ISSN : 2278 – 1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 1, Issue 4, June 2012

Speech synthesizer And Feature Extraction Using DWT With classification By Euclidian Distance and neural network of EEG signals

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Abstract— ***The goal of proposed work is the development of an electroencephalogram (EEG) based BCI system. The overview of this work is, the user thought is extracted from the brain activity of a healthy person. Pre-processing is performed using filters and wavelet transforms to extract the features and classify them to their respective class. The intention of this work is to enhance human interaction with computers, providing a communication channel between human brain and computer. Patients who suffer from severe motor impairments and are unable to speak may use such an EEG based BCI system as an alternative form of communication by mental activity.***

Keywords— ***Brain Computer Interface (BCI), Electroencephalogram (EEG), European data format (EDF), wavelet transform (DWT), Euclidian distance, neural network.***

I. INTRODUCTION

The patients who suffer from severe motor impairments (like late stage of Amyotrophic Lateral Sclerosis (ALS), severe cerebral palsy, head trauma and spinal injuries) cannot express their thoughts as healthy human beings, because they are not capable of talking or moving. But still they are conscious and capable of performing mental tasks equivalent to healthy individual, using brain signals. The communication system for person with severe disabilities helps him to express thoughts for translating their actions into activity using BCI. This improves the quality of life of dumb people [2]. The advantage of this proposed work is. There is no need of any caretakers for assistance of patients and can be controlled by user alone. It uses EEG signals as input and produces output signals in European data format (EDF).

A brain computer interface (BCI) is a communication system between human brain and computer that enables generation of control signals from brain signals, such as sensory motor rhythms and evoked potentials, therefore, it constitutes a novel communication option for people with severe motor disabilities. In general non-invasive approach is followed because of easy applicability and low procedural risk, by placing EEG electrodes on surface of scalp that captures brain signals and can be processed. The recording of electrical activity of brain is called as Electroencephalogram (EEG). We have used motor imagery and non-motor imagery signals to perform certain tasks such as meditation, hand rotation, leg rotation, and push object to represent the different thoughts of the user. The user thoughts are expressed in form of speech using speech synthesizer.

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 extraocular 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 [1]), 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

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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.

II. METHODOLOGY

The methods used in Fig. 1are explained in detail bellow.

1) *Training of system:* The brain waves of the user are record when he/she performs certain motor task such as meditation and hand rotation.
2) *Preprocessing:* This is done before feature extraction to enhance the signal by increasing signal to noise ratio (SNR).This process is decomposing or de-noising the

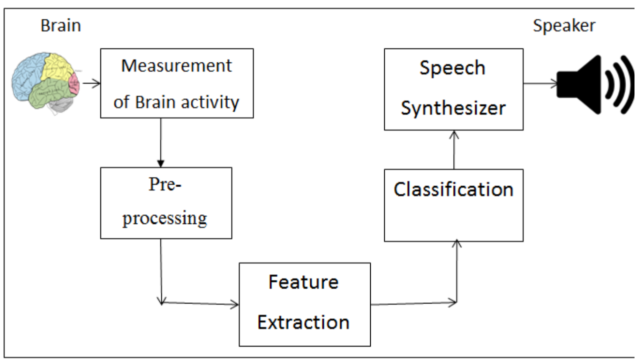

Fig.1: Proposed system model

3) capture signal in order to remove noise from raw EEG signal.
4) *Feature extraction:* The EEG signal is decomposed into number of scales, where each scale represents a particular feature of the signal under study.
5) *Classification:* Here we assign a class to set of features extracted from the signal. This class corresponds to the kind of the metal state identified.

The feature extraction and matching part are coded in MATLAB.

III.DATA ACQUISITION

Speech impaired patients who are referred to as subjects here are made to sit in a room with silent environment. Subjects are asked to close their eyes, with no finger movements and jaw movements to prevent noise caused by eye blinking, jaw movement and other muscle activity [4]. Noise by eye blink produces signal called Electroculogram(EOG) which are with high amplitude when compared with EEG signals.Removal of these artifacts from EEG should be the first step to be done. We use a non-invasive technique to capture the signals. Emotive epoch is a headset (device) used to extract EEG signals. The total time for capturing each EEG signal is 10sec. signals are recorded from 2 electrodes placed at P7 and P8 locations of thescalp electrodes as shown in Fig.2.

