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Brain Computer Interface issues on hand movement

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EEG

Abstract This paper focuses on the Brain Computer Interface (BCI) application and its issues. Further the attempt was made to implement left and right hand movement classification after removal of the artifacts in the acquired signals of the various hand movements.

Contents

1. Introduction

The Brain Computer Interface (BCI) involves a combination of the brain and device both sharing an interface to enable communication channel between the brain and an object that have to be controlled externally. The human brain has innumerable neurons which are connected to each other for transmission of impulses. As an electrode chip is implemented into the brain via surgical methodology the electrical signals produced by the neurons are transmitted to the computer which then translates the signals into data. These data are interpreted

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to control a computer device. In 2013, Lebedev successfully coupled the brains of two rats making use of an interface to enable direct sharing of information (Pais-Vieira et al., 2013). Minute fluctuations in voltages between neurons are measured and signals are amplified to produce graphs. While the Invasive BCIs focus on direct implementation into the grey matter of the brain to produce the highest quality of signals by neurosurgery, Non Invasive BCIs make use of techniques like Electroencephalography (EEG), Magneto Encephalography (MEG) and function Magnetic Resonance Imaging (fMRI). EEG techniques experience placing of electrodes on the scalp accompanied by a conductive gel or paste. Many systems are known to use electrodes which are attached to separate wires. Over the years, BCI has been instrumental in developing intelligent relaxation devices, providing enhanced control of devices like wheelchairs and vehicles, controlling robots and computer cursors and providing an additional channel of control in computer games. Bionic eyes have been known to restore sight for people having vision loss (Krishnaveni et al., 2012).

Considering the case of a motor imagery which refers to a mental process wherein an individual replicates an action. Thus, a mental representation of movement prevails without an actual body movement. Imagination efficiency is hard to control. Hence controlling EEG enables an individual to communicate despite the inability to control voluntary muscles. Interface substitute for nerves and muscles and the signals are incorporated into the hardware and software to be translated into physical actions. EEG based BCIs can record and classify EEG changes through different types of motor imagery like imagination of right and left hand and activity, consequently motor imagery as means to enhance motor function and motor learning. It has made a significant contribution in the field of neurological rehabilitation, cognitive neuroscience and cognitive psychology. Clinical applications have procured a great deal of aid from motor imagery ranging from enhancing mobility and locomotion to reduce neuropathic pain (Malouin and Richards, 2013). Analysis and interception of data are challenging as EEG signals are vulnerable to varying fluctuations often termed as noise. Various strategies have been devised for prevention and removal of noise. In this paper, we apply Butterworth filter mechanism to eliminate noise from the signals to enhance the data quality. Besides we concentrate on feature extraction to transform raw signals into informative signals. We make use of Support Vector Machine for the same. Feature extraction contributes significantly in image processing.

A step by step process involved in Brain Computer Interface system is shown in the Fig. 1. Signal is acquired through various means such as invasive (ECog, Neurosurgery) and Non-invasive (EEG, fMRI, MEG) techniques. The channel selection is one of the important considerations since most of the EEG channel represent redundant information (Sleight et al., 2009).

Fig. 2 shows the EEG channel placement on the human scalp. Each scalp electrode is located at the brain centres. In 2001 Pfurtscheller (Wolpaw, 2002) identified that many of the neural activity related to fist movements are found in channels C3, C4 and Cz as shown in Fig. 2 B. F7 is for rational activities, Fz is for intentional and motivational data, P3, P4 and Pz contain perception and differentiation, T3, T4 is for emotional processes, T5, T6 has memory functions and O1 and O2 contain visualization data.

In order to remove the noise from the obtained signal, any of the suitable filtering techniques may be adopted. Further the extracted data may move for classification phase.

