BRAIN COMPUTER INTERFACE FOR SECURITY APPLICATION BASED ON INTERSUBJECT INFORMATION

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ABSTRACT

This paper presents a Brain Computer Interface for Locker Safety in which we are implementing a safety opening of the locker using individual person brain signal. It is scientifically proved that the brain signal image is unique for each person; no way it is related to other person. Here we proposed a system to open the locker only when the authenticated person thinks that it should open, it will be highly secured. In this proposed prototype system the brain signals are stored in the system as a binary file in a directory, this will act as a temporary database. And whenever the user give the image to the system it will perform the array comparison with the image which is already stored in the system, if it gets matched the system will perform the function in order to open the locker, if image does not get matched, the operation will not be performed.

Keyword: *BCI, EEG, Locker Safety*

1.INTRODUCTION

People who are paralyzed or have other severe movement disorders need alternative methods for communication and control. Currently available augmentative communication methods require some muscle control. Whether they use one muscle group to supply the function normally provided by another (e.g., use extra ocular muscles to drive a speech synthesizer) or detour around interruptions in normal pathways (e.g., use shoulder muscles to control activation of hand and forearm muscles, they all require a measure of voluntary muscle function. Thus, they may not be useful for those who are totally paralyzed (e.g., by amyotrophic lateral sclerosis (ALS) or brainstem stroke) or have other severe motor disabilities. These individuals need an alternative communication channel that does not depend on muscle control. They need a method to express their wishes that does not rely on the brain's normal output pathways of peripheral nerves and muscles.so in order to make a communication in an effective way we are going for an EEG signal.

The use of EEG signals as a vector of communication between men and machines represents one of the current challenges in signal theory research. The principal element of such a communication system, more known as "Brain Computer Interface", is the interpretation of the EEG signals related to the characteristic parameters of brain electrical activity. The role of signal processing is crucial in the development of a real-time Brain Computer Interface. Until recently, several improvements have been made in this area, but none of them have been successful enough to use them in a real system. The goal of creating more effective classification algorithms, have focused numerous investigations in the search of new techniques of feature extraction. The main objective of this project is the establishment of a Time – Frequency method, which allows EEG signal classification between two given tasks as well as the familiarization with the state of the art in time-frequency and Brain Computer Interface.

A basic BCI experimental set-up might use left-arm imagined movement versus right-arm imagined movement as the basis for a communication strategy. This requires the application of two optets, each one situated over the appropriate parts of the motor cortex. The sets of mental states to be distinguished can be further enriched through monitoring left and right frontal cortex activity such that linguistic and arithmetic tasks can be separated. This would involve the application of two more optets.

List 1 details typical activation strategies:

1. Actual movement of a particular limb

2. Imagined movement of a particular limb

3. Imagined tongue movement

4. Engagement in mental arithmetic

5. Engagement in language task.

In Proposed System:**,** Man machine interface has been one of the growing fields of research and development in recent years. Most of the effort has been dedicated to the design of user- friendly or ergonomic systems by means of innovative interfaces such as voice recognition, virtual reality. A direct brain-computer interface would add a new dimension to man-machine interaction.

A brain-computer interface, sometimes called a direct neural interface or a brain machine interface, is a direct communication pathway between a human or animal brain (and brain cell culture) and an external device. In one BCIs, computers either accept commands from the brain or send signals to it but not both. Two way BCIs will allow brains and external devices to exchange information in both directions but have yet to be successfully implanted in animals or humans. Brain-Computer interface is a staple of science fiction writing. There have been several recent steps toward interfacing the brain and computers.

In this definition, the word brain means the brain or nervous system of an organic life form rather than the mind. Computer means any processing or computational device, from simple circuits to silicon chips (including hypothetical future technologies like quantum computing). Research on BCIs has been going on for more than 30 years but from the mid 1990's there has been dramatic increase working experimental implants. With recent advances in technology and knowledge, pioneering researches could now conceivably attempt to produce BCIs that augment human functions rather than simply restoring them, previously only the realm of science fiction.

A Brain-Computer Interface (BCI) is a system that acquires and analyzes neural signals with the goal of creating a communication channel directly between the brain and the computer.

The common structure of a Brain Computer Interface is the following

1**. Signal Acquisition**: the EEG signals are obtained from the brain through invasive or non-invasive methods (for example, electrodes). After, the signal is amplified and sampled.

2. **Signal Pre-Processing**: once the signals are acquired, it is necessary to clean them.