These signals are placed in the P7, P8 Parietal positions of the human brain. The function of this lobe is to integrate sensory information from various parts of the body. Different motor tasks are used in order to give inputs to BCE. Subjects are instructed to do any one from the following tasks.

1) Baseline Task – The subjects are asked to relax & retain the state of relaxation.
2) Hand Rotation Task – The subjects are asked to mentally imagine the rotation of their hand or asked to rotate their hand physically.
3) Leg Rotation Task – The subjects are asked to imagine the rotation of their legs or asked to rotate their legs.
4) Object Pushing Task – The subjects are asked to imagine a 3D cube in space and to push it with certain amount of pressure. The signals are captured during the imagined push period.

The signals capture form headset is in European Data Format (.edf). All the above mentioned tasks generate unique EEG signals with variations from specific regions & frequency which makes them easy to differentiate; usually beta and mu waves are dominant.

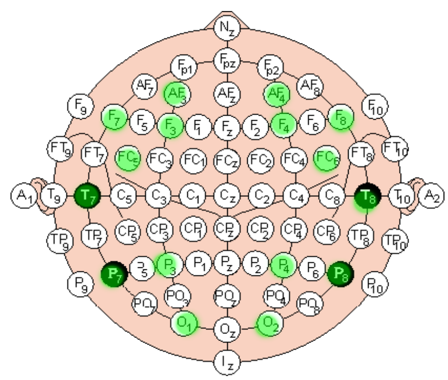

Fig. 2: Location of Electrodes P7 and P8

IV. PREPROCESSING

This is done before feature extraction to increase signal to noise ratio (SNR). This process is decomposing or de-noising the captured signal in order to remove noise and to enhance the EEG signal [11]. Various steps are as follows.

1) Sampling – Signal is sampled at 128 Hz. The range of beta and mu waves is 8 to 13 Hz and 13 to 30 Hz respectively, so it is sampled.

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2) Filtering – The traditional way to improve SNR is to filter the EEG signals using band pass filter. Here the sampled signal is subjected to low pass filter to block signals above 30 Hz.
3) Channel extraction – Processing the whole edf file is complex, so signal values from required channel are extracted out separately from the filtered signal.
4) Wave Decomposition – The length of the wave is decreased by reducing the number of values in signal and retaining the original waveform. Here the signal is reduced to $1/4^{th}$ of the original signal using Discrete Wavelet Transformation (DWT) function.

We use EEGLAB to get the raw signal produced from emotive headset available in MATLAB. pop_biosig() function is used to make raw EEG signal in EDF format available in MATLAB. This function takes the pathname of EDF file and parameters.

```
outeeg = pop_biosig (path to the .edf file)
Signal_matrix_mediation = outeeg.data;
```

This function returns a 35*5632 matrix, which is raw EEG signal. Here 35 channels are the number of row and time in millisecond is the column of the matrix.

Channel Extraction: EDF file has raw EEG signal recorded with 35 channels. Processing the whole EDF file is complex, so signal values from required channel are extracted out separately from the raw EEG signal. We are interested in p7 and p8 channels among the 35 channel. It is the 9^{th} and 12^{th} row in 35*5632 matrix. The code to extract P7 and p8 channel is.

```
Signal_matrix_handrotate_p7_channel = Signal_matrix_handrotate(9:9,:);

Signal_matrix_handrotate_p8_channel = Signal_matrix_handrotate(12:12,:);
```

The signal of task from P7 and p8 is shown in Fig.3

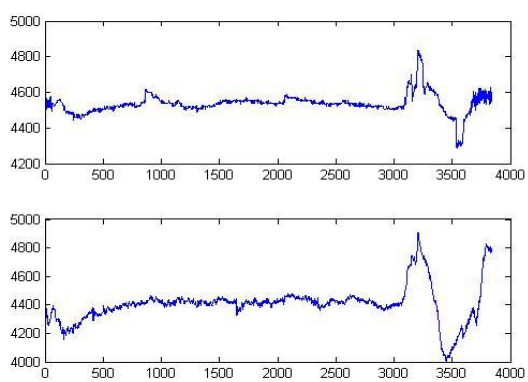

Fig. 3:Preprocessed signal ofhand rotate signal from p7 and p8 respectively

V.ANALYSIS USING DWT

A number of digital signal analysis techniques have been developed and applied to represent the transient sound signals. Discrete wavelet transform is the most suitable of these techniques because ofits localization in both time and frequency.