1.1. Applications

Some of the popular applications of the BCI system are shown in Fig. 3 and each of them are discussed below:

The applications shown in Fig. 3 have been mentioned below:

i. BCI for communication and control: BCI for communication for and control mainly incorporate applications like spelling devices, environmental control and Functional Electric Stimulation (FES) or prosthetic devices. Non-muscular communication and control are not only limited to guesswork. It has been reported in Graimann et al. (2007) that a direct contact between the brain and external world is attainable and can be used for several useful purposes. BCIs are yet to achieve the ability to fly airplanes and most likely not anytime soon. Currently implemented BCIs at most are capable of reaching 25 bits/min. This modest capacity may be valuable for those who lack voluntary muscle control or for those in whom the remaining control is weak, easily fatigued, or unreliable. Patients with immobile condition (e.g. by ALS, brainstem stroke, or severe polyneuropathy) or lack any 778 J.R. Wolpaw et al./Clinical Neurophysiology 113 (2002) 767–791 useful muscle control (e.g. due to severe cerebral palsy), a BCI aids in giving the ability to answer simple questions and control the environment (e.g. lights, temperature, television, etc.). It may also be instrumental in performing slow word processing (i.e. with a predictive program, 25 bits/min could produce 2 words/min. It is possible for an intelligent wheelchair to automatically avoid collisions and hazardous events or a robot arm to independently manage specific movement scenarios and identify and rectify safety issues which may be suitably

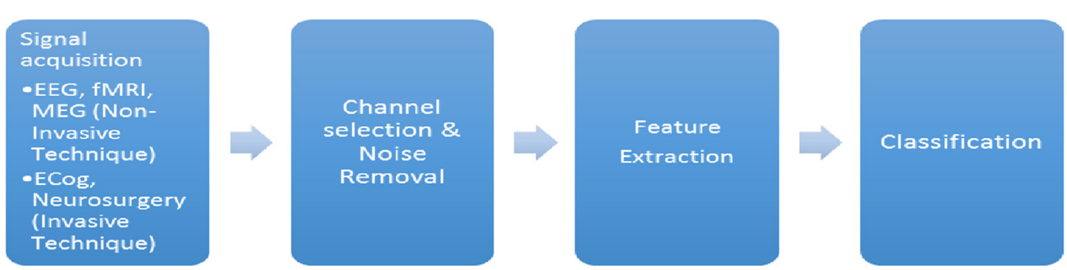

Figure 1 Process involved in brain computing interface system.

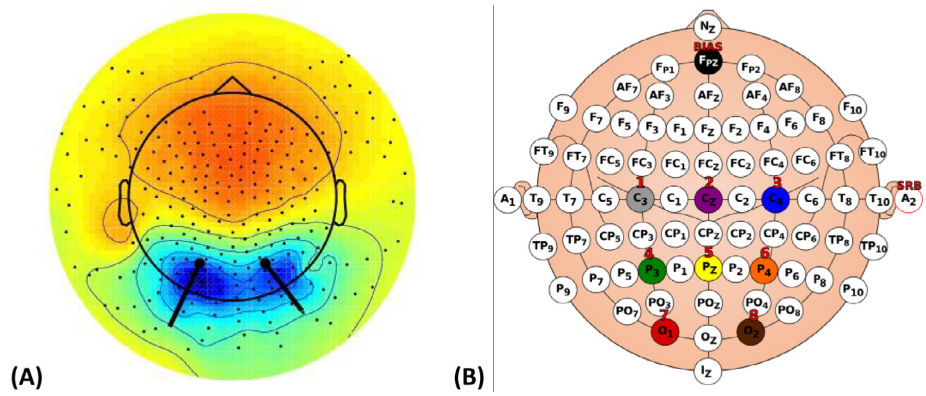

Figure 2 EEG channel placements on the human scalp (http://static.wixstatic.com/media/1c3d1a_0df53d200a402620889eb084e288ad18.jpg/v1/fill/w_475,h_437,al_c,lg_1,q_80/1c3d1a_0df53d200a402620889eb084e288ad18.jpg; http://blog.jfrey.info/images/openbci_p300_coadapt/channels_P300.png).

