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# Enhancing the Classification Accuracy of SSVEP based BCI using CWT method along with ANN

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***Abstract*—** This paper reviews the application of continuous wavelet transform (CWT) with artificial neural network (ANN) for the neurological waveform detection and pattern analysis. A brain-computer interface (BCI) is a promising communication channel used to connect the brain to external electronics devices. SSVEP signals are used as basis for BCI because of its reliability, high information transfer rate, minimum training and flexibility. The continuous wavelet transform (CWT) offers a valuable tool for the analysis of the signals as it provides precise location in term of high frequency components. The selection of mother wavelet having high correlation with the signal under study provides a more accurate time frequency analysis. This paper reviews the application of the artificial neural network (ANN) along with the CWT method to the waveform detection and pattern analysis of the SSVEP signal. ANN methods are shown to be an excellent way of incorporating expert knowledge about the brain into a mathematical framework with minimal assumptions about the statistics of signals and noise.

**Keywords—** BCI- Brain Computer Interface, EEG-Electroencephalography, SSVEP- Steady State Visual Evoked Potential, SNR- Signal-to-Noise Ratio, CWT- Continuous Wavelet Transform, ANN-Artificial Neural Network.

## I. INTRODUCTION

**Brain-**computer interface (BCI) are communication system that translate brain electrical activity typically measured by electroencephalogram (EEG) into computer command, and hence assist to reconstruct communicative and environmental control abilities for severely disabled people and can be used for industrial / robotic applications. Event –related potential (ERP), steady-state visual evoked potential (SSVEP) and event–related (de)synchronization (ERD/ERS)) are usually adapted for development of BCIs [4]. In recent years, SSVEP-based BCI has been increasingly studied. Since it requires less training to the user and provides relatively higher information rate (ITR).When subject focuses attention on the repetitive flicker of a visual stimulus, SSVEP is elicited at the same frequency as the flicker frequency, and also it's harmonics over occipital scalp areas [1]. Accordingly, SSVEP based BCI is designed to detect the desired commands through recognizing the SSVEP frequency in EEG. Although original SSVEP responses present relatively stable spectrums over time, they are likely to be contaminated by ongoing EEG activities and other background noises. Therefore, the development of an effective algorithm to recognize the SSVEP frequency with a high accuracy and a short time window length (TW) is considerably important for development of an SSVEP-based BCI with high performance.Various approaches have been proposed to recognize SSVEP frequency for BCI applications. In this research work, we are going to use CWT method to extract the features from the SSVEP signals and after that ANN is applied for the classification and command generation for the desired purpose. EEG signals are non-stationary whose frequency components vary as a function of time. The analysis of such signals can be facilitated by wavelet transform which provide flexible time-frequency resolution. Another advantage of wavelet transform analysis is that it is easy to choose different mother wavelet functions to analyze different types of signal [1] [4]. Proper selection of mother wavelet is thus important to obtain good performance in analyzing different EEG signal using CWT method.

ANNs are considered to be good classifier due to their inherent features such as adaptive learning, robustness, self-organization, and generalization capability. ANNs are particularly useful in situation where the simpler classification algorithm fails. ANN methods are shown to be an excellent way of incorporating expert knowledge about the brain into a mathematical framework with minimal assumptions about the statistics of signals and noise [9].

## II. SYSTEM ARCHITECTURE

**The**EEG database used for this study includes EEG signals recorded from the range of 5 Hz to 30 Hz, in which we specifically use 8 Hz, 14 Hz, and 28 Hz for the study. In this research project a combination of software and hardware platform is setup to support the BCI application that performs the implementation of signal acquisition, signal processing, classification, and generation of command signals had interfacing with the device.

The system architecture consists of mainly four components:-

1.) SSVEP signals acquisition and de-noisingit.
2.) Extract features from the SSVEP signals by CWT method andClassification of the features and generation of the command signals for the predefined task is done by ANN.
3.) Develop a prototype and demonstrate the device interface.

### 1) SSVEP Signal Acquisition

**The** database used in this study is obtained from the given reference [11]. These signals are in **.mat** format. This EEG-SSVEP database consists
ofthree databases having five trails of each 8 Hz,14 Hz and 28 Hz signals. The data are sampled at the rate of 256 Hz.

