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Brain Signal Analysis: Methods and Techniques Used in Nanotechnology

Talal A.Aldhaheri[1], Sonali B.Kulkarni[2], Pratibha R.Bhise[3]
[1, 2, 3]*(Department of Computer Science and Information Technology Dr.BabasahebAmbedkarMarathwada University, Aurangabad, Maharashtra, India)*
[1]*(Information Systems Department, Rada'a, Al-Baydha University, Yemen)*

Abstract:
This study aims to present a comprehensive survey of the methods and techniques that are applied in the different stages of processing the brain activities, whether the functional or cognitive activities. In the first part, the common methodologies in each phase were listed in detail. They are signals acquisition, signals preprocessing, features extraction and signals classification. While in the second part a review of previous studies regarding the methods and techniques used, where the focus was only limited to the EEG technology. And the third part presents an initial idea of how to use the nanotechnology in the process of effective recording of the brain waves.
***Key Word**: BCI; Electroencephalogram; Signals-Acquisition; Signals Preprocessing; Features Extraction; Signals Classification; Nanotechnology.*

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I. Introduction

Computer brain interfaces is a science concerned with studying and developing all the systems related to connecting the brain with the surrounding environment in the form of commands and instructions to carry out operations similar to those carried out by the human brain. Computer brain interfaces mainly depend on several methods and techniques for imaging the brain. There are essentially two kinds of Brain Computer Interface (BCI) frameworks. They are Invasive Brain Computer Interface and Non-Invasive Brain Computer Interface. The vast majority of the Interested want to the Non-obtrusive BCI frameworks because of their moderateness and adaptability in catching the signs from the cerebrum [6]. A BCI framework is made out of four stages. They are signals acquisition, signals preprocessing, features extraction and signals classification [1].

II. Signals Acquisition

Different methods are used to obtain brain signals of all kinds; the most common ones are electroencephalography, Functional Magnetic-Resonance Imaging (FMRI), Near-Infrared Spectroscopy (NIRS) and Brain-Magnetic-Imaging (MEG).

Richard Caton was the first to do an electroencephalography test on animals in 1875. Then it was applied to humans by Hans Berger in 1929. It is considered the most widely used method because of its ease, high time accuracy and low cost. It is the best method in many applications, the most important of which is epilepsy control [8][2].

Functional Magnetic Resonance Imaging (fMRI) is suitable for clinical laboratories Depends on the level of hemoglobin in the blood inside the brain, it is characterized by high spatial accuracy but requires more preparation cost [6][9].

Near-Infrared Spectroscopy (NIRS) is a particular exploration imaging strategy that utilizations close infrared light to inspect the capacity of the living cerebrum. Examination members can be standing, sitting, resting, or even occupied with dynamic practices (strolling, driving, and working out) while getting a fNIRS check [4][9].

MEG technology is measures magnetic activity in brain generated by electrical activity. This procedure gives more extensive frequency range and magnificent spatiotemporal goal yet requires costly and substantial measured gear [7][9].

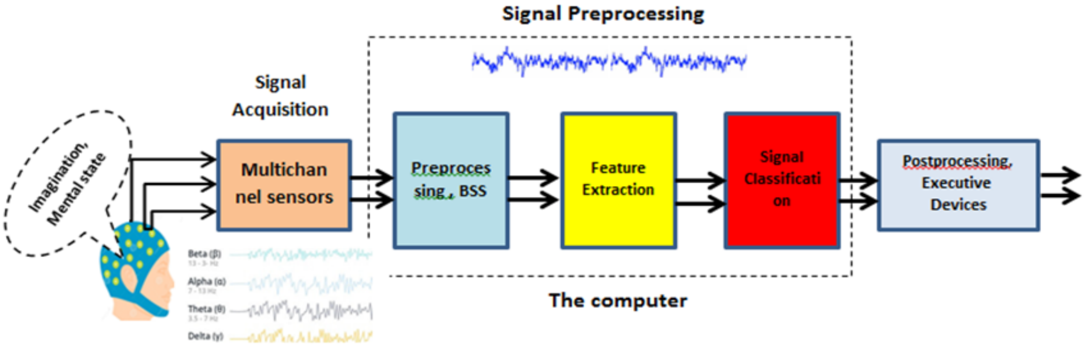

Figure no1: Phases of Analysis Brain Activity (BCI system).