3**. Signal Classification**: once the signals are cleaned, they will be processed and classified to find out which kind of mental task the subject is performing.

4. **Computer Interaction**: once the signals are classified, they will be used by an appropriate algorithm for the development of a certain application.

2. RELATED WORK

"Filter Bank Common Spatial Pattern (FBCSP) in Brain-Computer Interface [1]". In motor imagery-based Brain Computer Interfaces (BCI), discriminative patterns can be extracted from the electroencephalogram (EEG) using the Common Spatial Pattern (CSP) algorithm. However, the performance of this spatial filter depends on the operational frequency band of the EEG. Thus, setting a broad frequency range, or manually selecting a subject-specific frequency range, are commonly used with the CSP algorithm. To address this problem, this paper proposes a novel Filter Bank Common Spatial Pattern (FBCSP) to perform autonomous selection of key temporal spatial discriminative EEG characteristics. After the EEG Measurements have been band pass-filtered into multiple

Frequency bands, CSP features are extracted from each of these Bands. A feature selection algorithm is then used to automatically select discriminative pairs of frequency bands and corresponding CSP features. A classification algorithm is subsequently used to classify the CSP features. The results show that FBCSP, using a particular combination feature selection and classification algorithm, yields relatively higher cross validation accuracies compared to prevailing approaches.

To address the problem of manually selecting the operational subject-specific frequency band for the CSP algorithm, several approaches have been proposed. One approach is the Common Spatial-Spectral Pattern (CSSP), which optimizes a simple filter that employs a one time delayed sample with the CSP algorithm.

This paper proposed a novel machine learning approach called Filter Bank Common Spatial Pattern (FBCSP) for processing EEG measurements in motor imagery-based BCI. FBCSP addresses the problem of selecting an appropriate operational frequency band for extracting discriminating CSP features. FBCSP is capable of learning subject-specific patterns from the high-dimensional EEG measurements without operator intervention as well as yielding relatively high classification accuracies. Since any feature selection and classification algorithms from the machine learning and computational intelligence literature can be employed, FBCSP is more generalized than existing approaches such as the Sub-band Common Spatial Pattern (SBCSP).

"Sub-band Common Spatial Pattern (SBCSP) for Brain-Computer Interface [2]". Brain-computer interface (BCI) is a system to translate human thoughts into commands. For Electroencephalography (EEG) based BCI, motor imagery is considered as one of the most effective ways. Different imagery activities can be classified based on the changes in alpha and beta rhythms and their spatial distributions. However, the change in these rhythmic patterns varies from one subject to another. This causes an unavoidable time-consuming fine-tuning process in building a BCI for every subject. To address this issue, we propose a new method called Sub-band Common Spatial Pattern (SBCSP) to solve the problem. First, we decompose the EEG signals into sub-bands using a filter bank. Subsequently, we apply a discriminative analysis to extract SBCSP features. The SBCSP features are then fed into Linear Discriminant Analyzers (LDA) to obtain scores which reflect the classification capability of each frequency band. Finally, the scores are fused to make decision. We evaluate two fusion methods: Recursive Band Elimination (RBE) and Meta-Classifier (MC).

People suffering from Amyotrophic Lateral Sclerosis (ALS) loses their muscle movement degenerative and at a later stage may become totally paralyzed. Nevertheless, for most ALS patients, their minds are un-affected. Brain computer interface (BCI) addresses this concern by making it possible to translate human thoughts directly to the outside world. Electroencephalography (EEG) has been chosen to capture brainwaves for BCI applications because of its simplicity, inexpensiveness and high temporal resolution. In the imagination of limb movement, suppression of EEG signals happens in the specific region of the motor and somatosensory cortex due to loss of synchrony in alpha and beta bands, classically defined in the 12-16Hz and 18-24Hz respectively, is termed event-related de-synchronization (ERD). This brain rhythm will benefit ALS patients as it can be used as a control signal for assistive devices like wheelchair and neuroprosthesis.