Wavelet transform is a spectral estimation technique in which any general function can be expressed as an infinite series of wavelets. The basic idea underlying wavelet analysis consists of expressing a signal as a linear combination of a particular set of functions (wavelet transform, WT), obtained by shifting and dilating one single function called a mother wavelet [5][6][7]. The decomposition of the signal leads to a set of coefficients called wavelet coefficients. Therefore the signal can be reconstructed as a linear combination of the wavelet functions weighted by the wavelet coefficients. In order to obtain an exact reconstruction of the signal, adequate number of coefficients must be computed. The key feature of wavelets is the time-frequency localization. It means that most of the energy of the wavelet is restricted to a finite time interval. Frequency localization means that the Fourier transform is band limited.The advantage of time-frequency localization is that wavelet analysis varies the time-frequency aspect ratio, producing good frequency localization at low frequencies (long time windows), and good time localization at high frequencies (short time windows). This produces a segmentation, or tiling of the time-frequency plane that is appropriate for most physical signals, especially those of a transient nature. The wavelet technique applied to the EEG signal will reveal features related to the transient nature of the signal, which are not obvious by the Fourier transform. In general, it must be said that no time-frequency regions but rather time-scale regions are defined. All wavelet transforms can be specified in terms of a low-pass filter g, which satisfies the standard quadrature mirror filter condition.

$$G(z)G(z^{-1}) + G(-z)G(-z^{-1}) = 1 \quad (1)$$

Where G(z) denotes the z-transform of the filter g. Its complementary high-pass filter can be defined as.

$$H(z) = zG(-z^{-1}) \quad (2)$$

A sequence of filters with increasing length (indexed by i) can be obtained

$$G_{i+1}(z) = G(z^{2^i})G_i(z)$$

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$$H_{i+1}(z) = H\left(z^{2^i}\right) G_i(z), \quad i = 0 \ldots \ldots I - 1, \text{(3)}$$

With the initial condition G0(z) = 1. It is expressed as a two scale relation in time domain Where the subscript.

$$g_{i+1}(k) = [g]_{\uparrow 2^i} g_i(k), h_{i+1}(k) = [h]_{\uparrow 2^i} g_i(k) \text{ (4)}$$

Indicates the up-sampling by a factor of m and k is the equally sampled discrete time.

The normalized wavelet and scale basis functions $\phi_{i,k}(k), \psi_{i,k}(k)$ can be defined as

$$\phi_{i,l}(k) = 2^{\frac{i}{2}} h_i(k - 2^i l)$$
$$\psi_{i,l}(k) = 2^{\frac{i}{2}} h_i(k - 2_i l) \text{(5)}$$

Where the factor $2^{\frac{i}{2}}$ is inner product normalization, i and l are the scale parameter and the translation parameter, respectively. The DWT decomposition can be described as:

$$a_i(l) = x(k)\phi_{i,l}(k)$$
$$d_i(l) = x(k)\psi_{i,l}(k) \text{(6)}$$

Where $a_i(l)$ and $d_i(l)$ are the approximation coefficients and the detail coefficients at resolution, i, respectively (Daubechies,1990 and 1992), (Solttani, 2002).

DWT analyses the signal at different frequency bands, with different resolutions by decomposing the signal into a coarse approximation and detail information. DWT employs two sets of functions called scaling functions and wavelet functions, which are related to low-pass and high-pass filters, respectively. The decomposition of the signal into the different frequency bands is merely obtained by consecutive high-pass and low-pass filtering of the time domain signal. The procedure of multi-resolution decomposition of a signal x[n] is schematically shown in Fig 4. Each stage of this scheme consists of two digital filters and two down-samplers by 2. The first filter, h[.] is the discrete mother wavelet, high-pass in nature, and the second, g[.] is its mirror version, low-pass in nature. The down-sampled outputs of first high-pass and low-pass filters provide the detail, D1 and the approximation, A1, respectively. The first approximation, A1 is further decomposed and this process is continued as shown in Fig 4

