A Review of SSVEP Decompostion using EMD for Steering Control of a Car

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Abstract- **Recently the EEG based systems have become the area of interest in automobile, brain science. In the present review the SSVEP based system is present. Two visual stimuli flickers of 8 Hz and 14 Hz are used for induce user's SSVEPs. The induced SSVEPs, where used to control two movement function (left and right) for steering control of a car. In this paper reference SSVEP signal is used for the project work. Here, the Oz channel was used for getting particular results as inducement of SSVEP is most in occipital region of brain. The SSVEP signals are decomposed using EMD (Empirical Mode Decomposition) into number of oscillation components which is known as intrinsic mode function (IOFs). The IOFs related with 8 Hz and 14 Hz IOFs are taken from series of IOFs. Here, SVM was used as classifier from that means accuracy and means ITR was calculated for three different subjects. As for only subject 1 the mean accuracy was around 90% when he/she gaze 8 Hz flicker the ITR was 85.17% and for right the mean accuracy was 77.5% and the ITR was 78.65% when subject gaze 14 Hz flicker-Components.**

Keywords: -SSVEP, Brain computer interface (BCI), EMD (Empirical Mode Decomposition), SVM classifier

I. INTRODUCTION

"The most beautiful thing we can experience is the mysterious. It is the source of all t rue art and all science. He to whom this emotion is a stranger, who can no longer pause to wonder and stand rapt in awe, is as good as dead: his eyes are closed" – Albert Einstein. Detection of SSVEP EEG (Electroencephalogram) signals is one of the major application areas under Brain Computer interface (BCI). BCI technology is communication system that enables human (known as ‗subject') to send commands to electronic device only by means of brain activity. The goal of developing this software code is to detect and classify movement SSVEP based brain activity of the subject. In recent years, brain–computer interfaces (BCI) based on non-invasive scalp electroencephalography (EEG) have become an increasingly active research area. Event-related potentials, mu and beta rhythms, event-related synchronization and de-synchronization, slow cortical potentials, and visual evoked potentials (VEP) are commonly used signals in EEG-based BCIs [1]–[3]. Different from other systems, the SSVEP-based BCI is considered a dependent BCI because the generation of the VEP depends on the control of eye movements via the output pathways of cranial nerves and extra ocular muscles. Therefore, for the few people with severe neuromuscular disabilities, who may even lack the output channel of extra ocular muscle control, this BCI is inapplicable. However, for most people, the SSVEP-based BCI is more feasible than other systems.

This system is specially developed for paralysed and healthy people, for automatic control of steering of an automobile using SSVEP signal. In this project, I specially worked on 8Hz and 14Hz sensorimoter rhythms for movement of a steering (i.e. 2 different directions movement viz. left, right,).Standard MATLAB toolboxes used for processing, as well as self-written programs. The MATLAB processing engine is based upon highly optimized matrix operations, allowing very high processing speed. Such a processing speed is very difficult to realize with self-written C code. Nowadays, there are many research groups working in the SSVEP BCI area, and a first major classification of the most used approach could be done in terms of ―invasive‖ (microelectrodes are implanted into the subject‘s brain to measure the activity of specific neural populations) and ―non-invasive‖ (i.e., the brain electrical activity is recorded from electrodes or other sensors placed on the scalp) BCI systems. Recent reports have proposed various techniques for the development of BCIs, based either on the electroencephalographic (EEG) non-invasive, magnetoencephalography (MEG) or other (firm, PET, optical imaging) measurements. Since all of these, except EEG, still represent technically demanding and expensive methods, the EEG-based BCIs tend to prevail. Modern BCIs are often classified into several groups based on the electrophysiological signals used, i.e., the different brain potentials, the mu and beta rhythms, the activities of single cortical neurons, etc.[4][5].Electroencephalogram (EEG), a measure of the brain's electrical activity, is widely used in Brain-related research studies. For BCI experiments the subject or the patient is connected via electrodes or sensors to a bio signal amplifier and a data acquisition unit (DAQ board) containing the antilog-to-digital conversion. Then the data is passed to the real-time system to perform the feature extraction and classification. EEG electrodes are normally distributed on the scalp according to the international 10-20 electrode system. Therefore the distance from the Inions to the Nation is first measured. Then, electrode Cz on the vertex of the cap is shifted exactly to 50 % of this distance [4]. Here we have used 128 electrodes system for capturing EEG from the subject.

