform has been used for spectral analysis of EEG signal. Since it does not have any time information, Fourier transform is not suitable for non stationary signal analysis like EEG if time information is also needed with frequency information. Both Fourier and Wavelet transforms were evaluated as feature extraction methods in this study. With direction of the results a low power system was implemented with FIR filters as feature extractors to meet the requirements of limited processing power and memory. Details of discrete Wavelet decomposition extracts the features in the mu and beta frequency bands which includes information related to motor imagery tasks. These features were used as inputs to a two-layer feed forward back propagation neural network for classification of motor imagery tasks like right or left hand movement imagery. These mu and beta frequency features were obtained using FIR band pass filters on the MSP430 microcontroller later.

The main objective of this study was to develop and implement a low power EEG based brain computer interface consisting of acquisition hardware, feature extraction and classification of patterns of motor imagery tasks into one of two classes: Right hand or left hand movement imagery. For this purpose, first an electronic circuit was implemented in the lab that detects, amplifies, filters and digitizes brainwave signals. After that, two different feature extraction methods were implemented in Matlab applying db10 level 4 discrete Wavelet transform and FFT transform to the EEG trials. Two different results were obtained; one uses statistics of wavelet coefficients in the mu and beta frequency bands of this decomposition and other frequency spectrum variables as features. These features were then applied as inputs to a two-layer back propagation feed forward neural network for classification of mental tasks. With the direction of these results, a low power BCI system was implemented which uses FIR band pass filters as feature extractors instead of Wavelet Decomposition to meet resource requirements.

Block diagram of a typical BCI system is shown in Figure 1.

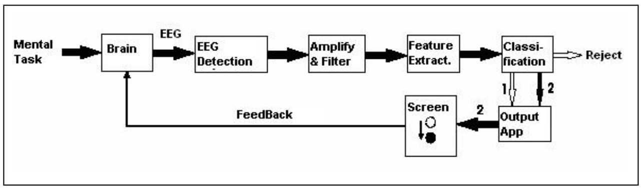

Figure 1: *A Typical Brain Computer Interface System. Cursor Control, BioFeedback or Control of a Robot arm are examples of Output Applications.*

2. METHOD

Basic building blocks of brain computer interface systems can be defined as:

- Signal Acquisition
- Signal Processing: Feature Extraction
- Signal Processing: Pattern Classification
- Output Application and Feedback

2.1 Signal Acquisition

Electrical activity of the brain is measured by electrodes over the scalp. Electrodes establish connections between the scalp and EEG recording device by converting ionic current into electrical current. Electrolytic gel is applied between the scalp and the electrodes to prevent attenuation of the signal. An electrode placement system accepted as international standard called 10-20 System is used to be able to compare the measurements taken [4].

EEG measurement can be done in one of two ways:

- Bipolar Recording
- Referential Recording

C3-F3 and C4-F4 bipolar electrode pairs according to the 10-20 System are used as two channels in this study in order to detect sensorimotor rhythms as recorded for BCI Competition II Dataset.

2.2 Signal Processing: Feature Extraction and Classification

Because of the high dimensions of original signals, instead of concentrating on the details of the original space the signal is reduced to a small subset that represents the vital information. This small subset is called the feature set or feature vectors. After digitizing the signal, one or more EEG control channels are derived from a linear combination of a selected set of the ear-referenced or bipolar channels provided by the amplifier. This process is known as Spatial Filtering. Most commonly, each of the EEG control channel derived is EEG activity at a location over sensorimotor cortex.

After the feature extraction phase, a classification must be done based on these features to discriminate between mental tasks. In brain computer interfaces, learning for classification comes in one of two ways or combination of them:

- Subject Learning
- Machine Learning

In this study, machine-learning approach was used, since it does not require extensive subject training. A feed forward artificial neural network was used for classification of patterns. Network was trained with the features extracted from the motor imagery trials taken from subjects. A series of methods were applied for local feature extraction, dimension reduction and classification to be able to use the oscillatory activities of a motor imagery EEG activity for a BCI task.

2.3 Output Application And Feedback

Output application of the system is usually a control task such as computer cursor control, biofeedback or robot arm control. Biofeedback is an important factor for subject training. Output of the low power system in this study is classification result displayed on a segmented LCD.