These signals were recordedusing a BIOSEMI EEG system having Ag/AgCl electrodes from 128 locations distributed over entire the head. The BIOSEMI EEG system contain miniature electronics to allow higher EEG signal-to-noise ratio and better sensitivity to weak brain signals. Electrodes were applied to the forehead or behind the ears using head caps, convert the ions current into electrical current and made connection between the scalp and EEG recording device. Electrolyte gel is applied between scalp and the electrodes to prevent attenuation of the signal [2] [3]. The total recording time for the SSVEP is 25 seconds. The SSVEP ONSET point is at second 5 from beginning of the data and the SSVEP OFFSET point is at second 20 from the beginning of the data is taken for the better result.

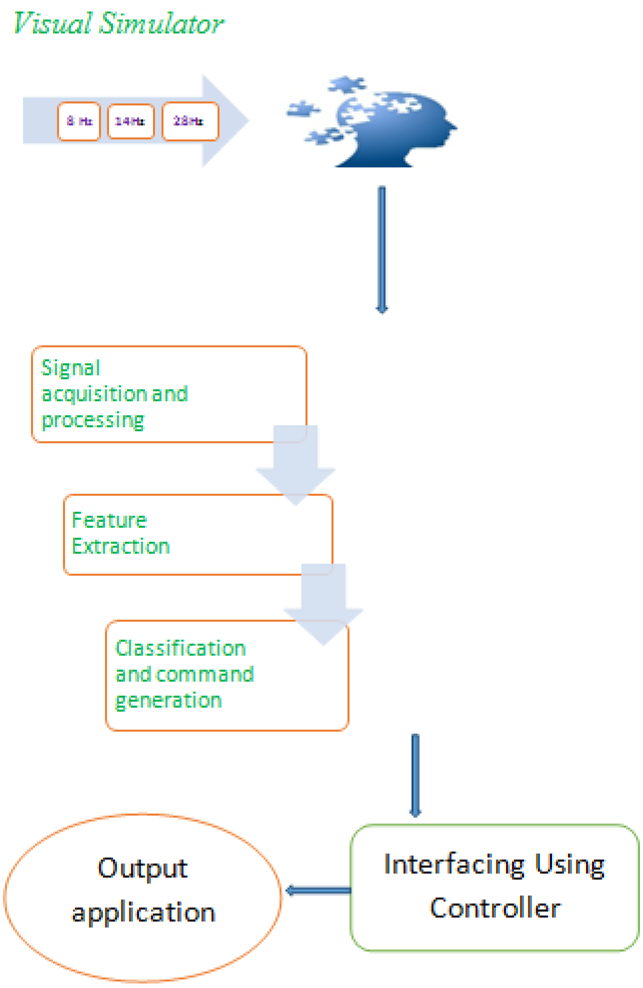



Fig 1: Block diagram of the system

## 2) CWT-Based SSVEP Feature Extraction And Classification

### A. Continuous wavelet transform :

**The** wavelet theory, originally proposed in the field of mathematics, was introduced into the field of signal analysis by Goupillaud , Grossman and Morlet in 1984.
Wavelet transform has its flexibility in the choice of analyzing functions, which overcomes the shortage of traditional Fourier transform method.

Mother wavelet can be defined by

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right) \quad \text{-- (1)}$$

a, b ϵ R , a≠ 0

**a** – scaling factor that measures the degree of compression.

The formula of continuous wavelet transform (CWT) is

$$W(a,b)=\frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} f(x)\psi^{*}\left(\frac{x-b}{a}\right)dx$$

---(2)

Where, f(x) is the time domain limited signal.Ψ(x) is the energy limited wavelet function or mother wavelet. **a** is the scale factor, **b** is the shift factor and * means complex conjugation. The adjustment **1/√a** is intended to normalize the energy content of each wavelet that goes into the reconstructing the original signal [4] [5]. A set of wavelet coefficient w(a,b) actually denote the extent of correlation between the scaled , shifted wavelet transform and one segment of the signal. Through wavelet transform, the signal x(t) is broken up into the shifted and scaled versions of the mother wavelet.

