Electroencephalogram Analysis Based on Empirical Mode Decomposition

by

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Master of Science in Electrical and Electronics Engineering

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Abstract

ELECTROENCEPHALOGRAM ANALYSIS BASED ON 
EMPIRICAL MODE DECOMPOSITION

by Ng Cheng Man

Thesis Supervisor: Associate Professor, Vai Mang I 
Electrical and Electronics Engineering

In recent years, several researches and developments have been made in biomedical engineering, which aim to improve the healthcare diagnosis and treatment. Signal analysis methods such as Fourier transform and Wavelet transform are widely used in this field. However, these methods are limited to the linear and stationary signal analysis. As a result, they are not well adaptive methods for biomedical signals, which in fact are mostly nonlinear and non-stationary signals.

Empirical Mode Decomposition (EMD) is a novel technique that has been widely applied in the signal processing. EMD has been demonstrated as a method for the data processing of nonlinear and non-stationary signals. This method is to decompose a signal into a sum of finite number of “intrinsic mode functions” (IMF). In this thesis, EMD scheme is applied to analyze the steady-state visually evoked potentials (SSVEP) in electroencephalogram (EEG). Based on the EMD, the oscillatory activities of the decomposed SSVEP signal are analyzed. It drives us to focus on the investigation of the very low frequency of the SSVEP signal. Based on the observation of the IMF, this thesis proposes a method to detect the transition response when a person turns from an attentively focusing stage into an unfocused attention stage during the experiment. As a consequence, this may be used for detecting the idle period of a SSVEP based Brain-Computer Interface (BCI) system. After the evaluation, the attention-to-rest transition is detected with an accuracy of 82.6%. The
occurrence of the very low frequency can be explained that the attention-to-rest transition will enhance the delta wave in EEG.

Keywords: Electroencephalogram (EEG), Empirical Mode Decomposition (EMD), Intrinsic Mode Functions (IMF), Steady-State Visually Evoked Potentials (SSVEP), Brain-Computer Interface (BCI)
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LIST OF ABBREVIATIONS

BCI. Brain-Computer Interface
EEG. Electroencephalogram
EMD. Empirical Mode Decomposition
ERP. Event-Related Potentials
FT. Fourier Transform
FFT. Fast Fourier Transform
IF. Instantaneous Frequency
IMF. Intrinsic Mode Functions
STFT. Short-time Fourier Transform
SSVEP. Steady-State Visually Evoked Potentials
WVD. Wigner-Ville distribution
WT. Wavelet Transform
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Last, but certainly not least, I also want to thank my family who gives me lots of support and care. Wholehearted thanks to my husband who gives me unlimited love and encouragement all the time.
1.1 BACKGROUND AND MOTIVATION

The human brain is the center of the human nervous system and is a highly complex organ [1]. It is still full of mystery and hence it is always the hot topic for investigation in order to understand more about ourselves. It has been established that the brain is functioning through its electric activities of billions of neurons. In recent years, several researches and developments have been made in biomedical engineering, with an aim to improve the healthcare diagnosis and treatment. Signal analysis methods such as Fourier transform and Wavelet transform are widely used in this field. However, these methods are limited by the restrict requirements of linear and stationary process [2][3]. As a result, it is not a well-adaptive method for the biomedical signals, which are mostly nonlinear and non-stationary signals.

One extensively used test of the electric activity is Electroencephalography. Electroencephalography is the neurophysiologic measurement of the electrical activity of the brain by recording from the electrodes placed on the scalp or, in special cases, on the cortex. The resulting traces are known as an electroencephalogram (EEG) [4], which reflects the electrical activity of a multitude of neural populations in the brain. It is a test used to assess brain damage, epilepsy and other problems. In some jurisdictions it is used to assess brain death. In short, EEG can be considered as a test to detect the abnormalities in the electrical activity of the brain. Hopefully through this research on the EEG, some insights about the responses of the brain could be revealed.

1.2 OBJECTIVE

This thesis is intended as an investigation of analyzing the steady-state visually evoked potentials (SSVEP) in EEG by the method of Empirical Mode Decomposition (EMD). It is mainly to focus on the transition point when a person turns from an attentively focusing stage into an unfocused attention stage.
1.3 METHODOLOGY

1.3.1 ELECTROENCEPHALOGRAM (EEG)

Electroencephalogram (EEG) is applied in this research since it has several strong sides as a tool of exploring the brain activity. For example, the time resolution of EEG is very high. As some other methods for researching the brain activity have time resolution between seconds and minutes, EEG has a resolution down to sub-millisecond [4]. In other words, EEG can provide more accurate data for deeper analysis.

1.3.1.1 WAVE TYPES IN EEG

There are four major types of continuous rhythmic EEG waves: alpha, beta, delta and theta. The other waves include gamma and sensorimotor rhythm [5]. These certain frequencies of operation determine one’s state of consciousness.

Alpha waves

It is the frequency range from 8 Hz to 12 Hz [5]. It is a characteristic of a relaxed, alert state of consciousness and is present by the age of two years. Alpha rhythms are best detected with the eyes closed. Alpha attenuates with drowsiness and open eyes, and is best seen over the occipital (visual) cortex. Figure 1.1 shows the amount of alpha activity varies when the eyes are closed and opened. The subject’s eyes were closed during the first two seconds. The opening of the eyes firstly resulted in suppressed alpha activity, and then speeded alpha when the eyes were again closed after eight seconds. An alpha-like normal variant called mu is sometimes seen over the motor cortex (central scalp) and attenuates with movement, or rather with the intention to move. Figure 1.2 shows the performance of alpha waves.
Beta waves

It is the frequency range from 12 Hz to 30 Hz [5]. Low amplitude beta with multiple and varying frequencies is often associated with active, busy or anxious thinking and active concentration. Rhythmic beta with a dominant set of frequencies is associated with various pathologies and drug effects. The beta waves are demonstrated in Figure 1.3.