III. Signals Pre-processing

The second stage after the signal acquisition stage in brain signal processing is signal enhancement or the so-called pre-processing of the signal as these signals are polluted with a lot of noise and artifacts, caused by eye flashes, eye movements, heartbeats and muscle movements, etc. There are many methods and techniques used in the pre-processing of signals we summarize in table no 1 [9][10].

Table no 1: Comparison of signals preprocessing methods

No	Methods	Pros	Cons
1	Independent Component Analysis (ICA)	- Computationally proficient efficiently. - Effectively handle big data and high performance. - The signals are broken down into spatially stable and independent components.	- Not be applicable in certain situations. - Takes several complex calculations to decompose.
2	Common Average Referencing (CAR)	SNR results improved The best reference styles, it beats them all	Restricted sample thickness and inadequate head inclusion cause issues with averaging
3	Surface Laplacian (SL)	- Really strong against artifacts from uncovered electrode cap areas - It can solve most electrode reference problems	- Sensitive to artefacts - Sensitive to spline patterns
4	Principal Component Analysis (PCA)	- Helps in reduction of feature dimensions - Positioning is done and helps in classification of data	- No does as independent component analysis.
5	Common Spatial Patterns (CSP)	There is no need to define and choose pre-defined subdomains	- Requires utilization of numerous anodes - Change in situation of anode may influence classification exactnesses.
6	adaptive filter	- The characteristics and features of the signals to be analyzed are capable of modification - High interaction with signals and artefacts within spectral interference nature	

IV. Features Extraction

Next stage, after filtering the signals and obtaining noise-free signals, is to extract the basic features from the brain signals. There are several feature extraction methods and techniques we mention in the table no 2 [3][9].

Table no 2: Comparison of features extraction methods

No	Methods	Pros	Cons
1	Independent Component Analysis (ICA)	- High of Computationally effective. -Shows High execution for huge estimated data. - Analyzes and breaks signals into independent, immediate and fixed-potential parts (components).	- in specific cases cannot be applicable - Decomposition requires many complicated mathematical processes
2	Principal Component Analysis (PCA)	powerful tool for separating and for diminishing the dimensionality of information without critical loss of data	-The data are assumed to be continuous and linear. - Forked-principal component analysis significantly fails to process data.
3	Wavelet Transformation (WT)	- Capable to analyze signal with discontinuities through factor's window size. - It can dismember signals both as recurrence and time spaces. - Can eliminate energy, distance or gatherings, etc	- WT lacks a clear methodology for applying to diffuse noise. - Performance is limited by Heisenberg uncertainty
4	AR	- Data records require a shorter time - It provides the best frequency accuracy and reduces	- The properties of EEG signals face challenges and difficulties to determine them

		spectrum loss problems	- Not suitable to applied on unstable signals
5	Wavelet Packet Decomposition (WPD)	suitable to analyze on unstable signals	computation operations require more time
6	Fast Fourier Transformations (FFT)	The most powerful and best way to analyze frequency	- It only applies to static signals and linear random operations. - Suffers from high sensitivity to noise. - Inadequate bad timing for all types of applications

V. Classification

The last stage in the processing of brain signals is the stage of classifying the signals into different categories. There are many techniques and methods used to classify the signals depending on the purpose of the analysis. We mention it's in the table no 3 [5][9].

Table no 3: Comparison of classification methods

No	Methods	Pros	Cons
1	Linear Discriminant Analysis (LDA)	- It has low mathematical requirements. - Easy to use. - Gives good results.	- It fails when the discriminatory function not in mean but in variance of the features. - For non-Gaussian distributions it may not preserve the complex structures.
2	Support Vector Machine (SVM)	- It provides a good fit generalization. - Performance is not biased by one linear classifier, not sensitive to overfitting.	- It has a high degree of computational complexity. - Not suitable for nonlinear problems, and not the best choice for a large number of features.
3	Artificial Neural Networks (ANN)	- Easily operate and implement when processing and overall storage on the network. - Strong work without fully prior knowledge in nature. - The ability to learn machine by gaining prior knowledge of events. - Needs relatively small training requirements.	- Hard to construct. - Performance relies upon the quantity of neurons in shrouded layer.
4	nonlinear Bayesian classifiers (NBC)	- Requires just limited quantity of training data to gauge parameters. - Only variance of class factors is to be figured and no compelling reason to process the whole covariance grid.	- Fails to deliver a decent gauge for the right class probabilities.
5	k-NN	- Very simple to understand. - Easy to implement and debug.	- Poor runtime performance if training set is large. - Sensitive to irrelevant and redundant features. - On difficult classification tasks out performed by other classification methods.