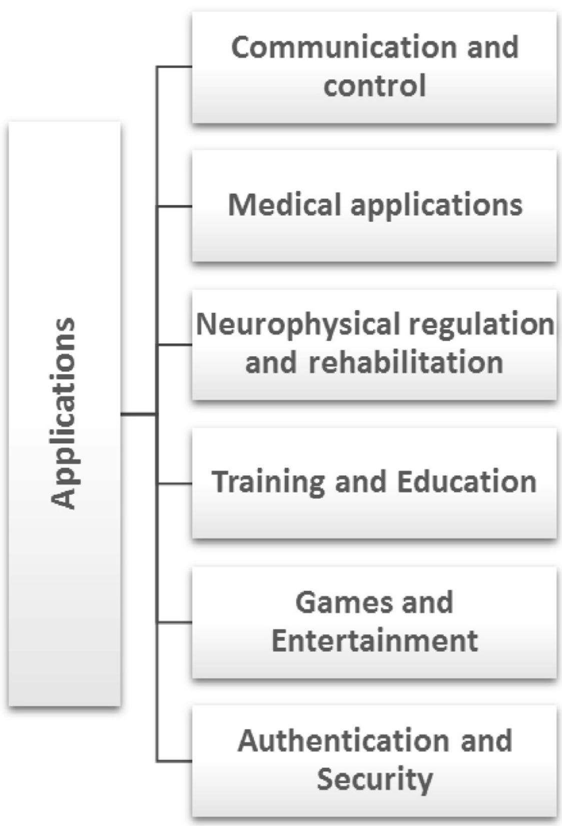

Figure 3 Some applications of BCI system.

controlled by unreliable control signals like those imparted by a BCI (Ang et al., 2011).

Accordingly the future value of BCI technology will rely significantly on the increase in information transfer rate.

ii. Medical applications: Medical applications of BCI have helped severely disabled people to work independently improving their quality of life. It has also helped prevention and detection of various conscious level detection systems. The major impact of smoking and alcohol on brain waves has been stressed upon. Tumor is generated from unrestricted self-dividing of cells and may be identified using the EEG as a cheap secondary substitute for MRI and CT-SCAN. EEG-based brain tumor detection systems have attracted many researchers as pointed out in focuses on identifying breast cancer with the help of EEG signals. Measuring brain behavior may diagnose dyslexia which is a brain disorder.

iii. Neurophysical regulation and rehabilitation: Neurophysical regulation and rehabilitation have a broad range of feasible applications. One could anticipate that BCI dependent neurofeedback therapies are additionally fruitful in comparison to normal neurofeedback. Neurological disorders which may be successfully treated are attention deficit hyperactivity disorder (ADHD), memory disorders, epilepsy, and stroke (Ang et al., 2011). Consequently a BCI system may be contemplated as the most facilitating neurofeedback system of all systems available. BCI system supports neurophysiological regulation and rehabilitation, and focuses primarily on self-regulation of brain patterns along with the cortical reorganization and compensatory cerebral activation of the entire brain section. Predominant performance measures like high information transfer rates and accurate control serve as secondary for the BCI applications (communication and control applications).

Patients with mobility issues rely on rehabilitation for restoring their lost functions and regaining former levels of mobility for adapting to their acquired incapacity. Lack of oxygen leads to collapsing of brain cells resulting in a condition called stroke. Such a situation forces the patient to lose the ability to speak and deal with memory problems. Often the left side of the body gets paralyzed. Brain signals have been known to provide solutions for various disabilities and brain strokes. It has been proclaimed in Birbaumer et al. (2013) that it is possible to reorganize brain structures corresponding to stroke injuries. Moreover, restoration of disrupted motor functions may be performed by neuroplasticity (Ruiz, 2014; Anupama et al., 2012).

iv. Training and Education: Training and education is related to the brain and its plasticity. The brain is capable of changing, growing and remapping itself. Determining plasticity leads to improved training techniques and individual training regimens. Neuro-feedback training is an application to Modular EEG devices 46 R.A. Ramadan et al. which aims at effective working, attention, executive functions and memory. Neuroergonomics is an evaluation application for the purpose of estimating the perfect match between human abilities and technology. BCI finds its use in education and training methods (Zander and Jatzev, 2009). BCI based on EEG can enable a patient to control or move the cursor in accordance to mental thoughts wherein the patient may select words or letters. A collaborative BCI is responsible for enhancing the effectiveness of training and education programs. This can be achieved by monitoring either the student's attention/concentration or ability to participate effectively. Real-time detection of emotions, frustration, or surprise (Jackson and Mappus, 2010) enables training or educational applications to adapt in various ways which are successful in enhancing the learning rates of the students.

v. Games and Entertainment: Games and entertainment in BCI apply to playing games like augmented reality, certain applications on entertainment and 3D games. With the use of 3D monitors, glasses and an EEG headset may be deployed to control the game by thoughts.