Delta waves

It is the frequency range up to 4 Hz and is often associated with the very young and certain encephalopathies and underlying lesions [5]. It is seen in stage 3 and 4 sleep. Figure 1.4 shows the delta waves.
Theta waves

It is the frequency range from 4 Hz to 7 Hz and is associated with drowsiness, childhood, adolescence and young adulthood [5]. This EEG frequency can sometimes be produced by hyperventilation. Theta waves can be seen during hypnagogic states such as trances, hypnosis, deep day dreams, lucid dreaming, light sleep, the preconscious state just upon waking, and just before falling asleep. The performance of theta wave is depicted in Figure 1.5.

Gamma waves

It is the frequency range approximately 30 Hz to 80 Hz. Gamma rhythms appear to be involved in higher mental activity, including perception, problem solving, fear and consciousness. It also correlates with binding and attention. Binding is the process of combining sensory input to form the perception of one or more objects. The gamma waves are shown in Figure 1.6.
Sensorimotor Rhythm (SMR)

It is a middle frequency (about 12–16 Hz) associated with physical stillness and body presence. Figure 1.7 shows the SMR waves.

In addition to the above types of rhythmic activity, individual transient waveforms such as sharp waves, spikes, spike-and-wave complexes occur in epilepsy, and other types of transients occur during sleep.

In the transition from wakefulness, through Stage I sleep (drowsiness), Stage II (light) sleep, to Stage III and IV (deep) sleep, first the alpha becomes intermittent and attenuated, then disappears. Stage II sleep is marked by brief bursts of highly rhythmic beta activity (sleep spindles) and K complexes (transient slow waves associated with spindles, often triggered by an auditory stimulus). Stage III and IV are characterized by slow wave activity. After a period of deep sleep, the sleeper cycles back to Stage II sleep and/or rapid eye movement (REM) sleep, associated with dreaming. These cycles may occur many times during the night.

EEG under general anesthesia depends on the type of anesthetic employed. With halogenated anesthetics and intravenous agents such as propofol, a rapid (alpha or low
beta), nonreactive EEG pattern is seen over most of the scalp, especially anterior; in some older terminology this was known as a WAR (widespread anterior rapid) pattern, contrasted with a WAIS (widespread slow) pattern associated with high doses of opiates [5].

1.3.2 **EMPirical MODE Decomposition (EMD)**

The research method, namely Empirical Mode Decomposition (EMD), is adopted for the EEG analysis in this thesis. This method is chosen because EEG signal is an extremely complex, nonlinear and non-stationary signal. Other traditional signal processing methods such as Fast Fourier Transform, Wavelet Transform and Wigner-Ville distribution are not effective to analyze the EEG signals since these methods require the processed signals to be linear and stationary.

EMD is a novel technique that has been widely applied in the signal processing. It is due to the fact that EMD is an effective method for the data processing of nonlinear and non-stationary signals [2]. This method is to decompose any time-series signal into the sum of a finite number of intrinsic mode functions (IMF). By means of EMD, the instantaneous attributes are extracted and can be analyzed accordingly. Details of the method of EMD applied in this thesis will be elaborated in Chapter 2.

1.3.3 **Steady-state Visually Evoked Potentials (SSVEP)**

In recent years, steady-state visually evoked potentials (SSVEP) have been widely used in Brain-Computer Interface (BCI) system. SSVEP are signals that are natural responses to visual stimulation at specific frequencies. They are resonantly neural responses mainly evoked by the visual cortex and are stable responses that can be measured all over the scalp, when a person is attentively focusing on a flashing light source with flickering frequency above 4 Hz [6].

1.4 **RESEARCH TARGET**

The main interest of this research focuses on the idle period of a SSVEP based BCI system. Our target is to find a method to detect the occurrence of the transition point when the person turns from an attentively focusing stage into an unfocused attention
stage in the SSVEP signal with the help of the EMD. As mentioned above in section 1.3.2, EMD is an efficient tool for the analysis of nonlinear and non-stationary signal, this method is therefore being chosen for the analysis of the SSVEP based BCI system in this research.

1.5 RESEARCH PLAN

In this thesis, SSVEP is the main subject to be examined. Our concern is to consider the transition point when the volunteer changes from an attentively focusing stage to an unfocused attention stage. That is to say, we will concentrate on the transition period when the volunteer turns from the 6s attention stage into the 4s resting stage.

First of all, the database of the signals is obtained from 7 volunteers, ranging from the ages of 18 – 30. They are asked to continuously focus on the flashing lights for every 6 seconds, with 4 seconds of resting time between each 6 seconds of attention duration. Each volunteer repeats the experiment for 6 times. As a result, the EEG database is composed of a total of 42 full-set signals. Sampling of the database will be described in full details in Chapter 4.

Secondly, the resultant SSVEP signals are decomposed by using the method of EMD. The signal is extracted into a series of IMFs and one residue, ordering from high to low frequencies. The components are then compared with regards to the attention-to-rest transition response.

Thirdly, from the oscillatory activities of the extracted SSVEP signal, hopefully the IMF which shows the most obvious response during the attention-to-rest transition can be identified. Then this IMF will be selected for the next stage of examination.