VI. Literature Review

The second part of this survey deals with the methods and techniques of collecting and processing brain signals that were used in several previous studies. We made a comprehensive survey of previous studies related to brain fields to understand the pros and cons of the methods used. Following table displays the studies surveyed by us, as we dealt with the main stages applicable to each study.

Table no 4: STAGES OF PROCESSING BRAIN SIGNALS USED IN PREVIOUS STUDIES

S. N	Author & Year	signals acquisition	Signals preprocessing	Features extraction	Classification
1	Soman et al. (2019)[11]	EEG	Spectrogram of temporal average of trials	Short Time Fourier Transform (STFT)	Support Vector Machine (SVM) and linear kernel function
2	Hashim et al.(2018) [12]	EEG	---	Mel Frequency Cepstral Coefficients (MFCC)	k-NN algorithm
3	Sereshkeh et al.(2017) [13]	EEG	Independent Component Analysis (ICA), ADJUST algorithm	Discrete wavelet transform (DWT)	Multilayer Perceptron Neural Networks (MLPNN)
4	Sereshkeh et al.(2017) [14]	EEG	Independent Component Analysis (ICA), ADJUST algorithm	Discrete Wavelet Transform (DWT)	Linear-Support Vector Machine (SVM)
5	Gonzalez-Castaneda et al.(2017) [15]	EEG	Common Average Reference (CAR) method	Discrete Wavelet Transform (DWT)	SVM - Naive Bayes is a probabilistic classifier (NB)
6	Nguyen et al. (2017) [16]	EEG	notch filter at 60Hz, bandpass filter between 8-70	Morlet wavelet transform	Relevance Vector Machines classifier (RVM)

			Hz, electro-oculogram (EOG)		
7	Herff et al(2017) [17]	ECoG	Spectrogram and Waveform Reconstructions	Short-Time Fourier Transform (STFT)	complex linear model
8	Martin et al.(2016) [18]	ECoG	Notch filters at 60 Hz, 120 Hz and 180 Hz	Hilbert transform, high gamma (HG) frequency	support vector machine (SVM) And Gaussian kernel
9	Ramsey et al. (2018) [19]	ECoG			Support Vector Machine (SVM) and two filters (SMF filter , SMF filter)
10	Yoshimura et al. (2016) [20]	EEG/ fMRI	SPM8 and inverse filters	VBMEG (Variational Bayesian Multimodal EncephaloGraphy)	Sparse logistic regression(SLR)
11	Kang et al (2015) [21]	EEG	Independent Component Analysis (ICA)	Frequency Domain,conventional index and candidate indices	Support Vector Machine (SVM)
12	Kumar et al. (2018) [22]	EEG	Moving Average (MA) filter	Standard Deviation (SD), Root Mean Square (RMS), Sum of Values (SUM), and Energy (E)	using RF classifier to classification three categories of coarse-level
13	Prat et al. (2016) [23]	qEEG	frequency ranges(Beta)	Fast Fourier Transform, average power spectrum	Mini-Mental State Examination (MMSE)
14	Chikara et al. (2019) [24]	EEG	independent component analysis (ICA), Butterworth filter	the power spectral analysis	K-means clustering EEG coherence analysis
15	HoutanJebelli et al. (2017) [25]	EEG	Independent Component Analysis (ICA) and filtering methods	Power Spectral Density (PSD)	the mean PSD in the beta frequency range
16	Divyaet al. (2017) [26]	EEG	time-frequency domain	Wavelet Transform (WT)	the artificial neural network
17	Dashet al. (2019) [27]	MEG	removed from the MEG data by EOG and ECG	Daubechies wavelet	DNN/long short-term memory recurrent neural network (LSTM-RNN)
18	Sudaryat et al. (2019) [28]	EEG	time-frequency domain	Fast Fourier Transformations (FFT)	power spectral density (PSD) analysis

VII. Nanotechnology with Brain Signals

As we know all brain signals are generated as a result of many different nerve activities such as emotions, perception, thinking, languages, etc. In this section, we present an initial overview of how nanotechnology can be used in the effective recording process of signals of brain .One of the main drawbacks of EEG technology is its limited spatial accuracy, as it is difficult to capture any nerve activity that takes place under the upper layers of the brain (the cortex), due to the smallness of the resulting signals. They are large in the inner layers of the brain and diminish as they go to the outer layers, which is why we present our proposal to use nanotechnology to improve the quality of recording these signals as follows:

1- Including nanotechnology recording electrodes, whether nanoFET sensors or others, in order to improve the quality of the recorded waves.