The entertainment industry is extremely agile in introducing new concepts and paradigms. Human computer interaction is an alluring concept.3-Dtelevision, gesture-based game controllers, and games have been developed exclusively to be supported by EEG headsets. The past few years have witnessed numerous products by companies such as Neurosky, Emotiv, Uncle Milton, Mind Games, and Mattel.

EEG serious games deployed for emotional control and/or neuroprosthetic rehabilitation may contain either a new game idea or a revised one. The Brainball game by Tan and Nijholt (Mathan, 2008) intends to drop the stress level. The only way to move the ball is by relaxing; enabling the calmer player to be the winner. Players tend to learn about controlling their stress while being entertained.

vi. Authentication and Security: Authentication and security have introduced vast research in BCI for security systems. EEG signals generated from driving behavior may be authenticated according to several researchers. The detection of abnormal behavior and apprehensive objects may be underpinned by EEG alone or a combination of EEG and eye movements (Panoulas et al., 2010). It suggests a situation where a group of 10 observers is assigned the work of watching CCTV recordings or baggage scans. EEG and eye movements have the potential to identify likely targets which may not be noticed. The system is designed to monitor an observer's arousal state and instigate a break whenever required. Even though EEG is a formidable means for lie detection, reliability of BCI systems is questioned for ethical use in practical situations (Nakanishi et al., 2011). A simplified driving simulator with mental task condition may be utilized to substantiate the driver's identity Nakanishi et al., 2013; Revett et al., 2010; Upreti, 2014 describes unconscious driver authentication.

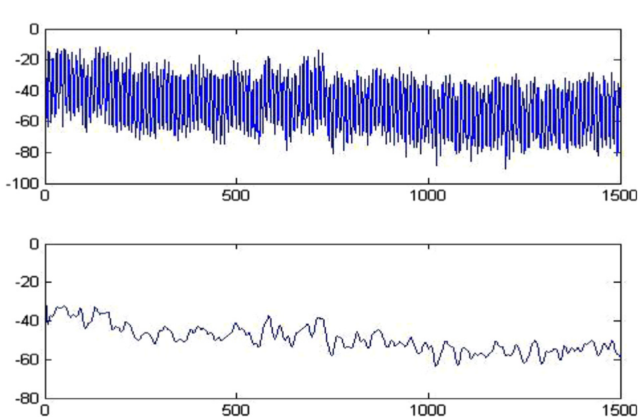

Figure 4 Original & filtered signal of left hand movement.

1.2. Challenges

BCI has been an exciting forum for scientist, engineers and medical practitioners. BCI researchers and developers must engage themselves to tackle three critical problems for an exciting future: signal acquisition hardware, reliability and training process and it is not free from challenges given in Fig. 4.

- Signal acquisition hardware: The signal acquisition hardware up gradation necessary for developing usable nonmedical BCI applications is a core challenge. EEG sensors must be dry, agreeable, appropriate to use, and easy to modify since before BCI systems must be favorable for utilization beyond laboratories and hospitals. Deployed Sensors must impart good signal quality even in extremely noisy environments having mobile users. It has already been presented by researchers that BCIs can be used outside laboratories or with a mobile user however performance is comparatively poorer than in laboratory conditions. The work must satisfactorily focus on developing better active electrodes with active shielding.
- Reliability: BCI systems have poor reliability for most of the applications. It is important that a BCI system must be appropriate for real time execution and well founded for muscular actions in the human body. Without advancements, the actual usability of BCIs will continue to be the only most used communication functions for users with severe disorders. The main problem is dependent on identify and capture of 3 major issues: the intermediate role of a robust and interactive BCI system; the requirement in deploying a BCI system which emulate the diffuse the working of central nervous system; and a system which realizes the necessity of integrating extra brain signals providing a feedback mechanism (Liao et al., 2014).
- Training Process: Training the user is a time-consuming activity. It finds its importance in either controlling the user through the procedure or the number of sessions that have been recorded (Nakanishi et al., 2011). Either the preliminary phase or the classifier calibration phase can be used for the training process. The user may handle the system to control his/her brain feedback signals in the preliminary phase.