Fourthly, the features of the chosen IMF will be magnified for further investigation. To do this, a band-pass filter is applied in order to preserve that frequency range of the original SSVEP signal.
At last, the filtered EEG signal will be analyzed in order to identify the transition responses. The findings of the important instances will be interpreted in the coming chapters.

1.6 ORGANIZATION OF THESIS

This thesis is composed of six chapters:

Chapter 1 describes the background, motivation, objective, methodology and research plan of the thesis.

Chapter 2 elaborates the principles and detail steps of EMD, including the definitions of IMFs.

Chapter 3 further describes the SSVEP signal and its application in BCI system.

Chapter 4 interprets the SSVEP signal analysis by the application of the EMD method in order to extract the components of the attention-to-rest transition.

Chapter 5 demonstrates that the delta activity is increased when the volunteer is transiting from an attentively focusing stage into an unfocused attention stage. It is performed by the use of a band-pass filter in order to preserve only the very low frequency of the original signal.

Chapter 6 summarizes the experimental results and the conclusion is made.
CHAPTER 2: EMPIRICAL MODE DECOMPOSITION

In this chapter, the principles and detail steps of Empirical Mode Decomposition (EMD), including the definitions of IMFs will be elaborated.

The EMD was firstly proposed by Huang et al. [7] as an efficient method for non-stationary and nonlinear signal analysis. This method is intuitive, direct, and adaptive, with a posteriori-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.” 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 2.1.

![Figure 2.1 Flow chart of EMD](image-url)
2.1 INTRINSIC MODE FUNCTION

The objective of the EMD method is to decompose a signal into a sum of finite number of intrinsic mode functions (IMFs) [7]. Each IMF is a function that satisfies the following two definitions:

- In the whole data set, the number of extrema and the number of zero-crossings must be either equal or differ at most by one.
- At any point, the mean value of envelope of local maxima and envelope of the local minima is zero.

To implement this method, a signal $x(t)$ is decomposed into IMF by the following steps [2][8] (“sifting process” [7]):

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, $h_1 = x(t) - m_1$;
5. Repeat the above steps for $k$ iterations until the normalized squared difference between two successive sifting operations defined as

$$SD_k = \frac{\sum_{t=0}^{T}|h_{k-1}(t) - h_k(t)|^2}{\sum_{t=0}^{T}h_{k-1}^2}$$ (2.1)

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 $c_1 = h_k$, and repeat steps (1) to (5) in order to obtain the other IMFs, $c_2, c_3, c_4, ..., c_n$;
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

\[
x(t) = \sum_{j=1}^{n} c_j + r_n
\]  

(2.2)

in which \( n \) is the number of extracted IMFs, and the final residue \( r_n \) can either be the mean trend or a constant.

At this point, the process of the empirical mode decomposition is completed. The signal \( x(t) \) can be reconstructed from the sum of all IMFs and the final residue. In order to illustrate the detailed steps of the EMD sifting more clearly, the sifting process will be represented diagrammatically in the following section.

2.2 DEMONSTRATION OF THE SIFTING PROCESS

The test signal is given in Figure 2.2. All the local extrema are identified, and then connect all the local maxima by a cubic spline line so as to form the upper envelope. The procedure for the local minima is repeated to produce the lower envelope. The upper and lower envelopes should cover all the data between them, as shown in Figure 2.3. Their mean is designated as \( m_i \), also shown in Figure 2.3, and the difference between the data and \( m_i \) is the first component \( h_i \) shown in Figure 2.4.
Figure 2.2 The test signal

Figure 2.3 The data (blue) upper and lower envelopes (green) defined by the local maxima and minima respectively, and the mean value of the upper and lower envelopes given in red
Ideally, $h_j$ should satisfy the definition of an IMF, for the construction of $h_j$ described above should have made it symmetric and have all maxima positive and all minima negative. However, even if the fitting is perfect, a gentle hump on a slope can be amplified to become a local extrema in changing the local zero from a rectangular to a curvilinear coordinate system. After the first round of sifting, the hump may become a local maximum. New extrema generated in this way actually reveal the proper modes lost in the initial examination. In fact, with repeated siftings, the sifting process can recover signals representing low-amplitude riding waves. The sifting process serves two purposes: 1. to eliminate the riding waves, and 2. to make the wave profiles more symmetric. While the first purpose must be achieved for the Hilbert transform to give a meaningful instantaneous frequency, the second purpose must also be achieved in case the neighboring wave amplitudes have too large a disparity. Toward these ends, the sifting process has to be repeated as many times as is required to reduce the extracted signal to an IMF. In the subsequent sifting processes, $h_j$ can be treated only as a proto-IMF. In the next step, it is treated as the data; then,

$$h_{11} = h_{1} - m_{11}$$ (2.3)
After repeated siftings in this manner, shown in Figure 2.5a and Figure 2.5b, up to \( k \) times, \( h_{1k} \) becomes an IMF; that is,

\[
h_{1k} = h_{1(k-1)} - m_{1k}
\]  

(2.4)

then, it is designated as

\[
c_I = h_{1k}
\]  

(2.5)

the first IMF component from the data is shown in Figure 2.6. Here, a critical decision must be made: the stoppage criterion. Historically, two different criteria have been used: The first one was used in Huang et al. (1998). This stoppage criterion is determined by using a Cauchy type of convergence test. Specifically, the test requires the normalized squared difference between two successive sifting operations defined as

\[
SD_k = \frac{\sum_{t=0}^{T} |h_{k-1}(t) - h_k(t)|^2}{\sum_{t=0}^{T} h_{k-1}^2(t)}
\]  