In this paper, we have developed a new framework to overcome the problem of a time-consuming fine-tuning process in building a BCI for each subject. This problem is prevalent in BCI research and it causes more trouble when researchers try to benchmark and compare different methods. As such fine-tuned system is hardly repeatable by other research groups. We propose a Sub-band CSP (SBCSP) framework, which provides an alternative solution to address this issue

"An Adaptive Filter Bank for Motor Imagery based Brain Computer Interface [3]".Brain Computer Interface (BCI) provides an alternative communication and control method for people with severe motor disabilities. Motor imagery patterns are widely used in Electroencephalogram (EEG) based BCIs. The dominant frequency bands are subject-specific and therefore performance of motor imagery based BCIs are sensitive to both temporal filtering and spatial filtering. As the optimum filter is strongly subject dependent, we propose a method that selects the subject-specific discriminative frequency components using time-frequency plots of Fisher ratio of two-class motor imagery patterns. We also propose a low complexity adaptive Finite Impulse Response (FIR) filter bank system based on coefficient decimation technique which can realize the subject-specific band pass filters adaptively depending on the information of Fisher ratio map. Features are extracted only from the selected frequency components. The proposed adaptive filter bank based system offers average classification accuracy of about 90%, which is slightly better than the existing fixed filter bank system.

EEG is widely used in detecting brain activities by recording electric signals from the scalp. Intentions can then be recognized by analyzing the neurological phenomenon from the EEG signals. It gives rise to a new communication and control channel, dubbed brain computer interface (BCI), which does not depend on the brain's normal output pathway of nerves and muscles. BCI can be used as a communication tool for people with severe neuromuscular disabilities, such as amyotrophic lateral sclerosis, brain-stem stroke, spinal code injury, etc., to control external devices such as a computer, wheelchair, neuroprothesis etc. EEG based BCIs use various neurological phenomena, such as visually evoked potentials, slow cortical potentials, P300 potentials, mu and/or beta rhythms and event related de synchronization (ERD/ERS), etc. Motor imagery is one of the effective methodologies employed in EEG-based BCIs. Preparation for actual movement or imagination of a movement is accompanied by a rhythmic power decrease or increase in counter-lateral primary sensorimotor areas, which are called event related de synchronization (ERD) and event related synchronization (ERS) respectively. The predominant frequency bands are very much subject-dependent, which will be the main concern of this paper. In order to detect motor imagery intention, the common spatial pattern (CSP) algorithm was found to be effective in calculating subject-specific discriminative spatial filters for detecting ERD/ERS effects.

"Robust Filter Bank Common Spatial Pattern (RFBCSP) in motor-imagery-based Brain-Computer Interface [4]". The Filter Bank Common Spatial Pattern (FBCSP) algorithm performs autonomous selection of key temporal-spatial discriminative EEG characteristics in motor imagery-based Brain Computer Interfaces (MI-BCI). However, FBCSP is sensitive to outliers because it involves multiple estimations of covariance matrices from EEG measurements. This paper proposes a Robust FBCSP (RFBCSP) algorithm whereby the estimates of the covariance matrices are replaced with the robust Minimum Covariance Determinant (MCD) estimator. The performance of RFBCSP is investigated on a publicly available dataset and compared against FBCSP using 10 to 10-fold cross-validation accuracies on training data, and session-to-session transfer kappa values on independent test data. The results showed that RFBCSP yielded improvements in certain subjects and slight improvement in overall performance across subjects. These results revealed a promising direction of RFBCSP for robust classifications of EEG measurements in MI-BCI.

The Common Spatial Pattern (CSP) algorithm is effective in constructing optimal spatial filters that discriminates two classes of EEG measurements in motor-imagery-based Brain-Computer Interface (MI-BCI). The Filter Bank Common Spatial Pattern (FBCSP) algorithm was recently proposed to select subject-specific operational frequency band for extracting discriminative CSP features.

The FBCSP algorithm used the classical estimation of multivariate covariance matrices from the EEG measurements for a filter bank of CSP. However, EEG measurements are often contaminated with outliers, such as artifacts or non-standard noise sources that deviate from the usual pattern of the majority of the data. If the EEG measurements are contaminated with even a few extreme outliers, the multivariate covariance estimates typically differs substantially from the estimate without the outliers. Hence, FBCSP is sensitive to outliers in the training Data Robust techniques such as channel removal, outlier trial removal, and normalization was first proposed to reduce the influence of outliers in EEG-based BCI in. However, certain robust technique improved performance of some subjects but deteriorated the performance of others. Hence the study suggested that there is no overall best robust technique and that subject-specific robust technique has to be chosen. Recently, a robust CSP algorithm was proposed to replace the estimation of the covariance matrices with the robust Minimum Covariance Determinant (MCD) estimator, and the computation of the variance of the CSP projected EEG with the Median Absolute Deviation (MAD).