2. Related work

In 2013, Vighneshwari (Sleight et al., 2009), has analyzed the EEG signals for the left and right hand movements. A block diagram of Brain Computer Interface has been presented consisting of signal acquisition; signal processing, Feature extraction, Classification and output. Typical filtering solutions are not sufficient to eradicate White Gaussian Noise, and the random noise interferences present in the EEG dominant frequency energy cannot be removed easily. WGN cannot be removed entirely and therefore highlights the necessity of feature extraction. One method of feature extraction is by making use of wavelet transform. Continuous Wavelet Transform analyses signals on the basis of functions which relate to each other by virtue of scaling and translation. In Discrete Wavelet Transform digital filtering techniques are deployed to obtain a time scale representation of a digital signal. Filtering operations determine the resolution of the signal. Another method for feature extraction is analysis of time and domain features. The features are Integrated EEG, Mean Absolute Value, Modified Mean Absolute Value 1, Modified Mean Absolute Value 2, Simple Square Integral, Variance, Root Mean Square, Waveform Length, Zero Crossing, Slope Sign Change and Mean Absolute Deviation. All the features bear some sets of mathematical calculations which trigger the Experimental Results. The signal undergoes experimentation by being analyzed first and then being filtered by Signal Processing Toolbox in MATLAB. Applying DWT to the signal yields Beta and Alpha bands of frequencies. The percentage error is calculated and the average percentage error for each movement in the data set is evaluated thus giving the SNR ratio. Six features are inspected for Left Open, Left Close, Right Open and Right Close hence classifying the EEG signals.

In 2013 [25], Jae Won Bang proposed a method which could detect the head movement by the average error rate of 3.22% comparatively less to other methods. The use of frontal viewing camera along with the EEG acquisition hardware for eliminating the noise produced by other activities on the head movement and detection of the moving features taken by the frontal camera made it possible to eliminate the noise in the EEG data. Linear discriminant analysis and Support vector machine were used to reduce the dimensions and perform the classification of the dataset for improving the accuracy in detecting the movements.

In 2014, Dokare (Wolpaw, 2002), classified EEG signals for Imagined left and right Hand movements for BCI applications. Major difficulties included in the motor imagery pattern recognition procedure are to successfully estimate, visualize and represent the ERD/ERS phenomenon in a feature vector. Feature extraction technique uses of Discrete Wavelet tool for feature extraction of the EEG signal. Support Vector Machine SVM has been applied to classify the obtained features into the right and left hand activity. The analysis has been carried out using MATLAB. The work heavily relies upon wavelet transform methodology, for decomposing an n input signal into elementary waveforms called as wavelets. The Discrete Wavelet Transform (DWT) analyzes the signal at different frequency bands with different resolutions by breaking down the EEG signal into a rough approximation of carrying out by multi resolution analysis. DWT engaging two functions, scaling functions and wavelet functions, is associated with the low-pass and high-pass band filters. Successive high-pass and low-pass filtering decomposes the signal into different frequency bands called as sub bands. The low pass filter gives the approximation coefficients, while the high-pass filter gives the detail coefficients. Hence the features may be used as classifier for different finger movements.

In 2014, Ke Liao (Liao et al., 2014), used the EEG signals to identify individual finger movements from one hand. The experiment was carried out with 11 healthy right handed subjects, the obtained EEG data were high passed at 0.3 Hz making the use of elliptic Infinite Impulse Response (IIS) filter in EEGLAB toolbox. To identify and evaluate finger movements Power Spectral Density (PSD) and Principal Component Analysis (PCA) were calculated. The feature selection procedure was carried out using spectral PCA where every dataset was divided into testing and training sets with respect to fivefold cross validation having the entire dataset uniformly separated into 5 commonly absolute subsets. The research concluded that the movement related to spectral structure in finger movements can be decomposed using the spectral PSD which could be employed to calculate individual finger movements with a calculation accuracy of 77.11% promising to increase the control dimension in EEG (noninvasive) based BCI techniques.

In 2011 (Bang et al., 2013), A. K. Mohamed used the EEG signals for showing the difference between EEG related to the wrist and finger movements. For extracting unique features based on ERS/ERD (Event Related Synchronization) the Independent component Analysis (ICA) was used whereas for feature reduction the Bhattacharya distance was used which helped selecting the best feature with respect to separate classes. Further it was stated that Mahalanobis distance is found giving good performance in BCI research. It was used to calculate the distance between each trial signal in a selected class to its own average class. Alternatively, Artificial Neural Network (ANN) was employed to divide the data into training and testing set with the accuracy of 65% and 71% proving the offline differentiation of hand and wrist movement possible.

3. Experiment on the scenario of the hand movement

Our assumption for the scenario of the hand movement is based on Fig. 1 and the work focused on non-invasive BCI system. The experimented system performs filtering the raw obtained signal applying Butterworth filter and the feature extraction technique using supervised learning model, the Discrete Wavelet Transform. We thereby deploy a dataset to ensure that all the steps are in accordance (Wolpaw, 2002).

The experiment has been conducted using the data sets obtained by NUST (http://static.wixstatic.com/media/1c3d1a_0df53d200a402620889eb084e288ad18.jpg/v1/fill/w_475,h_437,al_c,lg_1,q_80/1c3d1a_0df53d200a402620889eb084e288ad18.jpg). The data set was recorded at 500 Hz from a subject 21 year old right handed male with no known medical conditions. This data set consists of actual left and right hand movement recorded during his closed eyes. The order of the hand movement was random and the recording was done using Neurofax EEG system. From the obtained dataset, we considered the channels C_3, and C_4 as these channels contains the needful information of the hand movement scenarios.

Whenever a signal is transmitted, it is to be received at another end or into the space. Certain disturbances are known to prevail. When thermal noise is generated due to electron movement, the noise is labeled as Additive White Gaussian Noise (AWGN). The common representation of the received signal is as

Table 1 RMS and MAV in the non-filtered signal.

Features	Left backward 1	Left backward 2
RMS	51.7895	61.3618
MAV	50.7707	58.5482

Table 2 RMS and MAV in the filtered signal.

Features	Left backward 1	Left backward 2
RMS	48.0030	59.3245
MAV	49.0439	58.5264

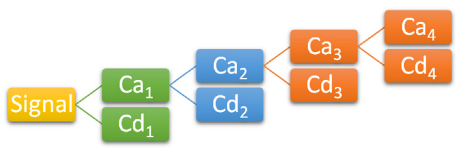

Figure 5 Wavelet decomposition of the signal in 4 levels.

$$Y(t) = X(t) + n(t) \tag{1}$$

where $X(t)$ is the original signal and $n(t)$ happens to be the noise. The probability of $n(t)$, zero is highest and considerably decreases as the magnitude of $n(t)$ is increased. The noise is unanimously present with the same power at every frequency and hence termed as Additive White Gaussian Noise. White Gaussian noise is often used to symbolize noise in EEG signal analysis and very difficult to eliminate completely.

Hence the signal is analyzed using the signal processing toolbox in MATLAB. The signal is low-pass filtered using Butterworth filtering technique to 0–64 Hz. The non-filtered and the filtered signal for the left hand movement are shown in the Fig. 4.

3.1. RMS and MAV calculations

In the section, the originally acquired signal data (non-filtered) of the left hand movement with the filtered signal data of the left hand movement within the consideration of the parameters say RMS and MAV has been calculated using Eqs. (2) and (3). The calculated values are recorded in Tables 1 and 2 respectively.

Root Mean Square (RMS): It is modelled as amplitude modulated Gaussian random process. It can be determined in real time and is also simple to implement. Its features are used in detecting onset activities, muscular contraction and muscle activities. Its standard deviation formulae can be expressed as

$$\mathrm{RMS} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{n}=1}^{\mathrm{N}}\mathrm{x}_\mathrm{n}^2} \tag{2}$$

Mean Absolute Value (MAV): It is similar to average rectified value (ARV). It is calculated by taking the average of the absolute value of the EEG signal which is an easy way for observation of the muscle contraction levels. MAV can be defined as:

$$\mathrm{MAV} = \frac{1}{N}\sum_{i=1}^{N}|x_n| \tag{3}$$

In the below Tables 1 and 2, two hand movement scenarios were taken to justify the results.