(2.1)

to be small. If this squared difference \( SD_k \) is smaller than a predetermined value, the sifting process will be stopped. This definition seems to be rigorous, but it is very difficult to implement in practice. Two critical questions need to be resolved: first, the question of how small is enough needs an answer. Second, this criterion does not depend on the definition of the IMFs. The squared difference might be small, but nothing guarantees that the function will have the same numbers of zero-crossings and extrema, for example. These shortcomings prompted Huang et al. (1999, 2003) to propose a second criterion based on the agreement of the number of zero-crossings and extrema. Specifically, a S-number is pre-selected. The sifting process will stop only after S consecutive times, when the numbers of zero-crossings and extrema stay the same and are equal or differ at most by one. This second choice has its own difficulty: how to select the S number. Obviously, any selection is ad hoc, and a rigorous justification is needed.
Figure 2.5a Repeated sifting steps with $h_1$ and $m_2$

Figure 2.5b Repeated sifting steps with $h_2$ and $m_3$
In a recent study of this open-ended sifting, Huang et al. (2003) used the many possible choices of S-numbers to form an ensemble of IMF sets, from which an ensemble mean and confidence were derived. Furthermore, through comparisons of the individual sets with the mean, Huang et al. established an empirical guide. For the optimal siftings, the range of S-numbers should be set between 4 and 8. More details will be given later.

Now assume that a stoppage criterion was selected, and that the first IMF $c_1$ was found. Overall, $c_1$ should contain the finest scale or the shortest period component of the signal. It follows that $c_1$ can be separated from the rest of the data by

$$r_1 = x(t) - c_1$$

Since the residue $r_1$ still contains longer period variations in the data, as shown in Figure 2.7, it is treated as the new data and subjected to the same sifting process as described above.
This procedure can be repeated with all the subsequent \( r_j \)'s, and the result is

\[
\begin{align*}
  r_2 &= r_1 - c_1 \\
  & \quad \vdots \\
  r_n &= r_{n-1} - c_{n-1}
\end{align*}
\]

(2.7)

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. Even for data with zero mean, the final residue still can be different from zero. If the data have a trend, the final residue should be that trend. By summing up (2.6) and (2.7), we finally obtain

\[
x(t) = \sum_{j=1}^{n} c_j + r_n
\]

(2.2)
Thus, a decomposition of the data into $n$-empirical modes is achieved, and a residue $r_n$ obtained which can be either the mean trend or a constant. As discussed here, to apply the EMD method, a mean or zero reference is not required; the EMD technique needs only the locations of the local extrema. The zero reference for each component will be generated by the sifting process. Without the need for the zero reference, EMD has the unexpected benefit of avoiding the troublesome step of removing the mean values for the large DC term in data with a non-zero mean.

2.3 INSTANTANEOUS FREQUENCY

The easiest way to compute the instantaneous frequency is by using the Hilbert Transform. Computation of Instantaneous Frequency (IF) of any time-series $X(t)$ implies to determine its associated analytical signal $Z(t)$ [9]:

$$Z(t) = X(t) + iY(t) = a(t)e^{i\theta(t)}$$  \hspace{1cm} (2.8)

$Z(t)$ is a complex-valued signal that preserves all information contained in the original signal $X(t)$.

From (2.8), it is possible to define instantaneous amplitude and instantaneous phase of the considered signal:

$$a(t) = \sqrt{X^2(t) + Y^2(t)}$$  \hspace{1cm} (2.9)

$$\theta(t) = \arctan\left(\frac{Y(t)}{X(t)}\right)$$  \hspace{1cm} (2.10)

Thus, instantaneous frequency of $X(t)$ can be obtained by differentiating $\theta(t)$:

$$f = \frac{d\theta(t)}{2\pi dt}$$  \hspace{1cm} (2.11)

According to the above definitions, a series of instantaneous frequency values changing from point to point in time domain is obtained. Only one frequency value at any given time can be obtained.
2.4 SUMMARY

In this chapter, the definition of the EMD is described and the sifting process of the EMD is illustrated by an example. After the decomposition of EMD, the time-scale of the decomposition will be adapted to the dynamic of the analyzed signal and the instantaneous frequency of each IMF is able to be analyzed. Based on the observation of the IMFs features, it gives us a clue to further analyze the chosen IMF and use it to find a method to detect the idle period of a SSVEP based BCI system. The details will be discussed in Chapter 4.
CHAPTER 3: STEADY-STATE VISUALLY EVOKED POTENTIALS BASED BRAIN-COMPUTER INTERFACE SYSTEM

This chapter further describes the basic principle of the SSVEP signal and its application in Brain-Computer Interfaces (BCIs) system. This also explains the reason why the EMD method is chosen for the analysis of SSVEP signal, instead of other signal processing methods.

3.1 BRAIN-COMPUTER INTERFACES

BCIs provide an alternative communication and control channel between human and environment through EEG produced by brain activities [10]. It is a direct communication pathway between a brain and an external device. BCIs are often aimed at assisting, augmenting or repairing human cognitive or sensory-motor functions. BCIs extend human’s control ability to control machines. EEG is the most studied potential non-invasive interface as BCIs, mainly due to its fine temporal resolution, ease of use, portability and low set-up cost. By analyzing the EEG signals we can abstract features which represent different status of human’s brain. In this way, signal processing is one of the key points of BCI system. We are going to consider the SSVEP based BCI system in this thesis. SSVEP are stable responses that can be measured all over the scalp, it becomes one of the useful input signals in BCI because of its advantages in high information transmission rate, short training time and scatheless for users [11]. Figure 3.1 shows the electrode positions of the fully equipped 65-electrodes cap.
3.2 BASIC PRINCIPLE OF STEADY-STATE VISUALLY EVOKED POTENTIALS (SSVEP)

The steady-state visually evoked potentials (SSVEPs) are resonantly neural responses mainly evoked by the visual cortex that can be investigated via noninvasive scalp electroencephalography (EEG), when a subject is attentively focusing on a flashing light source with flickering frequency above 4 Hz [6]. SSVEP based BCI system uses low frequency and middle frequency visual stimulation signals as their input. These signals can be recorded from the scalp over the visual cortex, with maximum amplitude at the occipital region. Photic driving 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 the measurement of SSVEP.