3. IMPLEMENTATION AND RESULTS

In the first phase of this study, two different feature extraction methods were evaluated in Matlab applying db10 level4 Discrete Wavelet Transform and FFT transform for feature extraction. After getting the results, as the second phase, for implementation with a microcontroller a resource efficient method was developed which FIR band pass filters utilized instead of Wavelet transform to extract sub band information.

3.1 Feature Extraction With Wavelet Transform

Through wavelet transform, the EEG signal were decomposed into the frequency sub bands using Discrete wavelet transform and a set for statistical features was extracted from the sub-bands to represent the distribution of wavelet coefficients according to the characteristics of motor imagery EEG signals. Continuous wavelet transform of x(t) is defined in Equations 1 and 2.

$$W(a,b) = \int x(t)\Psi^*_{(a,b)}(t)dt \quad (1)$$

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi(\frac{t-b}{a}), a > 0, b \in \Re \quad (2)$$

where a and b are scale and translation parameters, respectively, Ψ is the mother wavelet, * is the complex conjugate operator and W(a,b) is the continuous wavelet transform of x(t).

Scaled and translated versions of the basis functions are obtained from one prototype function, the mother wavelet. In principle, the CWT produces an infinite number of coefficients, thus it provides a redundant representation of the signal.

The DWT provides a highly efficient wavelet representation that can be implemented with a simple recursive filter scheme and the original signal reconstruction can be obtained by an inverse filter [5]. The procedure of multi-resolution decomposition of a signal x[n] is schematically shown in Figure 2.

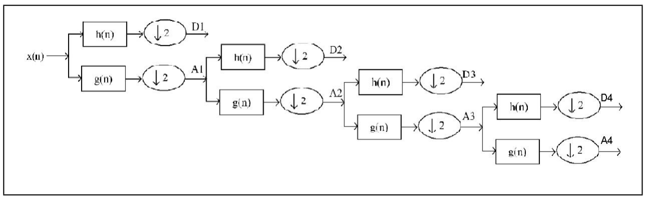

Figure 2: *Decomposition of DWT; h[n] is the high pass filter, g[n] is the low pass filter.*

The number of levels of decomposition is chosen on the basis of the dominant frequency components of the signal. According to the motor imagery EEG signals itself, level 4 and the wavelet of Daubechies order 10 was selected to extract μ and β rhythms as features [5]. As a result, the EEG signal is decomposed into the details D1-D3 and approximation A3. The ranges of different frequency bands for a 128 Hz sampled signal are shown in Table 1.

Table 1: *Frequencies correspond to different levels of decomposition for Daubechies order 10 wavelet with a sample rate 128 Hz*

Decomposed Signal	Frequency range Hz	Level
D1	32-64	1
D2	16-32	2
D3	8-16	3
A3	0-8	3

As seen in Table 1, frequency components of D2 and D3 detail levels of the wavelet decomposition are in the beta and mu bands, respectively. Daubechies order 10 wavelet with four decomposition levels were used to decompose all of the 280 trials of BCI Competition II Data Set into the three frequency bands. The extracted Wavelet coefficients show the distribution of the motor imagery signal in time and frequency. The original signal is sampled with 128 Hz rate and longs 9 seconds. It is down sampled by two in each decomposition level, so D2 level contains 288 and D3 contains 144 coefficients since the complete single trial composes of 1152 coefficients (128 Hz * 9 seconds).

Statistics over the set of wavelet coefficients of sub bands D2 and D3 were computed for each trial to reduce the total dimension of the feature vectors. The statistical features of each sub band are selected as follows:

- Standard deviation of coefficients in the sub band
- Mean of the absolute values of the coefficients in the sub band
- Maximum values of the coefficients in the sub band
- Mean absolute deviation of the coefficients in the sub band

These features represent the frequency distribution and the amount of changes in frequency distribution. Thus 16 statistical features of wavelet coefficients are obtained for two channels of C3 and C4 for each trial (4 statistical features of coefficients listed above for D2 level and same 4 again for D3 level for each two channels).