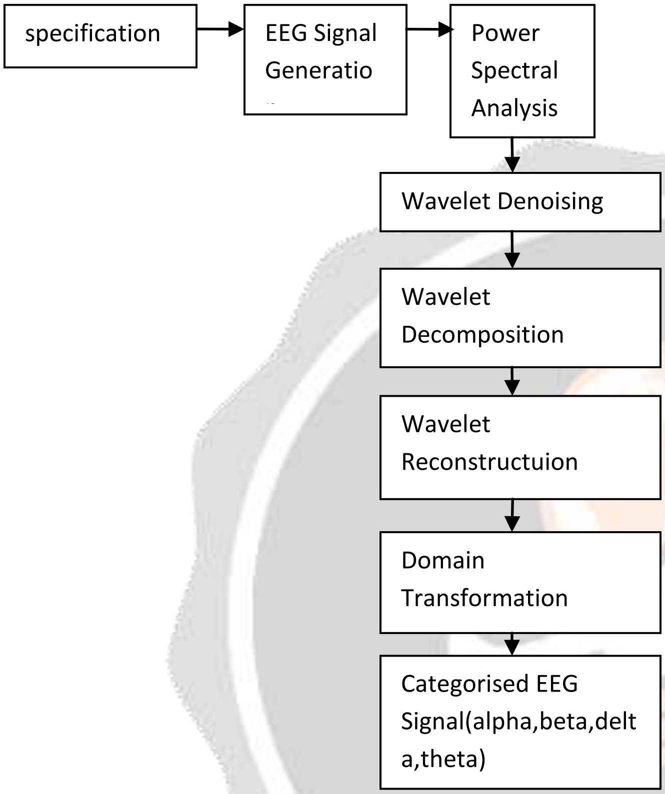
3. EXPERIMENTAL SETUP

3.1 Overview of EEG:

Electroencephalography is a medical imaging technique that reads scalp electrical activity generated by brain structures. The electroencephalogram (EEG) is defined as electrical activity of an alternating type recorded from the scalp surface after being picked up by metal electrodes and conductive media. The EEG measured directly from the cortical surface is called electrocardiogram while when using depth probes it is called electro gram since EEG measured from the head surface. Thus electroencephalographic reading is a completely non-invasive procedure that can be applied repeatedly to patients, normal adults, and children with virtually no risk or limitation.

The electrical nature of the human nervous system has been recognized for more than a century. It is well known that the variation of the surface potential distribution on the scalp reflects functional activities emerging from the underlying brain. This surface potential variation can be recorded by affixing an array of electrodes to the scalp, and measuring the voltage between pairs of these electrodes, which are then filtered, amplified, and recorded. The resulting data is called the EEG.

3.2 Block Diagram of EEG Signal Generation:



3.2.1 Signal Generation:

EEG signal are generated by placing the electrode n the scalp. It can be measured by brain voltage fluctuation as detected from the scalp electrode. It is an approximation of the cumulative electrical activity of neurons. Generally electrodes are attached to the scalp by using sticky gel. By placing an electrode at an appropriate position EEG signal is generated.

Thus the signals which are generated naturally have a noise in it so in order to de-noise the generated signal transform used is wavelet transform.

3.2.2 Wavelet De-noising:

Since Fourier transform does not produce approximate signal information with respect to time we are going for a wavelet transform. The two basic procedures for wavelet transform are wavelet decomposition and wavelet reconstruction.

3.2.3 Wavelet Decomposition:

Signal is given to low pass filter and high pass filter the signal from both the filters are down sampled thus the low pass filter gives an approximation coefficients where as an high pass filter gives an detailed coefficients

3.2.4 **Wavelet Reconstruction:**

An approximation and detailed coefficients are down sampled from decomposition are given to wavelet reconstruction where down sampled signals will get up sampled in the reconstruction. Thus a denoised signal will be produced from this signals are categorized in to alpha, beta, delta, theta signals.