The recorded value in Table 1 shows the value for left backward hand movement scenario 1 from the original signal having the RMS value as 51.7895 and MAV value as 50.7707. Similarly it is recorded for left backward hand movement scenario 2. As shown in Table 2, the value for left backward hand movement scenario 1 from the filtered signal having the RMS value as 48.0030 and MAV as 49.0439 and similarly for the left backward hand movement scenario 2. Comparing the RMS and MAV values obtained from both the original and non filtered signals, the filtered signal in Table 2 indicates better results upon applying the Butterworth filtering technique.

3.2. Feature extraction using Discrete Wavelet Transform (DWT)

The DWT has been adopted in the feature extraction phase where the multiple wavelets (filtered signals as a input) are sampled discretely with a specific window size. For each window the wavelet transform technique is applied. In Fig. 5 the level of decomposition of a signal is defined and divided into

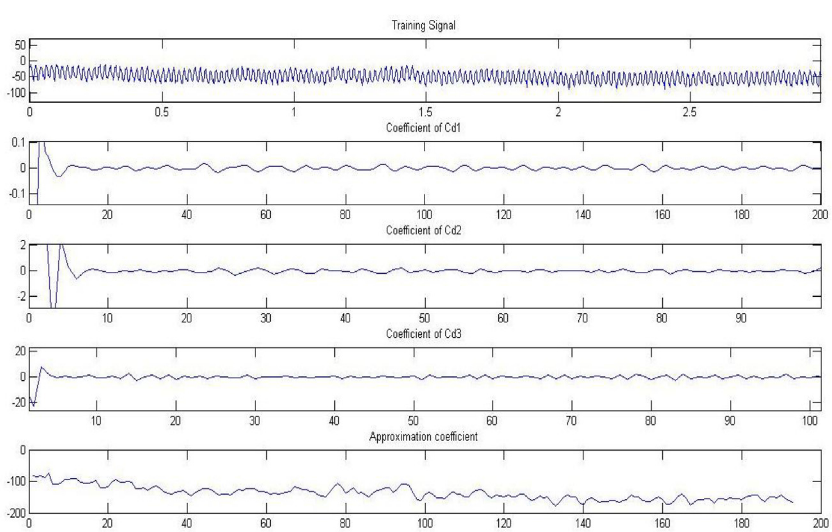

Figure 6 Training signal along with the detail wavelets coefficient for the left backward hand movement.

two wavelet coefficients namely the scaling coefficient and the detailed coefficient. As the data are arranged a threshold is provided to calculate the value of input data. In this experiment the threshold is considered as 250 Hz using the inverse function. The signals are decomposed at different frequency bands based on the threshold value. Successive high pass and low pass filtering ensure signal decomposition into sub bands and the lower pass filter is associated with approximation coefficients (Ca_1) while the high pass filter is associated with detailed coefficients (Cd_1). The amount of levels of decomposition is considered by the presiding frequency components which are a part of the signal (Fig. 6).

The filtered signal is divided into levels: cd1, cd2, cd3 and Cd4 of frequency ranges beta (16 Hz–32 Hz), alpha (8 Hz–16 Hz), theta (0 Hz–8 Hz) and delta respectively. The approximation coefficient is cA5. The sampling frequency was 500 Hz.

Further these wavelet coefficient decompositions can be used as the feature vector for the classifier in order to classify left/right hand movements using support vector machine (SVM) classifier.

These feature vectors having the entire coefficient make a large dimension, so we may only use cd2 and cd3 which has a frequency range of 8–15 Hz and 16–32 Hz respectively.

4. Conclusion

Brain Computer Interface has been providing assistance to severely disabled patients. Controlling the behavior of the brain and receiving the information from other body parts, it provides a channeling support between the human brain and technical equipment. Having numerous applications in the field of research and implementation BCI has always been attracting the research community. We conclude the work with the following:

- A small dataset of EEG signals for various finger and hand movements were taken and the artifacts were removed by applying low pass filtering technique and compared with the original datasets which gave satisfactory results. The alpha and beta band frequencies were extracted from the EEG signal using Discrete Wavelet Transform and hence considered forward for the classification of the signals.

In future we may study and compare various low-band filtering techniques for the removal of the artifacts present in the signal.

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