In this paper the EMD is applied as signal processing algorithm for various automobile applications like steering control of a car, speed control of a car and break control of a car. Here we have implemented EMD for a high-ITR SSVEP based system which is particularly developed for an automobile application. Here only one EEG channel at Oz position was used. The proposed system adopts EMD to decompose the input signal into a set of IOFs, representing the fine-to-coarse features for input signal. The gazed target for related component is than detected. This works on the sifting process. The proposed EMD based system utilizes to handle the movement of the steering of a car.

II. METHODS

VEPs are derived from the brain's response to visual stimulation. They reflect the visual information processing mechanism in the brain.SSVEP is a response to a visual stimulus modulated at a frequency higher than 6 Hz. SSVEP can be recorded from the scalp over the visual cortex, with maximum amplitude at the occipital region. Photicdriving response, which is characterized by an increase in amplitude at the stimulus frequency, results in significant fundamental and second harmonics. Therefore, it is possible to detect the stimulus frequency based on measurement of SSVEP.

The basic principle of SSVEP is that Large areas of the visual cortex are allocated to process the centreof our field of vision, so the acuity is greatest when the stimulus is located in the centre of the visual field [6], [7]. This effect is called central magnification, i.e., the amplitude of SSVEP increases enormously as the stimulus is moved closer to the central visual field. Different SSVEPcan be produced by directly looking at one of a number of frequency codedstimuli.

A. *System Configuration*

Fig. 1 is the block diagram of the system, which is similar to otherBCI designs [1]. It includes a visual stimulator, EEG acquisition equipment,signal processing algorithms, and device control methods. A virtualkeypad consisting of two buttons on a CRT monitor was designed as the stimulator [8]. The output device was controlled by alterationof the user's gaze direction.

Two buttons flash at different repetition rates, composing frequency-coded flashing matrix. The subject was asked to gaze at the target attentively, ignoring the other buttons in the operation. Atthis time, the target will be located in the centre of the visual field, only causing an increased response associated with the target. Then,signal processing technology can be used to determine the stimulusfrequency. The button, which matches the detected frequency, is thetarget the user wants to select.The task of signal processing is to detect the existence of the SSVEPand determine its frequency

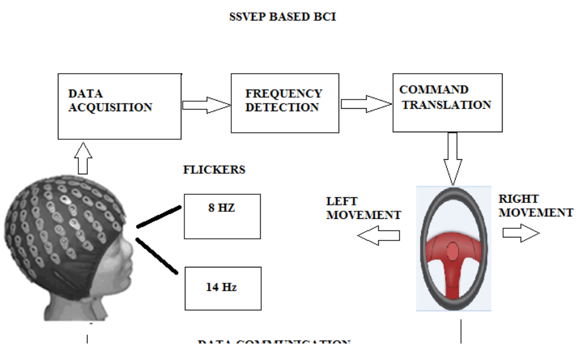

Fig. 1. Block diagram of system.

B. *Data Acquisition*

The volunteers will be stimulated with a series of flashing lights, corresponding to 28Hz, 14Hz, and 8Hz. The electrodes PO3, PO4, POz, Oz, O1 and O2 are used to be investigated. But in application we are just focusing on just 8Hz and 14Hz frequency. The signals are recorded with a sampling rate of 2048Hz. Firstly, The volunteer is asked to look at the flashing light attentively, with the first stimulus frequency of 8Hz for duration of 15s, and then rest for 5s. Secondly, the volunteer will look at the flashing lights at the stimulus frequency of 14Hz for the next 15s, and rest for 5s, and so on. The above 2 stimulus frequencies will be repeated for 1 time, resulting in a total experimental time of 100s. Signal processing technology is used to obtain the EEG signals.

C. *Data Analysis*

EEG signal is captured from a normal 21 year old subject using 128 channel (128 electrodes are, placed on the scalp of the subject). The database used for this is already pre-amplified and filtered from noise. Fig 2 shows the 128 channel active and passive electrode arrangement

1) *Signal Amplification and Filtration*: Both classes of noise differ from the control signal in their topographical and/or frequency distributions. The mu rhythm control signal is an 8-12 Hz component that is focused over sensorimoter cortex. The pre-processing step first filters the signal by applying a band filter of 2-60Hz and a 50Hz notch filter to get rid of the power line noise. A filtering method can increase the signal-to-noise ratio by enhancing the control signal and/or reducing noise.