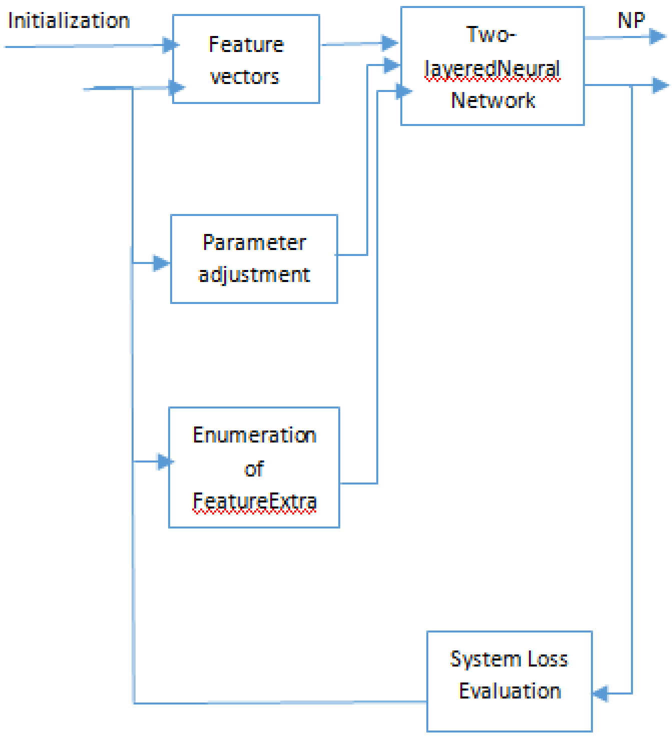
In this presented SSVEP-based BCI system, the Morlet wavelet transform is employed for feature extraction. To make wavelet co-efficient w(a,b) more easily interpretable, the scale factor 'a' has to be transformed into the frequency f.

$W^k(a,b) = W^K(f,t)\big|_{f=fs\text{-}fo/a,\ t=b}$

Where 'f'$_s$ denotes the samplingfrequency and 'f$_o$' is the central frequency of the morlet wavelet spectrum in Hz, and k represents the EEG trial number. Thus$W^k(f,t)$ denotes the time-frequency co-efficient at frequency f and time t of $k^{th}$ EEG trial data.

## B. Artificial Neural Network:

**Once** thefeatures are extracted by the CWT method, after that ANN is applied for the classification. ANNs are considered to be good classifier due to their inherent features such as adaptive learning, robustness, self-organization, and generalization ability. Here our approach is to use ANN's to select combination of application. Specific features for the classification from larger sets of features extracted by the CWT. The ANN's are then sequentially applied to each of the feature sets. Network topology is determined by the propagation of classification error back to connections and weighting of hidden units during training mode operation. To generate each network, the algorithm iterates a two- step procedure, first one is "network loss" is calculated for the two-layered network consisting of hidden threshold logic units (TLU's) previously chosen and each possible new hidden unit. Candidate TLU's are generated by the exhaustive enumeration of all feature subsets of a given size and computing a simple statistical classifier for each. The network loss is a function defined to reflect both the quantity and severity of classification errors. Error correction is propagated back to network parameter by minimizing this measure of the differencebetween the desired and actual output. This process iterates until adding more units doesn't result in significant improvements. Independent data are then passed through network to test the validity of the final network equations. The significance of this test is determined by the binomial distribution and by comparison to results obtained when data of random class are passed through the network. The performance of each network is fed back to guide featureselection. The final network parameters frequently yield useful information about the relevance of each feature for classification [9]. In this research work we are going to use Back-Propagation Error network.




- NP = Network Parameter
- ND = Network Decision

Fig 2: Artificial Neural Network for classification

## 1) Interfacing

Interfacing can be done by controller through serial port by the development of prototype using 8051 controller and the dc motor. The classification results are sent from MATLAB to controller through serial port as the input. The controller is programmed through the Keil software and output is shown by the rotation of DC motor.

## III. IMPLEMENTATION AND RESULTS

In the first stage of this work reference signals for four subjects were loaded in MATLAB. After that in the second stage the CWT method is used for the feature extraction and ANN is used for the classification. In the last stage interfacing is done by using microcontroller IC, a LED display and DC motor.

Phase 1:
Raw SSVEP signal of 8 Hz and 14 Hz.