The SSVEP signals have been widely used in the new applications in BCIs recently. A SSVEP based BCI system is based on the detection of increased amplitude that evaluates the focus of the subject’s gaze. SSVEP is an inherent response of the brain.
Therefore, compared to other types of BCIs, SSVEP based BCIs provides higher information transfer rates with minimal user training, and it requires fewer EEG channels [9].

3.3 SYSTEM CONFIGURATION

Figure 3.2 shows the block diagram of a typical SSVEP based BCI system [12]. It indicates a visual stimulator, EEG acquisition equipment, signal processing algorithms and device control methods.

![Block diagram of a SSVEP based BCI system](image)

In our experiment, the SSVEP based BCI system is operated by showing a number of flickering lights on the monitor. It is presenting to the user visual stimuli modulated at different frequencies. The subject was asked to gaze at the target attentively when it appears on the monitor. When the subject focuses his/her attention on a certain stimulus, the corresponding stimulating frequency and/or its harmonics dominantly appear in the spectral representation of the EEG. Thus, a dominant SSVEP is visible in the EEG, corresponding to an increased response associated with the target. Then, signal processing technology is used to detect the existence of the SSVEP and determine its stimulus frequency. The frequency of the SSVEP matches with the frequency of the stimulus or its harmonics. The target will induce a peak in the
amplitude spectrum at the stimulus frequency, which is larger than the mean amplitude of the lower and higher frequency bands.

3.4 DIFFERENT SIGNAL PROCESSING METHODS

There are traditional signal processing methods for time-frequency analysis, such as Fourier Transform (FT), Short-time Fourier Transform (STFT), Wigner-Ville distribution (WVD) and Wavelet Transform (WT). However, they are usually limited by uncertain principle. They cannot provide higher resolution both in time and frequency domain. In addition, the decomposition of signal is not adaptive. These traditional signal processing methods are to be reviewed in the following section.

3.4.1 FOURIER TRANSFORM AND SHORT-TIME FOURIER TRANSFORM

Fourier Transform (FT) has been demonstrated to work well in current BCI systems, but it has some shortages. The disadvantages of FFT based approach is that we have to ensure that the data within the time window is stationary and the spectrogram method has an additional problem of having a trade-off in time and frequency resolution [2]. Nevertheless, EEG is a non-stationary and nonlinear signal, thus it makes the EEG analysis unsatisfactory. The same shortcomings occur in STFT, which was first proposed by Gabor (1946). The approach by STFT brings up the difficulty that the estimated time-varying spectrum depends on the choice of the used data window.

3.4.2 WIGNER-VILLE DISTRIBUTION

Another time-frequency analysis method is WVD, it is computed by correlating the signal with a time and frequency translated version of itself. In WVD, there is no loss of resolution which is different from STFT [13]. However, it is limited by a serious cross terms interference which is indicated by the existence of negative power for some frequency ranges.

3.4.3 WAVELET TRANSFORM

Wavelet Transform (WT) has played an important role in signal processing area since 1980s. Wavelet analysis is an adjustable window signal processing technique to
handle non-stationary signals in which one can observe different parts of the signal by just adjusting the focus. Although WT appears similar to STFT, the basic wave components are not limited to sinusoidal functions. Therefore, it can overcome the limitations of the STFT. In the time domain, the WT has good resolution at high frequencies in order to identify transient signal features [14]. Due to its efficient representation of highly non-stationary signals, the wavelet transform has been found very useful in many signal processing applications, specially de-noising and image/video compression [13]. Neither continuous nor discrete wavelet analysis is basically a linear analysis. An appealing feature of the wavelet analysis is that it can provide a uniform resolution in any scale [15]. However, it is limited by the size of basic wavelet function, that is, mother wavelet.

3.4.4 Empirical Mode Decomposition

As mentioned before, EMD has been widely applied in signal processing due to its applicability to non-stationary and nonlinear signals. Although WT can work in EEG analysis, it has been demonstrated that EMD can express the EEG distribution in time and frequency domain more accurately than WT [3]. The EMD method will decompose the signal into a collection of IMFs. The IMF is a kind of complete, adaptive and almost orthogonal representation for the analyzed signal. The number of IMFs and frequencies of each IMF are inherently determined by these time scales. On the other hand, the structure of each IMF is determined by the natural amplitude variations in the time series. Higher frequency oscillations are captured in the first IMF and subsequent IMFs have lower average frequencies. As a result, the local and instantaneous frequency of EEG can be obtained. Therefore, EMD is a self-adaptive signal processing method that can be applied to nonlinear and non-stationary process perfectly [16].

3.5 SUMMARY

In this chapter, the SSVEP based BCI system is introduced. Different signal processing methods are reviewed, namely FT, STFT, WVD and WT. These traditional methods are limited by their corresponding shortcomings, which make
their applications to EEG analysis unsatisfactory. Instead, due to its applicability to non-stationary and nonlinear signals, EMD is the method that we apply in this thesis.

With the help of the EMD, the oscillatory activities of the decomposed SSVEP signal are studied. By investigating the characteristics of the specific IMF resulted from the EMD, we find out that the IMFs are the key point for the idle detection of the SSVEP based BCI system.