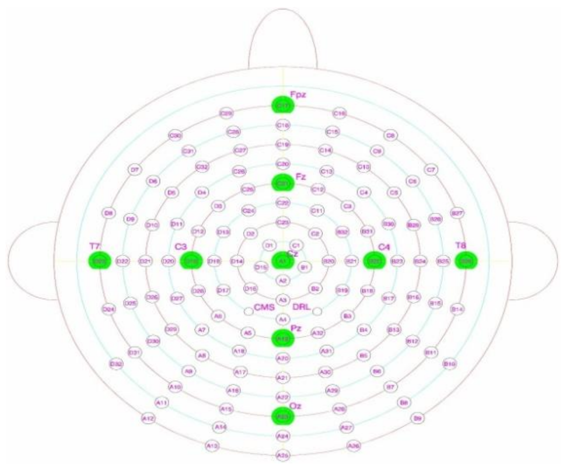

FIG.2 Active and passive electrodes

*2). EMD:*The EMD was firstly proposed by Huang *et al.* [9] as an efficient method for non-stationary and nonlinear signal analysis. This method is intuitive, direct, and adaptive, with a posterior-defined basis, from the decomposition method, based on and derived from the data. The decomposition is based on the simple assumption that any data is consisting of different simple intrinsic modes of oscillations. Each intrinsic mode, linear or nonlinear, represents a simple oscillation, which will have the same number of extrema and zero-crossings. Furthermore, the oscillation will also be symmetric with respect to the "local mean."

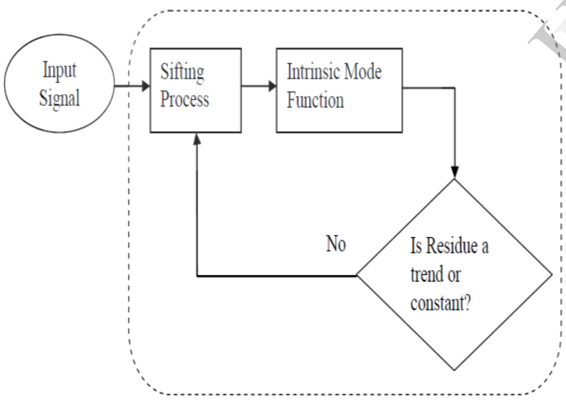

Fig 3.Flow chart of EMD

At any given time, the data may have many different coexisting modes of oscillations, one superimposing on the others. The result is the final complicated data. Each of these oscillatory modes is represented by an intrinsic mode function (IMF). The flow chart of EMD process is illustrated in Figure 3.

1. Identify all the local extrema of *x(t)*;
2. Connect all the local maxima/minima by a cubic spline line in the upper/lower envelope;
3. Determine the local mean *m(t)*, by averaging the upper and lower signal envelope;
4. Subtract the local mean *m(t)* from the signal *x(t)*, that is, $h1 = x(t) - m1$;
5. Repeat the above steps for *k* iterations until the normalized squared difference between two successive sifting operations defined as in (1).

$$SD_k= \Sigma^T_{t=0} |h_{k-1}(t)-h_k(t)|^2/ \Sigma^T_{t=0} h^2_{k}\text{-}1.......(1)$$

$SD_K$is to be small. If this squared difference $SD_k$is smaller than a predetermined value, the sifting process will be stopped;

6. The first IMF is $c1 = h_k$, and repeat steps (1) to (5) in order to obtain the other IMFs, *c2, c3, c4......cn*;
7. The sifting process can be stopped finally by any of the following predetermined criteria:

   - Either when the component $c_n$or the residue $r_n$becomes so small that it is less than the predetermined value of substantial consequence,
   - Or when the residue $r_n$becomes a monotonic function from which no more IMFs can be extracted.

The empirical mode decomposition of the signal *x(t)* can be defined as

$$x(t)=\Sigma^T_{t=0}c_j+r_n.................................(2)$$

D. Classification

In the classification the support vector machine is used giving the particular output that is steering of car. First te feature vector is created using this 8Hz and 14Hz signal.
So whenever the subject gaze this frequency flickers the data that is generated from gazing compared with this feature vector and if the match occurs the corresponding action will take place.

The feature vector is formed by calculating the signal Standard deviation, mean of the signal, minima of the signal and maxima of the signal.

In MATLAB environment we can define two classes of SVM. So the data related with the 8Hz and 14Hz can divided two classes, class 1 and class 2.