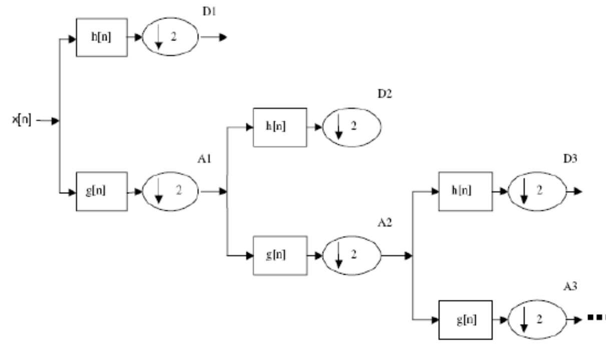
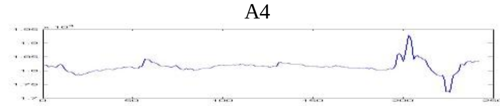


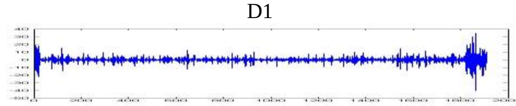
Fig. 4:Sub-band decomposition of DWT implementation; h[n] is the high pass filter, g[n] the low-pass filter

Selection of suitable wavelet and the number of decomposition levels is very important in analysis of signals using the DWT. The number of decomposition levels is chosen based on the dominant frequency components of the signal. The levels are chosen such that those parts of the signal that correlates well with the frequencies necessary for classification of the signal are retained in the wavelet coefficients. In the present study, since the EEG signals do not have any useful frequency components above 30 Hz, the number of decomposition levels was chosen to be 4. Thus, the EEG signals were decomposed into details D1–D4 and one final approximation, A4. Usually, tests are performed with different types of wavelets and the one, which gives maximum efficiency, is selected for the particular application. The smoothing feature of the Daubechieswavelet of order 2 (db2) made it more appropriate to detect changes of EEG signals. Hence, the wavelet coefficientswere computed using the db4 in the present study. The proposed method was applied on all data sets of EEG data. Fig. 5 shows approximation (A4) andDetails (D1–D4) of an epileptic EEG signal.

A4



D1



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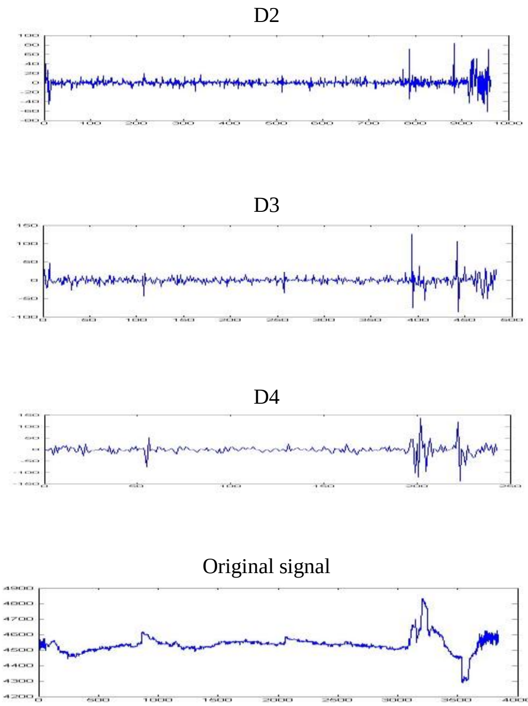

Fig. 5: Approximate and detailed coefficients of EEG signal taken from unhealthy subject (Hand rotate signal_P7).

VI. FEATURE EXTRACTION

The extracted wavelet coefficients provide a compact representation that shows the energy distribution of the EEG signal in time and frequency. Table 1 presents frequencies corresponding to different levels of decomposition for Daubechiesorder-4 wavelet with a sampling frequency of 128 Hz. In order to further decrease the dimensionality of the extracted feature vectors, statistics over the set of the wavelet coefficients was used. The following statistical features were used to represent the time frequency distribution of the EEG signals:

1) Maximum of the wavelet coefficients in eachSub-band.
2) Minimum of the wavelet coefficients in eachSub-band.
3) Mean of the wavelet coefficients in each sub-band
4) Standard deviation of the wavelet coefficients in each sub-band.

The level of decomposition is done based on the matrix column as shown in Table 1 [14] [15].

Tabel1: Different level of decompsition

Decomposed signal	Column of the signal matrix
D1	2828-5632
D2	1417-2827
D3	710-1416
D4	355-709
A4	1-354

Extracted features from electrodes class p7 and p8 shown in Table 2. The data was acquired using a standard electrode net covering the entire surface (see Fig. 1).The DWT was performed at 4 levels, and resulted in five sub-bands: d1-d4 and a4 (detail and approximation coefficients respectively).

Table2: The extracted features of hand rotate channel p8

features_hand_rotate_p8	in	ax	ean	D
A4	1.6079	1.9476	1.7620	0.0514
D4	-134.9	165.997	0.0256	26.3403
D3	-58.62	70.1909	-0.255	14.1829
D2	-42.31	46.3621	0.2692	8.0391
D1	-37.61	30.9387	0.0032	4.0017

Total recording time is 10sec, corresponding to 1x5632 matrix for p7 and p8 channel respectively. The sample was partitioned into window to reduce the volume of data. From these sub-samples, we perform the DWT and derive statistics.The type of wavelet used is daubechies wavelet transform of order 2. The number of decomposition level is chosen to be 4. Here EEG signals are decomposed into various sub bands through fourth level wavelet packet decomposition and wavelet coefficients are computed using db2. The four feature are maximum, minimum, mean and standard deviation of the wavelet coefficients in each sub-band. Function is given by

```
[c1,l1]=wavedec(signal_matrix_p7_channel,4,db2);
```

VII. CLASSIFICATION

The next step is to identify the neurophysiological signal in a BCI is translating the features into text. In order to achieve this step we use classification algorithms [8] [10]. The goal of the classification step is to assign automatically a class to features vector previously extracted. This class represents the kind of mental task by the BCI user. The transposed set of features that is used to describe a task is called as vector. Classification ID achieved using algorithms known as “classifiers”. Classifiers able to learn how to identify the class of feature vector, thanks to training set. These set are composed of feature vector label with their class of belonging.

1).Euclidean Distance method is the most commonly used algorithm in commercial spectral library search software packages. It is very similar to the Correlation algorithm and in cases where your submitted spectrum has no negative spikes and a good signal-to-noise ratio, it will produce equivalent results.

The main advantage of the Euclidean Distance method over the Correlation method is that it is reportedly slightly faster.

The goal of these classifiers is to find the minimum distance between sample-trained data pair and to approximate the sample data into corresponding trained data. Given an M-by-N, which is treated as m (1-by-n) row vector x1,x2,….xm. The various distances between the vector Xr and Xsis defined as follows.

Euclidian distance
(Dst)2 = (Xs-Xt) (Xr-Xt).

2).*PatternRecognitionandFeed-forwardNetworks:*Afeed-forwardnetworkcanbeviewedasagraphical representationofparametricfunctionwhichtakes asetofinput valuesandmapsthemtoacorrespondingsetofoutputvalues(Bishop, 1995).Fig 6shows anexampleofafeed-forwardnetworkofakindthatiswidelyusedinpracticalapplication s.Nodesinthe graph representeither inputs, outputsor'hidden'variables, whilethe edgesofthe graph correspond to theadaptive parameters.

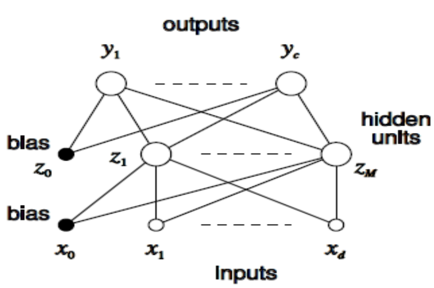

Fig.6:Afeed-forward networkhavingtwolayersofadaptive parameters.

We can write down the analytic function corresponding to this network follows. The output of the jth hidden node is obtained by first forming a weighted linear combination of the d input values x_i to give

$a_j = \sum_{i=1}^{d} u_{ji} x_i + b_j$ (7)

The value of hidden variable j is then obtained by transforming the linear sum in (9) using an activation function g(_) to give

$z_j = g(a_j)$ (8)

Finally, the outputs of the network are obtained by forming linear combinations of the hidden variables to give

$a_k = \sum_{j=1}^{M} v_{kj} z_j + c_k$ (9)

The parameters $\{u_{ji}, v_{kj}\}$ are called weights while $\{b_j, c_k\}$ are called biases, and together they constitute the adaptive parameters in the network. There is a one-to-one correspondence between the variables and parameters in the analytic function and the nodes and edges respectively in the graph.