In the next chapter, we are going to show that the SSVEP-related oscillatory activities during gazing at flickering lights can be extracted by the method of EMD. And we will discuss the detailed steps of the idle detection in chapter 5.
CHAPTER 4: EMD APPLICATION TO THE SSVEP SIGNAL

As the traditional signal processing methods are not effective in EEG analysis, we are going to analyze the SSVEP signals by the application of the EMD method in this chapter. The signal decomposition is demonstrated in details and the characteristics of each IMF are going to be compared and studied.

4.1 DATA ACQUISITION
The volunteers will be stimulated with a series of flashing lights, corresponding to 20Hz, 15Hz, 10Hz, 8Hz and 7.5Hz. The electrodes PO3, PO4, POz, Oz, O1 and O2 are used to be investigated. The signals are recorded with a sampling rate of 600Hz. Firstly, The volunteer is asked to look at the flashing light attentively, with the first stimulus frequency of 20Hz for duration of 6s, and then rest for 4s. Secondly, the volunteer will look at the flashing lights at the stimulus frequency of 15Hz for the next 6s, and rest for 4s, and so on. The above 5 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. Figure 4.1 offers a complete set of original SSVEP-EEG signals. The red areas refer to the time when the volunteer is gazing at the flickering lights of the specified stimulus frequency.

4.2 EEG DATABASE
The SSVEP signals are obtained from 7 volunteers, ranging from the ages of 18 – 30. Each volunteer repeats the experiment for 6 times. Therefore, the EEG database is composed of a total of 42 full-set signals.
Figure 4.1 Six channels of the original SSVEP signals
4.3 METHOD BASED ON THE EMPIRICAL MODE DECOMPOSITION (EMD)

4.3.1 EMD FOR SSVEP SIGNALS

Figure 4.2 shows the original EEG signal with the duration of 100s obtained from one trial on the second channel data (PO4). EMD is applied to decompose the SSVEP signal, the decomposed result based on the EMD method is shown in Figure 4.3. It denotes 11 IMFs and one residue decomposed from the original EEG signal. The IMFs are from low to high orders, namely imf1 to imf11 respectively from the top to the bottom as indicated in Figure 4.3. It is noted that the frequency content of each individual IMF decreases as the order of the IMF increases.

![Original EEG signal](image_url)

Figure 4.2 Original EEG signal
Figure 4.3 EMD decomposed signals of channel PO4 of EEG signal with 11 IMFs and residue
From the oscillatory activities of the 5\textsuperscript{th} IMF and the 6\textsuperscript{th} IMF, it indicates that every time after the volunteer watched the flickering light and turns into a rest condition, the amplitudes are greatly increased in each transition period. This transition phenomenon is most obviously shown in the 6\textsuperscript{th} IMF. Seven volunteers are invited to test the same experiment. Each person repeats the experiment for six times. All the experiments show the same result, that is, the transition phenomenon is most obviously shown in the 6\textsuperscript{th} IMF.

Figure 4.4 depicts the enlargement of the 6\textsuperscript{th} IMF from the corresponding EEG signal. The volunteers are not stimulated by the flickering lights between the intervals 6 – 10s, 16 – 20s, 26 – 30s, 36 – 40s, 46 – 50s, 56 – 60s, 66 – 70s, 76 – 80s, 86 – 90s and 96 – 100s. The red lines in Figure 3 indicate the locations of 6s, 16s, 26s, 36s, 46s, 56s, 66s, 76s, 86s and 96s. It is illustrated that there are obviously high amplitudes instantly at the beginning of each transition period. Therefore, it may be useful to look more closely at some of the more important features of the 6\textsuperscript{th} IMF.

![Figure 4.4 Enlargement of the 6\textsuperscript{th} IMF](image-url)
4.3.2 Frequency components analysis of each IMF

The frequency content of each IMF is being analyzed by Fast Fourier Transform (FFT). The corresponding Fourier Spectrums of each IMF are denoted in Figure 4.5a and Figure 4.5b. It is shown that the energies of the higher frequency components reduce gradually from the 1st IMF to the last one. In other words, the 1st IMF contains the highest frequency component while the last IMF contains the lowest frequency.
Figure 4.5a Fourier Spectrum of the 1st IMF to 6th IMF
Figure 4.5b Fourier Spectrum of the 7th IMF to 11th IMF
The main purpose of this part is to examine the phenomenon of the attention-to-rest transition, therefore the 6th IMF is the main frequency component that is going to be investigated. To better analyze the 6th IMF, the Fourier Spectrum of the 6th IMF is enlarged in Figure 4.6, showing that there is a peak at 1Hz. The frequency contents of the 6th IMF from all the signals in the EEG database are found to be at a very low frequency, between the ranges 0.5Hz – 2Hz. In this way, let us now attempt to extend this observation into the idea that during the period of attention-to-rest transition, there is a very low frequency occurs in EEG.

The SSVEP signals from other electrodes in our database, namely PO3, POz, Oz, O1 and O2, were also tested under the same procedures as mentioned above. All of the channel data showed the same results. That is, when the SSVEP signals from other electrodes were decomposed by the EMD, the 6th IMF obviously showed the phenomenon of the idle transition. The corresponding frequency ranges of the 6th IMF from each electrode were also noticed to be at a very low frequency, between 0.5Hz – 2Hz.