3.3 Classification of EEG Signal:

BRAIN WAVE TYPE	FREQUENCY RANGE	MENTAL STATES AND CONDITIONS
Delta	0.1Hz to 3Hz	3Hz Deep, dreamless sleep, non-REM sleep, unconscious
Theta	4Hz to 7Hz	Intuitive, creative, recall, fantasy, imaginary, dream
Alpha	8Hz to 12Hz	Relaxed, but not drowsy, tranquil, conscious
Low Beta	12Hz to 15Hz	Formerly SMR, relaxed yet focused, integrated
Midrange Beta	16Hz to 20Hz	Thinking, aware of self & surroundings
High Beta	21Hz to 30Hz	Alertness, agitation
Gamma	30Hz to 100Hz	Motor Functions, higher mental activity

3.4 Discrete Wavelet Transform:

Although the discretized continuous wavelet transform enables the computation of the continuous wavelet transform by computers, it is not a true discrete transform. As a matter of fact, the wavelet series is simply a sampled version of the CWT, and the information it provides is highly redundant as far as the reconstruction of the signal is concerned. This redundancy, on the other hand, requires a significant amount of computation time and resources. The discrete wavelet transform (DWT), on the other hand, provides sufficient information both for analysis and synthesis of the original signal, with a significant reduction in the computation time. The DWT is considerably easier to implement when compared to the CWT.

3.4.1 Wavelet-Based De-noising:

The general wavelet denosing procedure is as follows

Step 1: Apply wavelet transform to the noisy signal to produce the noisy wavelet coefficients to the level which we can properly distinguish the PD occurrence.

Step 2: Select appropriate threshold limit at each level and threshold method (hard or soft threshold) to best remove the noises.

Step 3: Inverse wavelet transform of the threshold wavelet coefficients to obtain a denoised signal.

Step 4: Signal are usually non-stationary, meaning that their time-domain and frequency-domain characteristics vary over short time intervals. Since Fourier transform cannot provide any information of the spectrum changes with respect to time.

So, an alternative mathematical tool- wavelet transform must be selected to extract the relevant time-amplitude information from a signal.

The two basic wavelet processes are decomposition and reconstruction

3.5 Decomposition of Signal:

In Existing method, Fourier decomposition is very mathematical and not at all obvious. Fourier decomposition is important for three reasons. First, a wide variety of signals are inherently created from superimposed sinusoids. Audio signals are a good example of this. Fourier decomposition provides a direct analysis of the information contained in these types of signals. Second, linear systems respond to sinusoids in a unique way: a sinusoidal input always results in a sinusoidal output. In this approach, systems are characterized by how they change the amplitude and phase of sinusoids passing through them. Since an input signal can be decomposed into sinusoids, knowing how a system will react to sinusoids allows the output of the system to be found. Third, the Fourier decomposition is the basis for a broad and powerful area of mathematics called Fourier analysis, and the even more advanced Laplace and z-transforms. This work accentuates the basis on the Fourier series to obtain the minimum integral square error between the original signal and approximate signal for the received complex signal

In proposed method, the Wavelet Decomposition is used to construct a time-frequency representation of a signal that offers very good time and frequency localization. If the same signal had been analyzed by the Fourier transform, we would not have been able to detect the instant when the signal's frequency changed, whereas it is clearly observable in wavelet analysis. Though wavelet analysis is advantageous for pure sinusoidal wave, its approximate shape can be distorted enough from main signal after high level decomposition and de-noising. It may be precarious for the lost of information during the recovering of the authentic signal at receiver portion. At 2 level wavelet decomposition, the de-noised signal is not unlike the original signal shown. At 3 level wavelet decomposition the noise eradication is better than 2 level wavelet decomposition but it distorts more than that depicted. Evaluation by wavelet decomposition at level 4 instead of level 2 and 3, the signal de-noising will be improved. But it is apprehensive because there is possibility to lose the signal information.