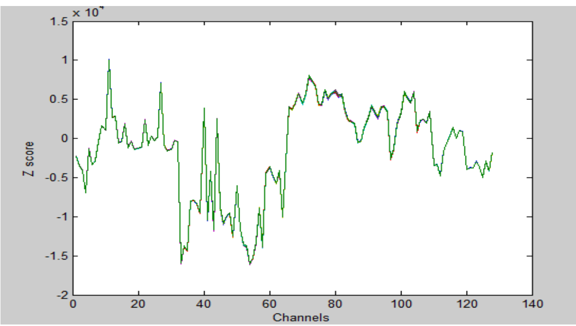



Fig 3: SSVEP Signal of 8 Hz

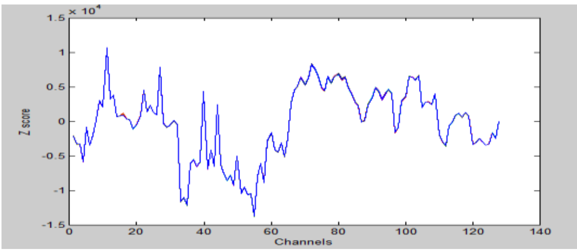


Fig 4: SSVEP Signal of 14 Hz

Phase 2:

Now we have to apply CWT method between the stimulus signals and the generated SSVEP signals. Here we will use the 14Hz frequency signal as a target/stimulus frequency for the subject one and SSVEP signals of 14 Hz signal which is generated. After that we will use 8 Hz as a target/stimulus frequency for the subject two, three and four and SSVEP signal of 8 Hz is generated. With the help of MATLAB tool we get the CWT co-efficient. The CWTco-efficient are used as the input for the ANN. Artificial Neural Network classify the features and generates the commands for the pre-defined task.