Figure 4.6 Fourier Spectrum of the 6th IMF
4.4 SUMMARY

In this chapter, an EMD scheme is applied to analyze the SSVEP based BCI system. The oscillatory activities of the decomposed SSVEP signal and the corresponding frequencies are demonstrated. From the results of the 6th IMF, the features of the attention-to-rest transition response are obviously shown. In other words, high powers are observed instantly after the volunteer turns from an attentively focusing stage into an unfocused attention stage. By means of the FFT method, the 6th IMF of the SSVEP signals is found to be corresponding to a very low frequency (0.5 – 2 Hz). All of this reflects that a very low frequency seems to occur during the idle period of the SSVEP signal. This drives us to look into that frequency range of the SSVEP signal in the next chapter.
This stage of investigation tries to demonstrate that when the volunteer is transiting from an attentively focusing stage into an unfocused attention stage, a very low frequency occurs which refers to the increase of delta wave. The occurrence of the very low frequency is proved by an application of a band-pass filter in order to preserve the very low frequency of the original signal.

5.1 APPLICATION OF THE BAND-PASS FILTER TO THE SSVEP SIGNAL

As discussed in the previous chapter, after the EMD decomposition, the 6th IMF is the main useful data for the development of the idle period detection. Since the 6th IMFs of all SSVEP signals in our EEG database correspond to the very low frequency (0.5 Hz – 2Hz), this range of frequency is the important point to be further investigated in this chapter.

Due to the fact that each IMF corresponds to the component of the whole signal, we need to avoid the disturbances from the components of other IMFs and concentrated on the 6th IMF. In order to preserve only the frequency content of the 6th IMF, a finite impulse response (FIR) equiripple band-pass filter (with low frequency at 0.5Hz and high frequency at 2 Hz) is therefore designed and applied to the original EEG signal.

The power spectrum of the filtered EEG signal is then found with an application of a window with length 500 ms moving along the signal. The filtered EEG signal is then divided into 10 segments of 10s duration (including 6s of time focusing on the flickering lights and 4s of time resting). The highest powers of each 10s duration are located and they are found to occur at times 6.832s, 17.03s, 26.77s, 36.99, 46.74s, 56.82s, 66.89s, 77.78s, 86.58s and 96.88s. All of them belong to the resting durations, the time is within 0.58s – 1.78s right after the volunteer stop gazing at the flickering lights. Figure 5.1 illustrates the power spectrum of the EEG signal after the band-pass
filter is applied, in which the highest power locations of each 10s duration are also marked.

![Power Spectrum of the filtered EEG signal](image)

Figure 5.1 Power Spectrum of the filtered EEG signal

5.2 ALGORITHM OF THE CORRECT DETECTION

From the phenomenon demonstrated in the previous section, it is observed that the highest powers generally occur at the beginning of the idle periods. We therefore define that when the SSVEP signal contains only the very low frequency after the application of the band-pass filter, the attention-to-rest transition is accompanied with the occurrence of highest power.

In this way, when the highest power of each 10s duration locates at the idle period, it is considered that the detection of the attention-to-rest transition is correct. In other
words, if the highest power occurs at the duration of watching the flickering light, it is then considered to be incorrect and fault in the accuracy.

Based on this algorithm, we count along the whole SSVEP signal in order to check how many times the highest powers are located at the idle period correctly. The correct occurrences are then counted according to the total number of segments to calculate the accuracy of the idle detection.

5.3 DETECTION OF THE ATTENTION-TO-REST TRANSITION

Figure 5.2 indicates a better demonstration on the locations of the highest powers for the filtered EEG signal. In this figure, the original SSVEP-EEG signal is shown in blue color, and the green areas are the 6s duration of gazing at the flickering lights, finally the red lines are the occurrences of the highest powers found in the filtered EEG signal. As expected, all the highest powers are located in the resting duration and they occur right after the volunteer stop watching the flickering lights.

Since the original EEG signal is filtered and contains only the very low frequency (0.5 – 2Hz), it can be concluded that a very low frequency really occurs at the beginning of the idle transition.

With the application of the band-pass filter to the original SSVEP signal, the idle transition points are spotted out successfully. Therefore, it is demonstrated that our method can be used for detecting the idle period of the SSVEP based BCI system.
5.4 ACCURACY

In order to further examine this phenomenon, the same analysis procedures are applied to all the SSVEP signals in our EEG database. Table 1 summarizes the results of the accuracy for detecting the attention-to-rest transition point for all volunteers. The mean accuracy is 82.6%. Accordingly, it is concluded that our method is able to be used in the idle detection of the SSVEP signal. The summarized accuracy is represented diagrammatically in Figure 5.3.

<table>
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<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
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<td>80%</td>
<td>90%</td>
<td>70%</td>
<td>90%</td>
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<tr>
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<td>70%</td>
<td>70%</td>
<td>80%</td>
<td>70%</td>
<td>80%</td>
</tr>
<tr>
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<td>90%</td>
<td>80%</td>
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<td>80%</td>
<td>100%</td>
<td>100%</td>
<td>90%</td>
</tr>
<tr>
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<td>100%</td>
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<td>81.67%</td>
<td>75.00%</td>
<td>95.00%</td>
<td>73.33%</td>
<td>83.33%</td>
</tr>
</tbody>
</table>

Table 5.1 Accuracy of detecting the attention-to-rest transition for all volunteers
5.5 EVOKED DELTA WAVES

The experimental results lead to the conclusion that a very low frequency is likely to occur during the attention-to-rest transition. Since this frequency band (less than 2Hz) belongs to the delta waves, it is reasonable to suppose that the attention-to-rest transition might be related to an increase in EEG delta activity. Although delta waves are usually found in the stage of sleeping, delta activity has been found during some continuous attention tasks [17].