3.6 Wavelet Decomposition:

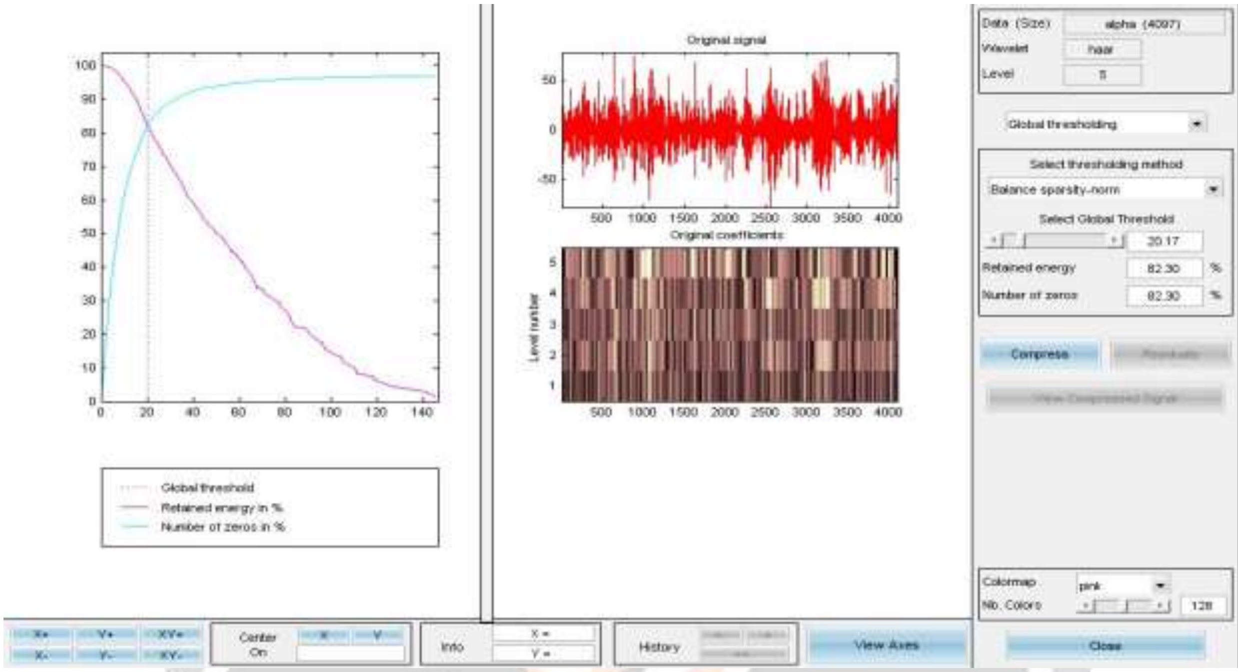
A single level decomposition puts a signal through two complementary low pass filter and high pass filter. The output of the lsow pass filter gives the approximate coefficients, while the high pass filter gives the detail coefficients.

DWT chooses only a subset of scales and positions. DWT works as filters where the signals are divided into two bands at each a specified level called approximations and details signals. The approximations (A) are the high-scale, low frequency components of the signal. The details (D) are the low-scale, high-frequency components. The samples of the signal are dividing by 2 and this is called sub-sampling. The data obtained after normalization stage serves as the input data to the DWT decompositions, which is also known as Sub-band Coding, and could be repeated for further decomposition. At every level, the sub-sampling will result in half the number of samples. The procedure of the sub-band coding of the EEG data can be visualized. In this work, a four-level multi-resolution decomposition using wavelets is implemented. Each level could characterize the frequencies of the EEG data band.

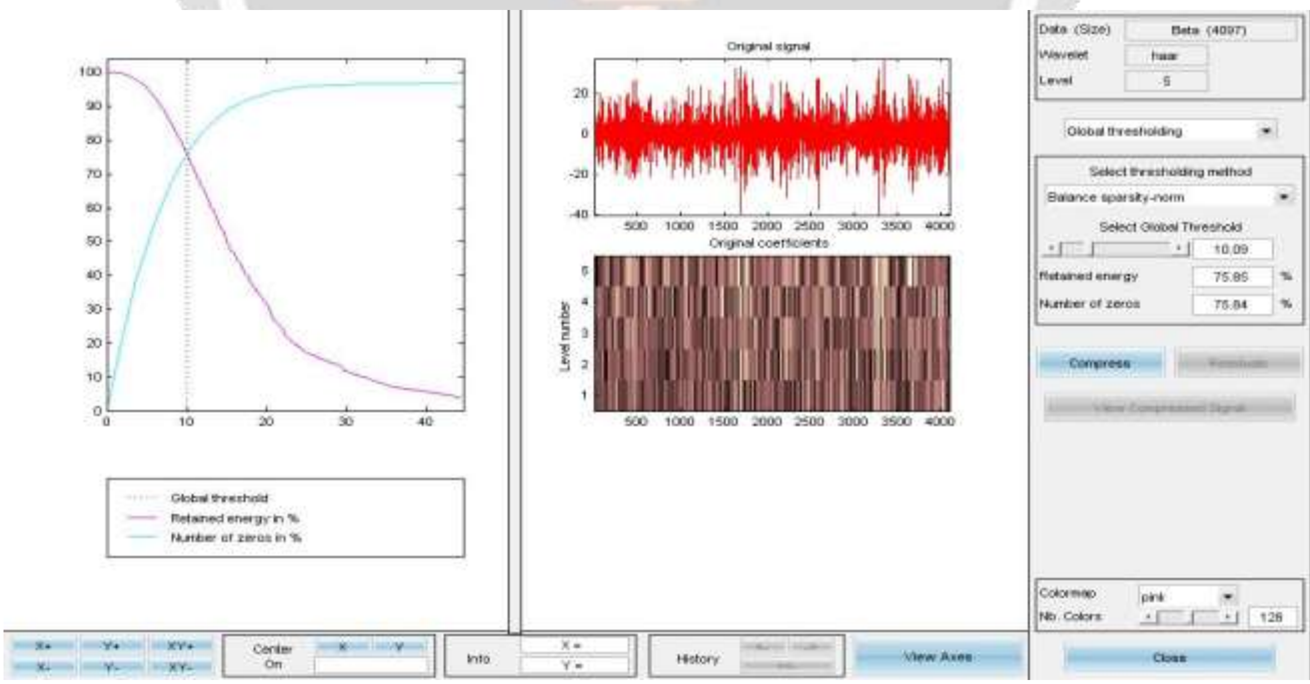
4. SIMULATION RESULTS

MATLAB provides functions for integrating C and C++ code, Fortran code, COM objects, and Java code with your applications. You can call DLLs, Java classes, and ActiveX controls. Using the MATLAB engine library, you can also call MATLAB from C, C++, or Fortran code. You can create your algorithm in MATLAB and distribute it to other MATLAB users directly as MATLAB code. Using the MATLAB Compiler (available separately), you can deploy your algorithm, as a stand-alone application or as a software module that you include in your project, to users