3.2 Feature Extraction With Fourier Transform

With Fourier transform approach, trials were transformed into frequency domain to extract features. Finally an Artificial neural network was utilized to classify computed features into different categories those represent the left or right hand movement imagery. Same classification method was used with extracting features by FIR band pass filters in the low power system implementation.

3.3 Feature Extraction With FIR filters for Low Power Implementation

A FIR filter can be seen in Figure 3 and described with Equation 3:

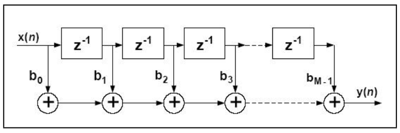

Figure 3: *Digital FIR Filter*

$$y(n) = \sum_{i=0}^{M-1} b(i) \cdot x(n-i) \tag{3}$$

Digital finite impulse response (FIR) filters form the basis for numerous digital signal processing applications. The basic operation needed to implement a FIR filter is the signed multiply-and-accumulate (MACS), which is traditionally performed using a hardware multiplier peripheral in any DSP device. Some of the MSP430 devices have an integrated hardware multiplier that can perform this MACS operation allowing these devices to run the FIR filter algorithm more efficiently than devices without a built-in hardware multiplier.

In addition to the MACS operation the processor handles the task of moving the digital samples and filter coefficients from memory to the MAC hardware, retrieving the results and storing them into memory. In a real-time digital filter algorithm, the computation and memory-move operations have to be completed within one sample period. The number of computations to be performed within one sample period depends on the number of taps of the filter, i.e., the order of the filter. The order of the filter is determined by the required filter performance characteristics. When higher order filters are combined with faster sampling rates, the demand on the processor becomes very high. This limits typical MCUs to handle a real-time FIR filter algorithm only at low sample rates and with a reduced number of filter taps [6]. Because of these limitations sampling rate was limited at 128 Hz in the MCU implementation in parallel with 3.5 seconds recording time to stay in the limits of the on chip memory in this study.

Because of these limitations a resource efficient model was developed using the results from Wavelet and FFT features classification. In this approach, band pass FIR filters were used instead of Wavelet Decomposition for feature extraction.

Since multiplication is the core operation of filtering, it must be done in an efficient way to save time and power. Hardware multiplier and multichannel Direct Memory Access (DMA) features are the main differences between a Digital Signal Processor (DSP) and a microcontroller (MCU). For this implementation FG4618 was selected from MSP430 MCU family which includes a hardware multiplier with low power features. Since it has a hardware multiplier, a FIR filter can be implemented in software easily. The designed solution has following key functions:

- Two FIR band pass filters, one for μ band and one for β band to extract the features like wavelet sub band decomposition
- Designed filter coefficients are scaled to integers to multiply with ADC samples efficiently.
- Absolute values of filtered sample arrays are computed
- Mean values of absolute arrays are computed as features
- These features are feeded to a trained MLP neural network with predefined weights for classification

Designed filter specifications are provided below:
Band Pass FIR Filter 1

- Filter length = 23
- Sampling frequency = 128 Hz
- Lower Cut-off frequency = 7 Hz
- Upper Cut-off frequency = 12 Hz

Band Pass FIR Filter 2

- Filter length = 27
- Sampling frequency = 128 Hz
- Lower Cut-off frequency = 17 Hz
- Upper Cut-off frequency = 23 Hz

3.4 Classification Results

3.4.1 Classification based on Wavelet features

A two layer feed forward back propagation neural network was used for classification of the trials. Extracted 16 statistical features of Wavelet coefficients for each trial were used as inputs to the neural network. The structure of the final designed artificial neural network is shown in Figure 4. The network has 20 neurons in the hidden layer with tanh activation function. The final layer has two neurons with logistic activation.