The goalin patternrecognition isto use a set ofexample solutions to someproblem to infer an underlying regularitywhichcansubsequentlybeusedtosolvenewinstances ofthe problem. Examples includehand-writtendigitrecognition, medical image screening and fingerprintidentification. In the caseof feed-forwardnetworks, thesetof examplesolutions (calledatrainingset),comprisessetsof input valuestogether with corresponding setsofdesired outputvalues. The trainingsetisusedtodefinean error function interms ofthe discrepancy betweenthe predictionsofthe network, forgiveninputs, and thedesiredvaluesoftheoutputsgivenbythetraining set. Acommonexampleofanerrorfunction would bethesquared differencebetweendesiredandactual output,summedoveralloutputsandsummed over allpatternsinthetrainingset. Thelearningprocesstheninvolvesadjustingthevaluesoftheparame ters tominimize the valueofthe error function. Onethenetwork hasbeentrained,i.e.oncesuitable values fortheparametershavebeendetermined,newinputs canbeapplied andthe correspondingpredictions (i.e.network outputs)calculated.

VIII. SPEECH SYNTHESIS

The textual data corresponding to the trained signal is given to the speech synthesizer. Speech synthesizer is the component that produces artificial speech for the given text as input. This allows java applications to incorporate speech technology in to the user interface. It defines a cross platform API to support to command and control dictation system.

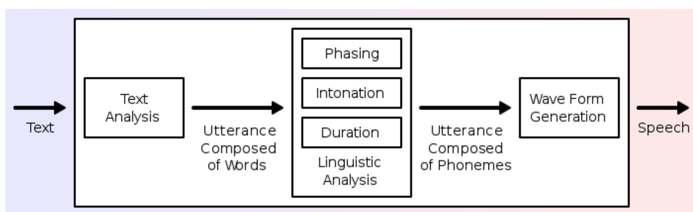

Fig 7: Overview of a typical text to speech system

Speech synthesis is the artificial production of human speech. A computer system used for this purpose is called a speech synthesizer, and can be implemented in software or hardware. A text-to-speech (TTS) system converts normal language text into

ISSN : 2278 – 1021

International Journal of Advanced Research in Computer and Communication Engineering
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speech; other systems render symbolic linguistic representations like phonetic transcriptions into speech.

IX. CONCLUSION

The project was developed using MATLAB for feature extraction and classification while the speech synthesizer was developed using java speech API's. Here raw EEG signals were the data sets which were previously taken from the subjects using Emotive head set and stored in computer. We have proposed an implementation of 3 tasks. Preprocessing is done before feature extraction to increase signal to noise ratio (SNR). This process is decomposing or de-noising the captured signal in order to remove noise and to enhance the EEG. The length of the wave is decreased by reducing the number of values in signal and retaining the original waveform. Here the signal is reduced to 1/4th of the original signal using Discrete Wavelet Transformation (DWT) function. The extracted wavelet coefficients provide a compact representation that shows the energy distribution of the EEG signal in time and frequency. Total recording time is 10sec, corresponding to p7 and p8 channel respectively. The sample was partitioned into window to reduce the volume of data. From these sub-samples, we perform the DWT and derive statistics. The type of wavelet used is Daubechies wavelet transform of order 2. The number of decomposition level is chosen to be 4. Here EEG signals are decomposed into various sub bands through fourth level wavelet packet decomposition and wavelet coefficients are computed using db2. The four features are maximum, minimum, mean and standard deviation of the wavelet coefficients in each sub-band. The next step is to identify the neurophysiological signal in a BCI is translating the features into text. In order to achieve this step we use classification algorithms. The classifiers used in this project are Euclidian distance and neural network which classify the signal to their respective tasks in form of text. The text data is given to speech synthesizer which gives us the voice output.

It will be good news for the serious disabled. However, there are still many problems waiting for solution. For example, it needs 1~2 hours to set up the whole equipment. The whole system is very expensive. In spite that the recognition rate is high, the recognition time of each direction test cycle still needs over 40 seconds. Recording of EEG signal is done in noise free environment, we should use better prepressing methods that removes noise in noisy environment. Training of subjects for different tasks requires high concentration and time commitment. All this problems will be useful to find better solutions.

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Biography

Stafford Michahialis presently doing Master"s degree in Digital electronics and Communication from AMCEC Bangalore. Currently he is a student at AMCEC Bangalore. My area of interest includes Neural Network, Data Mining, Image Processing, Communication etc. I have presented a paper in one of the national conference, and 2 international journal.

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