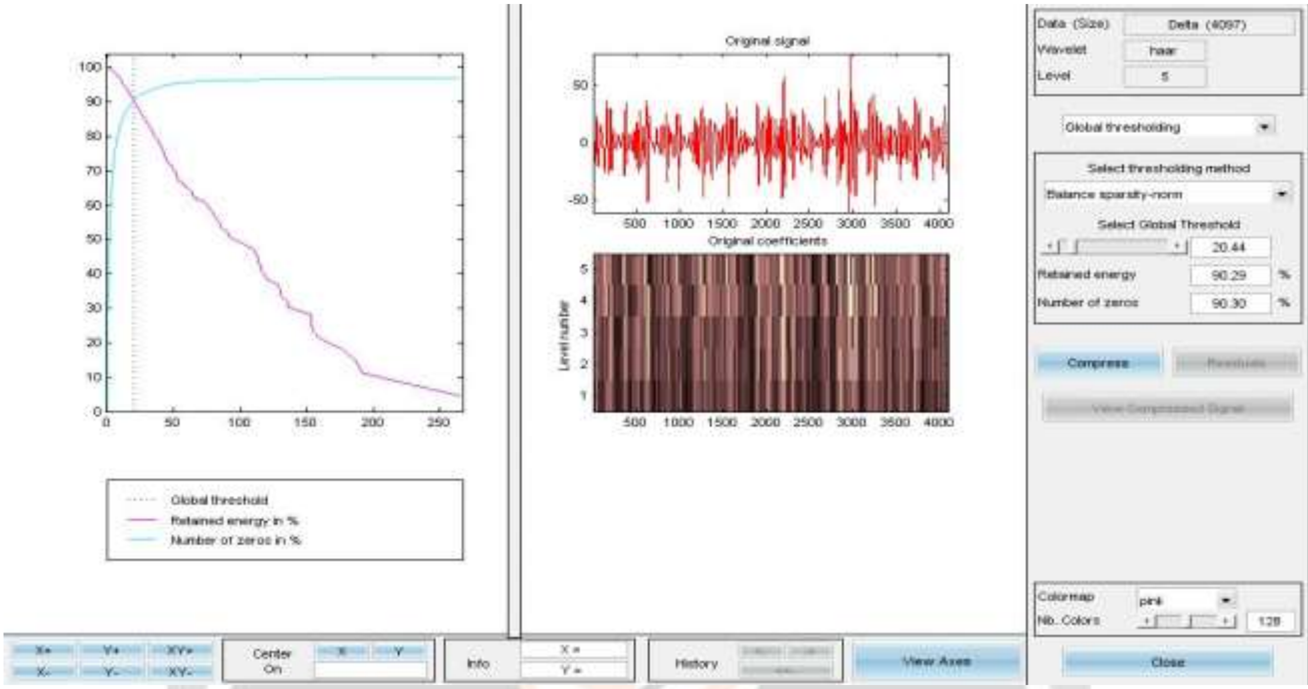
4.1 I-D Alpha Wavelet Compression



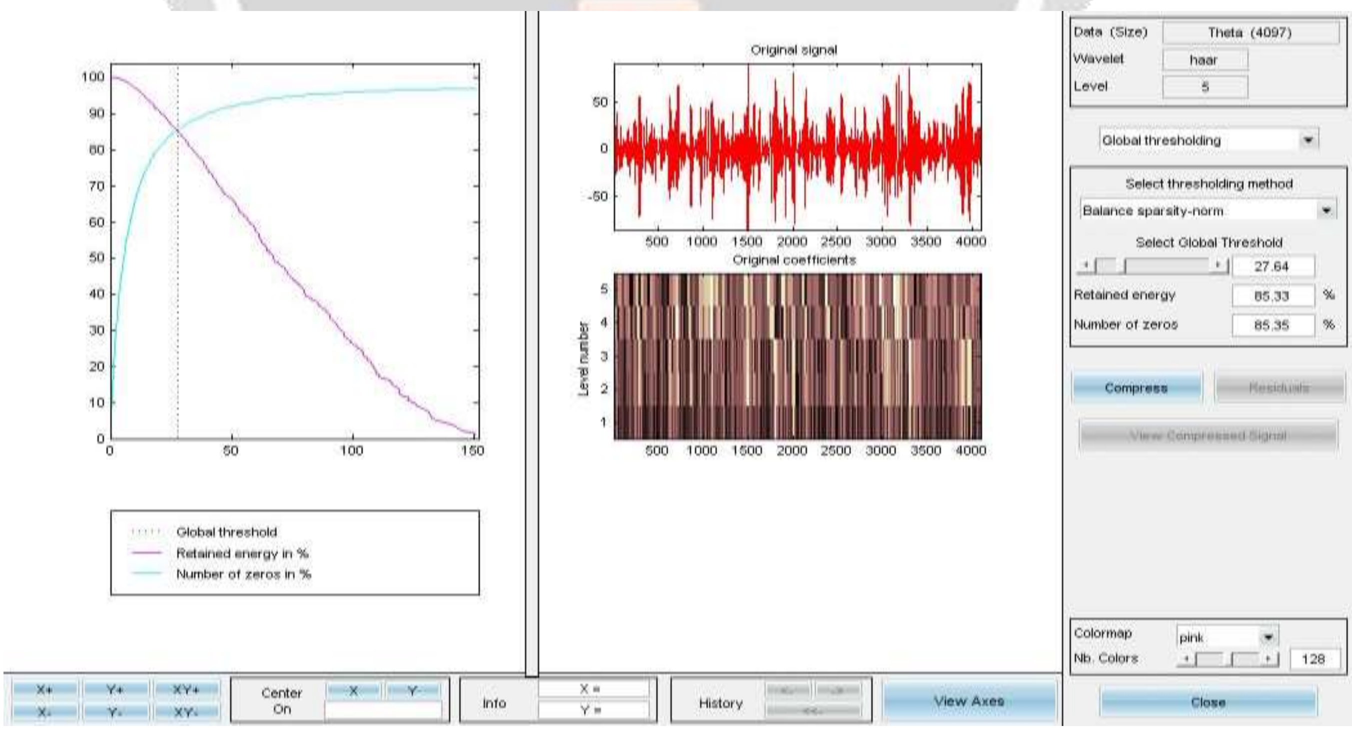
4.2 I-D Beta Wavelet Compression



4.3 I-D Delta Wavelet Compression



4.4 I-D Theta Wavelet Compression



5. CONCLUSION

Brain-Computer Interface (BCI) is a method of communication based on voluntary neural activity generated by the brain and independent of its normal output pathways of peripheral nerves and muscles.

The neural activity used in BCI can be recorded using invasive or noninvasive techniques. The BCI will improve as well and would provide wealth alternatives for individuals to interact with their environment. Electroencephalography belongs to electro biological imaging tools widely used in medical and research areas. EEG measures changes in electric potentials caused by a large number of electric dipoles formed during neural excitations. EEG signal consists of different brain waves reflecting brain electrical activity according to electrode placements and functioning in the adjacent brain regions. The role of signal processing is crucial in the development of a real-time Brain Computer Interface.

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