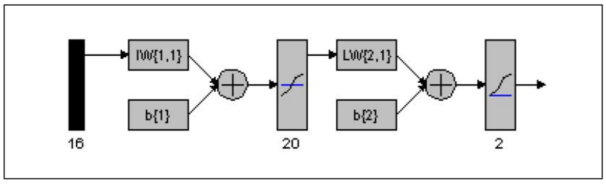

Figure 4: *Two layer Feed Forward Artifical Neural Network used for classification. First layer uses the tanh activation function, the second a normal logistic activation.*

The network was trained with 140 trials of training data set and tested against 140 trials of the testing data set to discriminate between right and left hand movement imagery tasks. Different numbers of hidden neurons and different feature vectors were used for classification. The results are displayed in Table 2. All of the trials of the data set correspond to one of the two classes. Because of that all of the false classifications are false positives.

Best classification result was taken from the Network2 and absolute statistics of feature coefficients of wavelet transform.

Table 2: *Properties of Neural Networks and Classification Results based on DWT features*

	Output Layer	Hidden Layer	Inputs	Train Function	Hidden Units	Vector Coeff.	True Classification Per.
Network1	Logistic	Tanh	16	Trainscg	4	absoluted	75
Network1	Logistic	Tanh	16	Trainscg	4	squared	68
Network2	Logistic	Tanh	16	Trainlm	20	absoluted	89
Network2	Logistic	Tanh	16	Trainlm	20	squared	74

3.4.2 Classification based on Power Spectrum features

To classify based on power spectrum features of C3 and C4 channels, FFT of each train and test trails was computed. The features used for FFT based classification are as follows:

- Mean of the power in μ band (8 - 12 Hz)
- Mean of the power in β band (19 - 24 Hz)
- Maximum value in μ band (8 - 12 Hz)
- Maximum value in β band (19 - 24 Hz)

The results are displayed in Table 3. All of the trials of the data set correspond to one of the two classes. Because of that all of the false classifications are false positives.

Table 3: *Classification Results based on FFT features*

Feature Vector	True Classification Percent
Ratio of mean values between two bands	75
Only Max value in μ band	72
Only Max value in β band	63

3.4.3 *Classification based on FIR filter based features*

Classification results displayed in Table 4. Hardware implementation of this developed method in laboratory is discussed in the next section.

Table 4: *Classification Results based on developed FIR filter based features to be implemented in embedded hardware*

	Output Layer	Hidden Layer	Inputs	Hidden Units	True Classification Percent
Network1	Linear	Tanh	4	4	61
Network2	Linear	Tanh	4	8	65
Network3	Linear	Tanh	4	20	69
Network3 with purification	Linear	Tanh	4	20	72

4. HARDWARE IMPLEMENTATION AND MEASUREMENTS

As discussed in previous sections, sensorimotor Rhythms of the EEG is needed for motor imagery BCI operation. First a signal acquisition system was developed in the laboratory with the use of ICs from Texas Instruments. During hardware design, Texas Instruments documentation and Modular EEG design of OpenEEG Project was used [7, 8]. Then the developed method which is presented in previous chapter was implemented on this hardware.

4.1 Signal Acquisition

The device was implemented in the lab with the use of Texas Instruments ICs and microcontrollers to create a circuit that amplifies, filters and digitizes brainwave signals. The design includes 1 INA333 Instrumentation Amplifier, 3 OPA333 Operational Amplifiers for each channel and 1 MSP430 Microcontroller which is on the experimenter board. Since low power and battery life are important considerations for portable or medical equipment, low power devices were particularly preferred for the design. Requirements of the acquisition system:

- Detect brainwave signals greater than 10 μ V
- Process signals, filter frequencies between 0.16 and 30 Hz
- Amplify signal to a ADC detectable level (volts)
- Convert analog signal to digital (12 bit resolution, 128 Hz sampling rate)
- Process the signal as described in the section 3.3

After analyzing the above requirements,the design was developed to detect,amplify and filter the brainwaves as shown in Fig 5.

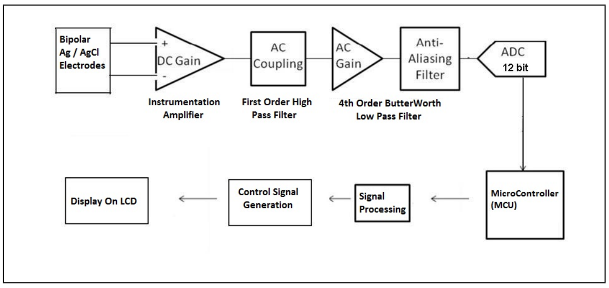

Figure 5: *Block Diagram Of the Acquisition System*

Firstly, to detect the brainwaves, Ag-AgCL electrodes were used. Their outputs were coupled into the input terminals of an instrumentation amplifier. Two pairs of electrodes were placed inside a bathing cap over C3 - F3 and C4 - F4 according to 10-20 system to have two EEG channels for SMR rhythms.

The differential amplifier used is the INA333 Texas Instruments Instrumentation Amplifier. This device was chosen because of its high CMRR, low noise, low offset and low power characteristics.

OPA333 Texas Instruments operation amplifier was used for further filtering and amplification stages. OPA333 is a micro Power operational amplifier with low voltage, low noise and single supply operation from ZeroDrift Series. This analog circuit was firstly simulated in TINA-TI software and then implemented on breadboard.

4.1.1 *Instrumentation Stage*

INA333 Instrumentation amplifier detects and amplifies the difference between two electrodes connected to its terminals. The electrode positions can be C3 and C4. Since the offset voltages put some DC content into the signal, the gain of the first amplifier was kept low (G=10) not to amplify the DC component. After INA stage, a first order high pass filter with a cut off frequency of 0.16 Hz was included to reject the DC component for AC coupling.

4.1.2 *Filtering*

For anti-aliasing and detecting a clean EEG signal, frequency components above 30 Hz must be filtered. A fourth order Butterworth Sallen Key Active low pass filter was implemented for that purpose. The Butterworth filter has a flat response in the pass band and fast and sharp attenuation in the stop band. In our case, the most important unwanted frequency is 50 Hz mains signal, and the designed cutoff frequency was 30 Hz with a gain of 40dB. Since the order of the Butterworth filter determines the sharpness of the stop band, the higher the order of the filter, the steeper the slope of the stop band. Fourth order is good enough to cancel the 50 Hz mains signal interference. Filter was simulated with a Spice simulation tool (TINA-TI Spice Simulation Software).

The gain of the final amplification stage was designed to increase the signal level to volts for ADC. The gain of the final amplification stage is 10. With the final amplification stage, total gain of the system became 80dB.

After filtering and a final stage amplification, the signal was converted into digital domain with the 12 bit SAR ADC embedded in MSP430 microcontroller. After the conversion, the processing method described in the section 3.3 was implemented on the microcontroller.

4.2 Signal Processing Software

After the amplification stage outputs of two channels were used as inputs to ADC inputs to the MCU. C3 channel was entered into A0 and C4 channel was entered into A1 analog input pins of the microcontroller. Since the supply voltages of the analog board are (-1.5 V, 1.5V), with internal +1.5V reference voltage of the MCU, an external -1.5V reference was used for conversion.

Texas Instruments MSP430FG461x/F20xx Experimenter's Board was used with the system since it has many peripherals needed for this project. Board includes an LCD display, two push buttons, 3 LEDs and headers / jumpers to access the pins of the microcontroller.

The flowchart of the developed software can be seen in Fig 6.

4.3 Discussions And Suggestions for The Design

A comparison between the Competition Data set signal of right hand movement imagery and the signal acquired with the developed hardware is provided in Figure 7.

The developed method presented in Section 3.3 was successfully implemented with the developed hardware presented in this section. The system could be able to detect two channel EEG and provide the classification results as designed. As presented in the results section, best results were obtained using Wavelet based features with an artificial neural network classification. The classification performance of the FIR band pass filter based approach used in this design can be increased to the levels of Wavelet based approach by implementing the suggestions provided below.