An increase in delta power has been reported in different types of mental tasks (Dolce and Waldeier, 1974; Tucker et al., 1985; Kakizaki, 1985; Etevenon, 1986; Valentino et al., 1993; Fernandez et al., 1995) [18]. This increase of the slow frequencies is neither due to the ocular movements nor to any other artifact. Research has been devoted that an increase in delta EEG activity may be related to attention to internal processing during the performance of a mental task [18]. Delta power will be increased in conditions such as attention, activation of working memory, letter identification etc [19][20]. It is pointed out in some Go/No-Go analysis, which are studied with event-related potentials (ERP), that there is a power increase at 1 Hz both
in Go and No-Go conditions. The increase in delta activities during the No-Go conditions is related to the inhibition of non-relevant stimuli (Harmony et al., 1996), signal matching and decision making (Basar-Eroglu et al., 1992) [19]. On the other hand, delta power will also become high during target relative to non-target processing, namely, in relation to a rest condition [21].

5.6 FACTORS THAT MAY AFFECT THE ACCURACY

As was noted previously, the accuracies for the seven volunteers are 91.67%, 78.33%, 81.67%, 75%, 95%, 73.33% and 83.33% respectively. In short, the accuracies are ranging from 73.33% to 95%. It can be stated that some people may perform better in the experiment, while some are not performing so well. The question to consider next is what are the factors affecting the accuracy. In particular, volunteer 6 gives the lowest average accuracy, so the EEG behavior of the volunteer 6 is going to be examined.

Figure 5.4 shows the original EEG signal obtained from Trial 5 of volunteer 6, which is the lowest accuracy (60%) among all the trials. It is illustrated that during 27s, 30s, 47s and 50s, the waveforms of the EEG signal fluctuate greatly and the amplitudes are increased unreasonably. The amplitude of the EEG signals larger than 100μV is considered to be abnormal. The performance of the suddenly and abnormally high amplitude means that during 27s, 30s, 47s and 50s, the volunteer’s head was moving which resulted in the poor connection between the head and the electrodes. In this way, the EEG signals obtained may be interfered by the loose connection and leaded to inaccurate result.

In addition to this, the poor contacts of the electrodes may also raise the problem of induced noise in the EEG signal. When the noise contributes a large proportion in the original EEG signal, it will contaminate the signal and make it difficult to extract only the useful data. Consequently, the filtered EEG may not be clear enough, which will affect the accuracy of the attention-to-rest detection.
Another reason that may lead to the low accuracy is that the volunteer is not in a fully concentrated mode. That is, he is not in an attentively focusing stage while gazing at the flickering light. In this way, no matter he is watching the flickering light or not, the attention-to-rest transition is not quite obvious in the resulting EEG.

5.7 SUMMARY

In this chapter, a band-pass filter is applied to the original SSVEP signal in order to analyze only the very low frequency band. Consequently, the phenomenon of the occurrence of very low frequency during the attention-to-rest transition is demonstrated. This phenomenon is examined with different SSVEP signals obtained from different person. As a result, the attention-to-rest transitions are being successfully detected and the mean accuracy is found to be 82.6%.

This result leads to the conclusion that during the attention-to-rest transition, a very low frequency occurs which means that delta waves are being evoked. To put it the other way round, when the volunteer turns from an attentively focusing stage to an
unfocused attention stage, there is an increase in delta EEG activity. This phenomenon may be related to the inhibition of non-relevant stimuli, signal matching and in a state of non-target processing [19].

From these remarks one general point becomes very clear: the method is able to detect the idle period of the SSVEP based BCI system.
In this thesis, we begin with analyzing the SSVEP signals by using the EMD method. The analyzed signal is decomposed into a series of IMFs and their characteristics are being studied. From the oscillatory activities of the decomposed SSVEP signal, it is observed that the 6\(^{th}\) IMF shows the features of the attention-to-rest transition response. Having made the point that the 6\(^{th}\) IMF of the SSVEP signals corresponds to a very low frequency (less than 2 Hz), we may go on to propose that a very low frequency occurs during the transition period. To put it more precisely, a band-pass filter is used to preserve only the very low frequency of the SSVEP signals. High powers are observed instantly after the volunteer turns from an attentively focusing stage into an unfocused attention stage. The occurrence of a very low frequency during the attention-to-rest transition is examined with different SSVEP signals. Finally, the attention-to-rest transitions are being successfully detected and the mean accuracy is found to be 82.6\%. This result leads to the conclusion that during the attention-to-rest transition, a very low frequency occurs which means that delta waves are being evoked. That is to say, when the volunteer turns from an attentively focusing stage to an unfocused attention stage, there is an increase in delta EEG activity. The increase of the delta wave is neither due to the ocular movements nor to any other artifact. This phenomenon may be related to the inhibition of non-relevant stimuli, signal matching and in a state of non-target processing [19].

In summary, by applying a band-pass filter to the SSVEP based BCI system, the transition points of the idle periods from the SSVEP signal can be detected by computing the power of the whole signal. The occurrences of the instantly high powers are right after the attention-to-rest transition points. As a consequence, the method applied in this thesis is able to detect the idle period of the SSVEP based BCI system.

EMD method offers a powerful tool for analyzing the nonlinear and non-stationary signal such as EEG. It offers the key to understand the components of the SSVEP
signals, in which the attention-to-rest transition is able to be detected by means of the features of the chosen IMF. All of this amounts to saying that the attention-to-rest transition is accompanied with the occurrence of a very low frequency. Since there is room for further improvement on the detection accuracy, the behavior of the EMD method and the IMFs can be analyzed in further research.
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APPENDIX A: PUBLICATIONS

CONFERENCE: