Implementation of a High frequency SSVEP based BCI using iterative filtering - empirical mode decomposition (IF-EMD)

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***Abstract*—Steady-state visual evoked potential (SSVEP) has been regarded as an efficient way to design a brain computer interface (BCI). However, most SSVEP-based BCIs utilize visual stimuli with flashing frequencies lower than 30Hz, owing to their higher signal-to-noise ratio (SNR). BCIs using SSVEP higher than 30Hz are rarely seen. In order to achieve the control of SSVEP-based BCIs at high stimulation frequency (>30Hz), we have implemented iterative filtering – empirical mode decomposition (IF-EMD) to classify the SSVEPs from viewing distinct high-frequency stimulators. EEG signals were recorded from dry EEG electrodes with impedance matching circuits. The EEG signals were pre-filtered within 35~55Hz as preprocessing (6th-order Butterworth IIR filter) to remove low-frequency drifts and 60Hz electricity noise. Three stimulation frequencies, designed at 47, 50, and 53 Hz were chosen to induce high-frequency SSVEPs, in order to control the leftward, upward, and rightward movements of the BCI cursor. Ten subjects were recruited, and each subject was requested to complete a control experiment of moving a cursor to reach three targets on a PC screen. The mean accuracy (Acc), command transfer interval (CTI), and information transfer rate (ITR) in the control experiment were 90.7±2.9%, 1.14±0.07 sec, and 54.94±5.41 bits/min, respectively. In the application experiment, the mean execution time and CTI were 30.0 · 4.69 sec and 1.50 · 0.31 sec, respectively.**

***Index Terms*—Iterative filtering, Empirical mode decomposition, Steady-state visual evoked potential, Brain computer interface.**

I. Introduction

Brain computer interface (BCI) enables paralyzed patients to communicate with external environments through their intentions. BCI measures brain signals induced from elaborately designed tasks, and then translates the measured brain signals into communication or control signals. The SSVEP has been used to accomplish several applications, such as mind spelling system, virtual reality operation, prosthesis and wheelchair control, etc. [1-4] In the operation of SSVEP-based BCI, users shift their eyes to gaze at chosen visual stimulators, in order to induce SSVEPs with designated frequencies or phases. Users' gazed targets can be discerned by analyzing the frequencies or phases of the measured SSVEPs. Owing to the frequency-preference characteristic of SSVEP, the amplitudes of SSVEPs are more prominent in low (<15Hz) and middle (~30Hz) frequency ranges, and are decreased with the increase of stimulation frequencies above 30Hz [5]. Most SSVEP-based BCI systems are designed with flickering frequencies lower than 40Hz, due to the better signal-to-noise ratio (SNR) of SSVEP in low or middle frequency ranges. However, viewing visual stimulus with lower flickering frequency for a long time can cause visual fatigue easily, and sometimes makes people feel dizzy [6]. For about 3% people, viewing flickers with frequency around 15~20Hz can even incur the risk of photosensitive epilepsy [7-9]. BCIs with SSVEPs higher than 40Hz are rarely rep

Several advanced signal processing techniques have been proposed to analyze non-linear and nonstationary signals [11-16]. Rejer and Cieszyński (2019) [17] adopted independent component analysis (ICA) for extracting SSVEPs, induced by LEDs flickering within 13~17Hz range, in a four-channel EEG system. Wang et al. (2004) applied ICA to a thirteen-channel EEG system, and separated the measured signals into signal group and noise group. [18]. Lin et al. (2007) organized the measured multi-channel EEG and the visual stimulation signals in to two sets of variables, and they developed canonical correlation analysis (CCA) to take both fundamental frequency and harmonic frequency components into consideration [19]. Zhang et al. (2014) constructed a multiset reference signals from observation of a certain quantity of samples. The multiset canonical correlation analysis (MCCA) provides a set of better reference signals for SSVEP identification [20].

One noteworthy signal decomposition method is the Hilbert-Huang transform (HHT). The HHT is a data-driven approach which utilizes empirical mode decomposition (EMD) through a sifting process to decompose the measured signal into a series of intrinsic mode functions (IMF). [21] In this study, we intend to implement a high-frequency SSVEP-based BCI using iterative filtering (IF) - EMD (IF-EMD) [22]. The IF-EMD was proposed by Lin et al. (2009) who found the mode mixing problem actually originates from inadequately tracing the mean of the upper and lower envelopes. The IF-EMD iteratively applies local filtering to trace the changes of baseline fluctuations in the measured signal. In this paper, we have applied the IF-EMD to extract SSVEP induced from 47Hz, 50Hz and 53Hz visual stimulators. A matched filter detector (MFD) was designed to identify the gazed target, and the MFD outputs were used to control our BCI cursor system.

II. Materials and methods

Ten subjects (seven males and three females; aged 26.3±4.01 years-old) were recruited in this study. All subjects had corrected

This research is supported by the Ministry of Science and Technology under Grant Number: 108-2634-F-008 -003 through Pervasive Artificial Intelligence Research (PAIR) Labs, Taiwan. This study was also funded by the National Central University, Ministry of Science and Technology 106-2221-E-008 -001 -MY3, 106-2221-E-008 -003 -MY3, 106 -2911-I-008-503, 106-2221-E-075B-001), Taipei Medical University Project (TMU102-AE1-B09), NCU-Landseed Hospital project, Taoyuan Hospital Intramural project (TYGH104048, TYGH103061).

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Snellen visual acuity of 6/6 or better, with no history of clinical visual disease. Subjects sat comfortably in an armchair and were requested to participate in this study. All subjects were instructed to move the cursor to touch the three targets following the order of left target -> right target -> top target. The cursor movements were controlled by requesting subjects to gaze at the 47Hz, 50Hz and 53Hz LEDs in order to generate commands for leftward, rightward and upward movements, respectively. For each target, subjects had to generate at least three valid commands in the correct direction to make the cursor touch the target. After one target had been correctly touched, the cursor was moved back to the center of the screen. All subjects gave informed consent, and the study was approved by the Ethics Committee of Institutional Review Board, Tao-Yuan General Hospital, Taiwan.

In this study, only EEG signals measured at Oz position, with a reference electrode placed at right mastoid and a ground electrode placed at forehead, were used to operate our BCI cursor system. EEG signals were sampled at 1 kHz with 24-bits resolution, pre-filtered within 42Hz ~ 58Hz with 60Hz notch filter (3rd-order Butterworth filter), subjected to the subsequent IF-EMD processing. The flicker timing and signal analyses were controlled by a PC (Intel(R) Core(TM) i7-2600 CPU @3.4 GHz 3.4 GHz, 32.0 GB RAM). The system architecture of the proposed IF-EMD BCI system is shown in Fig. 1.

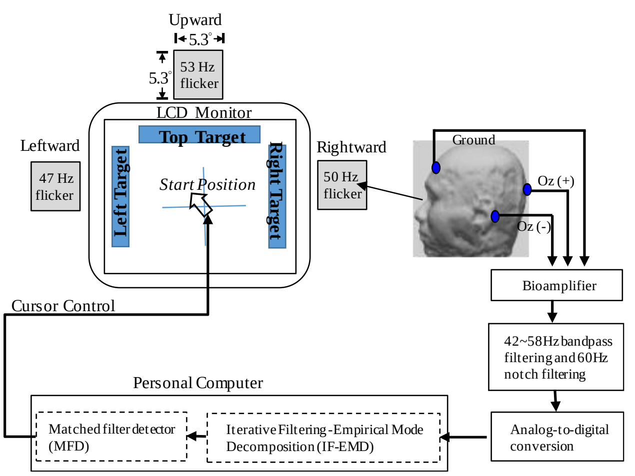

Figure 1. Architecture of the proposed IF-EMD SSVEP-based BCI system..

According to Lin et al. (2009) [22], the IF-EMD is proposed as an alternative algorithm for traditional EMD. Instead of iteratively subtracting the mean of spline fitted envelopes [24], the IF-EMD iteratively subtracts the trend of signal drifts in the inner loop of sifting process by applying a local filtering mask, in which the mask length is adaptively determined according to maximum frequency contained in the signal.

The pre-filtered EEG signals (42Hz~58Hz, 5th-order Butterworth IIR filter) were segmented into one-second epochs. The IF- EMD was applied to decompose each EEG epoch into IMFs.

For an EEG epoch $x(t)$ with L (L=2000) sampled points, the IF-EMD sifting process contains the following steps:

(1) Set $h^{(k)}(t) = x(t)$ and j,k=1 in the initial step;

(2) Identify all the local extrema in $h^{(k)}(t)$, including local maxima and local minima;

(3) Determine mask length, l_{mask}, by $l_{mask} = \alpha L / P$, where L is the EEG epoch length, P is the point number of local extrema in the EEG epoch with length L, and α is the scaling factor, set as 2 in this study.

(4) Calculate local mean curve by $m(t) = h^{(k)}(t) * w(t)$, in which $m(t)$ is the local mean curve, * is the circular convolution operator, and $w(t)$ is chosen as the double averaging filter in our study, with its values $w(t)=1/(t+1)^2$ and $-l_{mask} \le t \le. l_{mask}$;

(5) Calculate the pre-IMF, $h^{(k+1)}(t)$, by subtracting the local mean, $m(t)$, from $h^{(k)}(t)$, *i.e.*, $h^{(k+1)}(t) = h^{(k)}(t) - m(t)$, and set k=k+1;

(6) Repeat steps (2) to (5) until the difference between two continuing pre-IMFs, $SD^{(k)}$, reaches a user-defined stoppage criterion, ε, i.e.,

$$SD^{(k)} = \frac{\left\| h^{(k+1)}(t) - h^{(k)}(t) \right\|^2}{\left\| h^{(k)}(t) \right\|^2} < \varepsilon ,$$

where || . || denotes the Euclidean distance;

(7) Set $IMF_j(t) = h^{(k)}(t)$ as jth IMF;

(8) Calculate $r(t) = x(t) - \sum_{i=1}^{j} IMF_i(t)$, and set j=j+1 and k=1;

(9) Replace $x(t)$ in step (1) with $r(t)$ and repeat steps from (1) to (9) (sifting process), to find all IMFs;

(10) Stop the sifting process when the residue function $r(t)$ becomes a monotonic function that cannot extract any more IMFs.

(11) Calculate the Fourier spectrum of each IMF and choose the IMF with its maximal spectral peak at one of the three stimulation frequencies as SSVEP-related IMF.

(12) Summate all chosen SSVEP-related IMFs and use matched filter detector (MFD) to identify the gazed target.

The matched filter detector (MFD) detected user's gazed target by calculating the absolute values of the inner products between $S(t)$ and match filters, $f_m(t) = e^{j2\pi f_m t}$, in which $b_m = |\langle S(t), f_m(t) \rangle| = \left| \int S(t) f_m^*(t) dt \right|$ and $|\cdot|$ is the absolute value operator and $S(t)$ is the IF-EMD reconstructed SSVEP signal. The identification of the gazed target was achieved by finding the i^{th} visual stimulus which contributed maximum amplitude among all b_m, *i.e.*, $i = \arg\{\max_m b_m\}$, and the b_i was denoted as $b_{\max}$.

The gazed targets were detected every one second using MFD, and only those epochs with $b_{\max}$ exceeding a pre-defined threshold (see below) were recognized as significant epoch to produce a valid control command.

III. Results

Figure 2 shows the b_m (m=1,2,3), the absolute values of inner products from MFD, when subject II (Fig. 2a) and subject III (Fig. 2b) were executing the cursor movement task. In Fig. 2, the b_m values of valid commands were marked by orange ellipse, and the vertical axis marks the frequencies of matched filters (the 47Hz, 50Hz, and 53Hz). The gazed target was detected every one second. In the lower panels of Fig. 2a and 2b, the stimulation frequencies corresponding to the detected targets in every one second were shown with bold yellow lines. Each effective execution command required two consecutive valid commands (marked in orange ellipses), so that the execution time for completing the task depended on both the amplitude and the stability of SSVEPs.

The execution results of the ten subjects are listed in Table 1. The execution time, number of valid commands and CTI were 30.0±4.69 sec, 20.6±4.19 commands and 1.50±0.31 sec/min, respectively.

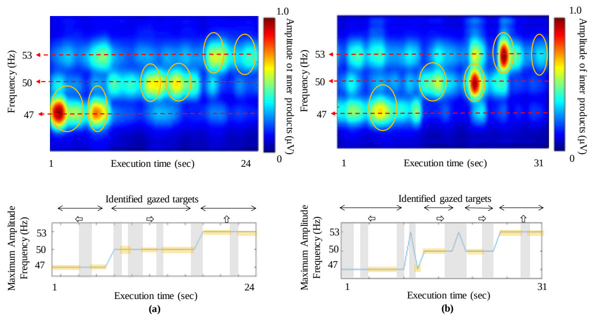

Figure 2. The b_m and detected b_{max} of application task in subject II and subject III are shown in Fig. 2a and Fig. 2b, respectively. Upper panel: the time course of bm; Lower panel: the recognized targets of valid commands.

Table 1. The results of execution time, number of valid commands, and CTI in the application experiment.

Subject index	Execution time (s)	Number of valid detections (commands)	CTI (s/command)
I	24	15	1.60
II	29	19	1.53
III	30	16	1.88
IV	21	18	1.17
V	32	21	1.52
VI	37	18	2.06
VII	33	21	1.57
VIII	29	25	1.16
VIII	31	27	1.15
X	34	26	1.31
Average	30.0±4.69	20.6±4.19	1.50±0.31

IV. Conclusion

It has been reported that the annoying low-frequency flicker (<30Hz) usually causes uncomfortable visual experience and the risk of inducing photoepileptic seizures. Though the use of high-frequency flicker (>40Hz) can solve this problem, however, the low SNR in high-frequency SSVEP usually degrades the accuracy of detection rate. This paper studied the feasibility of using IF-EMD to implement a high-frequency SSVEP-based BCI. The proposed BCI system was able to process EEG data in every one second, and the feasibility of the proposed system had been demonstrated in performing a cursor movement task. Two simulation studies were conducted to illustrate the stability of IF-EMD under noise-contamination and intermittent signal mixture conditions. The salient features of the proposed system include: (1) better visual comfort achieved by high-frequency flicker, (2) avoidance of being interfered with spontaneous brain rhythms, (3) reduction of false-positive error by setting a detection threshold bth from resting state, and (4) the removal of SSVEP-unrelated components by detecting the peak frequency in each IMF. All the ten participants were able to successfully complete the application experiment with acceptable Acc (~90%) and high ITR (~55bits/min). In future studies, we will explore more available SSVEPs in high-frequency range for BCI control.

Acknowledgment

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