2- Sensor distinguishing signals from the neural organization in enormous, which implies the sensor crossing out (or should test) countless neurons all the while, covering the neural organization at the most extreme scale conceivable.

3- The possibility of using nanotechnology in the outer cortex layer of the brain is implanted with a very small depth that acts as a mediator to strengthen the voltage and amplitude of the waves to be recorded.

4- All recorded signals are collected and stored in an external storage device as memory, etc. so that we can process them clearly.

To record the intracellular action potentials of the cell membrane with very high accuracy, winding nanowires are used in the shape of V or U and the nano FET is presented at a mesh tip covered with phospholipid layers (similar in structure to the cell membrane) that penetrate the cell membrane very easily and ensure the recording of the ability of the highly sensitive membrane to function and make These nanowires using a vapor-liquid-solid growth mechanism catalyzed by gold nanostructures (VLS) in a chemical vapor deposition (CVD) system. For intracellular, highly sensitive and high-resolution branching recording with the smallest size a nanotube probe (BIT-FET) is used.

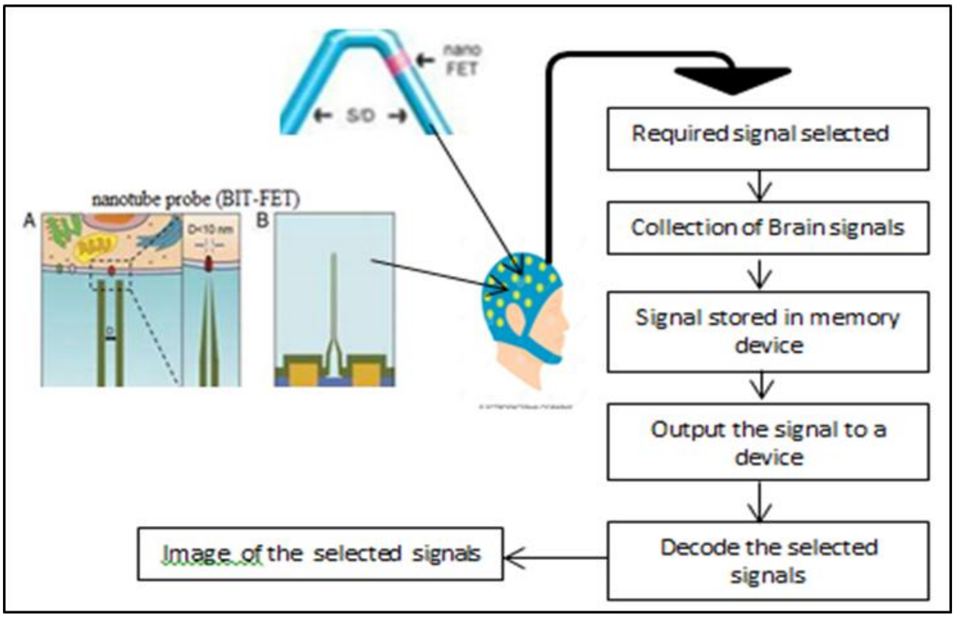

Figure no 2: Our conceptual of how nanotechnology can be used in the effective recording process of signals of brain by EEG technique.

VIII. Conclusion

The study presented a survey of the methods and techniques used in the different stages of treating activities of the brain signals; each of them has unique properties and advantages that differ from traditional methods. They are signals acquisition; signals pre-processing, features extraction and, signals classification. The study presents a detailed survey of recent studies to obtain basic and important information on the use of techniques and methods of acquiring and processing signals emanating from the brain, and we concluded the important of variation in their use depending on the type of main purpose of the signal to be studied. The study presented conceptual of how nanotechnology can be used for effective recording of the process of brain signals by EEG technique.

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