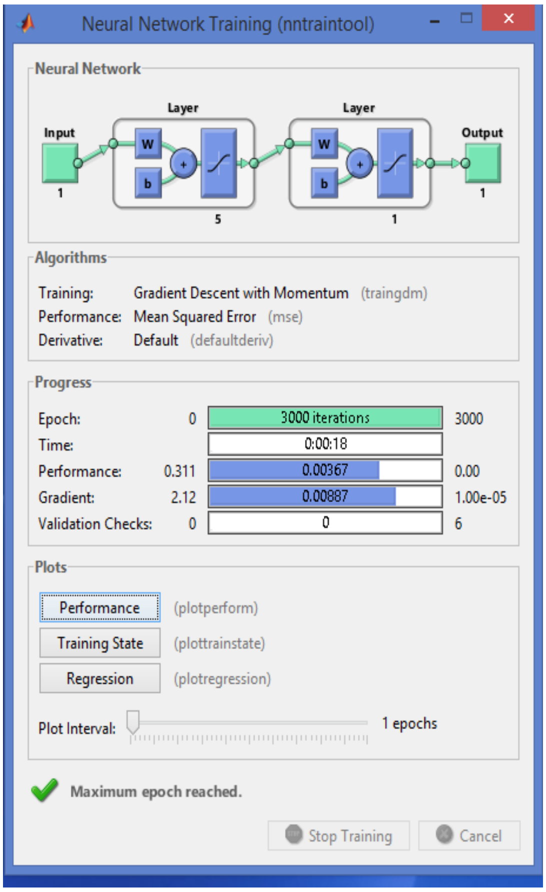


Fig 5: Artificial Neural Network

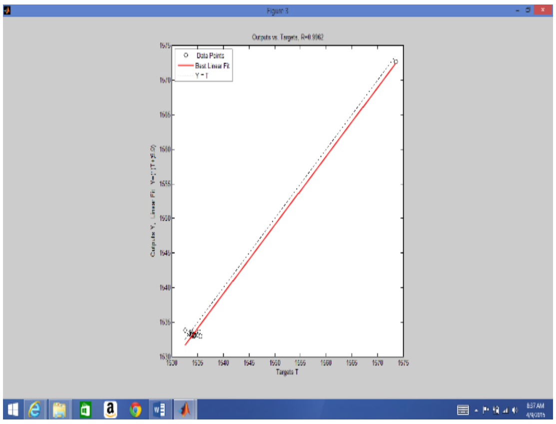


Fig 6: Regression Graph

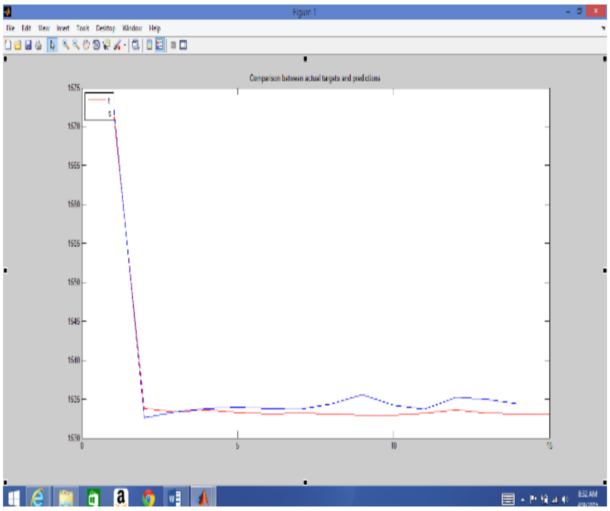


Fig 7: Target vs. Signal Graph

Phase 3:

In the last stage of this research work the interfacing is implemented by the using a microcontroller, a LED display and a dc motor; in which the generated command is used as a input signals.

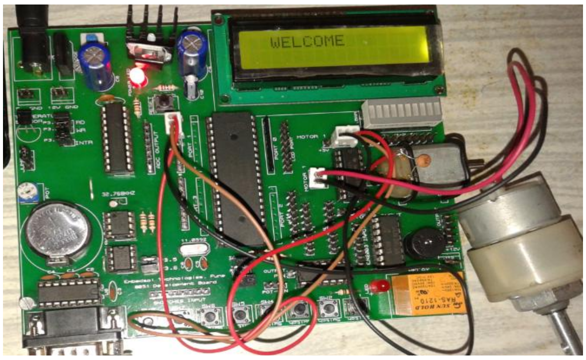



Fig 8: Hardware for interfacing

**RESULTS:**

| **Subject One** | **8 Hz** | **Non-8 Hz** | **Performance in percentage** |
|---|---|---|---|
| Trial 1 | 0.80424 | **0.90978** | **90.978** |
| Trial 2 | 0.83279 | **0.90883** | **90.883** |
| Trial 3 | 0.81826 | **0.93054** | **93.054** |
| Trial 4 | 0.76184 | **0.97955** | **97.955** |
| **Subject Two** | **8 Hz** | **Non-8 Hz** | **Performance in Percentage** |
| Trial 1 | **0.99723** | 0.88221 | **99.723** |
| Trial 2 | **0.98221** | 0.88678 | **98.221** |
| Trial 3 | **0.99341** | 0.89704 | **99.341** |
| Trial 4 | **0.99626** | 0.88468 | **99.626** |
| **Subject Three** | **8 Hz** | **Non-8 Hz** | **Performance in Percentage** |
| Trial 1 | **0.90237** | 0.73817 | **90.237** |
| Trial 2 | **0.88221** | 0.84357 | **88.221** |
| Trial 3 | **0.90838** | 0.86018 | **90.838** |
| Trial 4 | **0.94407** | 0.90069 | **94.407** |
| **Subject Four** | **8 Hz** | **Non-8 Hz** | **Performance in Percentage** |
| Trial 1 | **0.98842** | 0.94205 | **98.842** |
| Trial 2 | **0.94058** | 0.89045 | **94.058** |
| Trial 3 | **0.94059** | 0.95183 | **94.059** |
| Trial 4 | **0.99391** | 0.94571 | **99.391** |

## IV.CONCLUSION

**In** this project work, the features of SSVEP signals are extracted successfully by CWT and classified them with good accuracy by ANN method. After that we have generated control signals from classified data and developed a prototype using a microcontroller as an input datafor the desired output applications .It ismore user friendly and compatible for working in real time environment. The algorithm is the more efficient, accurate and easy method for processing of EEG signals used as the command for output applications. The CWT method is used for the feature extraction of the signal in terms of wavelet co-efficient. A set of wavelet co-efficient actually denotes the extent of correlation between the scaled, shifted wavelet transform and one segment of signal. The wavelet co-efficient are used as the input for the ANN. The ANN's are considered to be good classifier due to their inherent features such as adaptive learning, robustness, and self-organization and generalization ability. The result from the above table shows very good performance of the proposed system.

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