- Source code generates 40KB program code and uses 5KB RAM which are not available in many of the members of MSP430 family excluding MSP430X architecture and new MSP430x5xx.
- Hardware multiplier and DMA gives DSP like capabilities to FG4618. But many of the MSP430 devices lack MPY or DMA

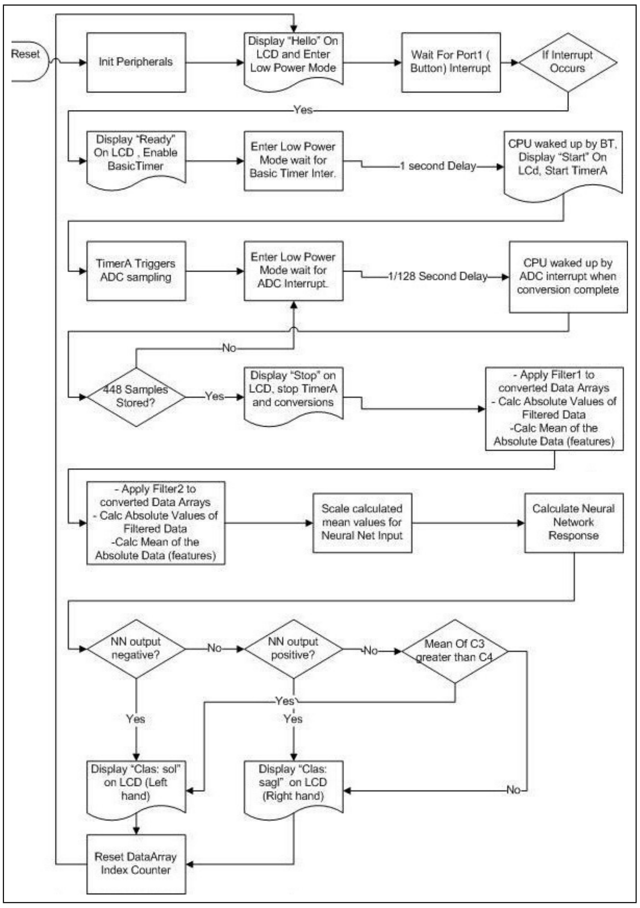

Figure 6: *The flowchart of the developed software*

can be very slow on multiplication. Because of that, if a low power system with a MCU is aimed, a device with a MPU should be selected.

- Different feature extraction bands can be applied by only changing the filter coefficients. ScopeFIR software can be used to design and scale filter coefficients.
- New features can be extracted by adding new calculations from filtered data such as maximum, minimum or median values.
- Neural network performance can be tested in a memory free environment. Neural network architecture can be easily customized by changing hidden neuron and learning rate variables.
- Active electrodes can be used instead of passive Ag-AgCl electrodes for permanent usage without applying gel and easy hair penetration.
- Sigma Delta ADC or an analog front end can be used instead of SAR ADC to reduce the analog board size. Sigma Delta ADCs provide higher resolution with oversampling, hence only an instrumentation amplifier and a first order low pass filter can be used before input to the ADC for each channel.

5. CONCLUSIONS

In this study, discrete wavelet transform was applied to the data set provided for BCI Competition II to extract the features in beta and mu bands. After extracting the features by means of wavelet coefficients, there features were used as inputs to an artificial neural network for motor imagery task classification. After different network and feature combinations, %89 true classification was achieved on test data set. Classification based on power spectrum has lower classification rates. But more efficient features can be computed to increase the level of accuracy.

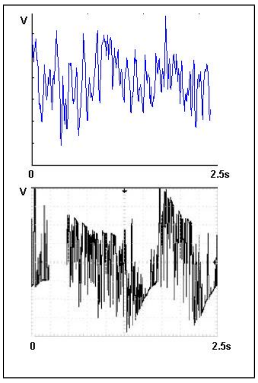

Figure 7: *Comparison between the Data set and the measurement of Right Hand movement imagery.Blue one represents the data set signal and black one represents the signal measured in the lab.*

The most important part of this study was the implementation of an efficient algorithm on a microcontroller to implement a low power embedded system. The system was designed uses efficient FIR filters instead of Wavelet sub band decomposition and implemented on the MSP430 microcontroller. Classification rates of this system can be increased with optimized neural network implementations and features. As future studies, following tasks may be considered:

- The system is low power and embedded, it can be assembled on the head of a subject. The commands can be sent wireless.
- A serial connection with a PC can be done to display a feedback and to implement more powerful algorithms in real time.
- Wireless module on the experimenter board can be used to transmit commands wirelessly to a robot arm or another effectors.
- A more powerful DSP such as TMS or ARM can be use to use more channels and higher sampling rates to have better resolution.

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