III. RESULTS

A. Intrinsic mode Function

As we are using 8 Hz and 14 Hz frequencies for the steering movement we found that IOF5 and IOF4 is practically suitable for 8 Hz and 14 Hz frequencies. That is shown in below figures

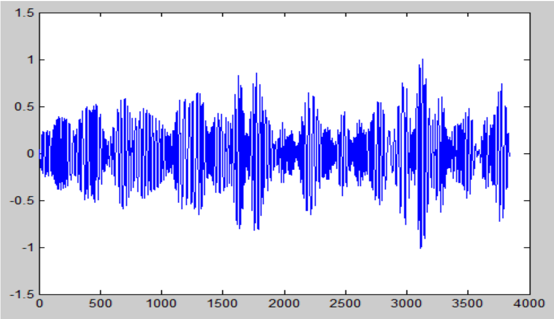

Fig.4 IOF5 for 8 Hz

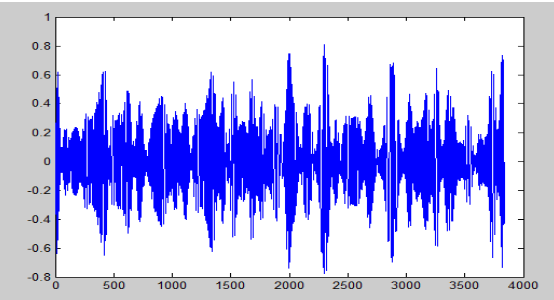

Fig.5 IOF4 for 14 Hz

As shown in above figures we observed that as the number of IOFs increases the frequency value of each component goes decreases.

B. FREQUENCY COMPONENTS ANALYSIS OF EACH IOF

The frequency content of each IMF is being analyzed by Fast Fourier Transform (FFT). In this the FFT based PSD is calculated for 8 Hz and 14 Hz frequencies. The main advantage of SSVEP based features is it just occurs when user gazes the particular frequency so that we have particular peak of that frequency in PSD. Below figures show the frequency analysis of IOF5 and IOF4.

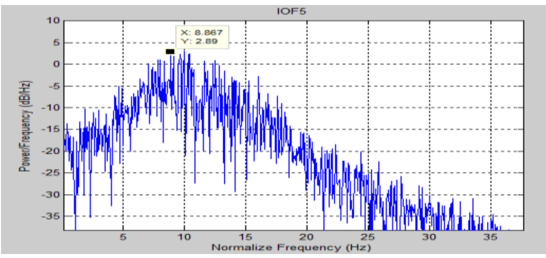

Fig.6 PSD of the 5th IMF for 8Hz signal

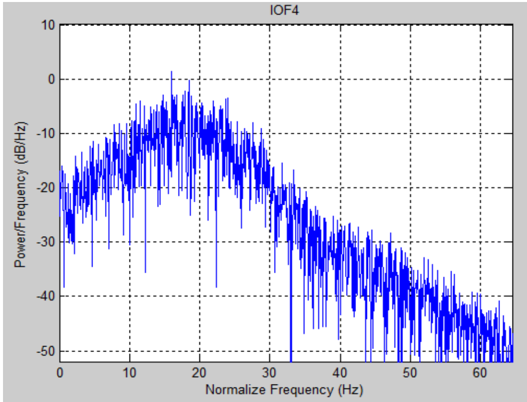

Fig. 7 PSD of the 4th IMF for 14Hz signal

CLASSIFICATION RESULTS

As we mentioned above that we have divided 8 Hz signal into class 1 and 14 Hz signal into class 2 the below values of accuracy and ITR shows that how accurately SVM works

ACCURACY when 8 Hz =**90%(left)**
ITR when 8 Hz **= 85.17(left)**
ACCURACY when 14 Hz =**77.5%(right)**
ITR when 14 Hz **= 78.65(right)**

NOTE: The results we have shown here is only for subject 1 not for subject 2 and subject 3. The results are taken for every three trails and after that the average value of accuracy and ITR is taken.

IV. CONCLUSION

In this paper we have studied software based EMD-based BCI system which takes the SSVEP signal as an input. Using MATLAB (R2011b we have found) the particular IOFs for 8 Hz and 14 Hz frequencies. This system has several advantages: 1) SSVEP can remove unrelated noise by deselecting SSVEP-unrelated IOFs; 2) the utilization of IOF achieves fast frequency recognition in short-time epochs; and 3) acceptable accuracy and ITR achieved by using SVM. In this we also studied that EMD algorithm as it processing takes some time to perform computations but it has an upper hand over any other algorithm like Wavelet Transform and Fourier Transform.

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