Recognition a Multi-pattern in BCI system Based SSVEPs

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Abstract*— Brain-computer Interfaces (BCI) is a significant communication channel, support a handicap people from suffering of disabilities such as amyotrophic lateral sclerosis (ALS). A multi-pattern of visual stimulus based on Steady-state Evoked Potential (SSVEP) is extract a particular stimulation to continuous pragmatic brain response. In this empirical study, which is depend on EEG signals by evoke the brain signals using a multi-patterns stimulation. Exploit the ability of multi-pattern flicker LEDs of visual stimuli based SSVEP foundation to extract the EEG signal features. The human-brain revealed a capability to distinguish between multi-patterns paradigms based on Regular/Irregular stimulus. Analysis of Variance (ANOVA) that utilize as preliminary result to discernment the brain response and demonstrate activity effect in each pattern based SSVEP. Dynamics brain waves are noisy, non-stationary and non-linear; therefore apply Hilbert Transform (HT) to analysis and extract the feature of stimuli responses in two agreements of phases and amplitude on each stimulus pattern. Practically observe a distinction differences between stimuli patterns, which are alert a dynamics wave brain represent different activity states. Differences of multi-patterns effects and effort of the brain activity are significant distinguishable between each other's which is demonstrated in our results.

Keywords*— *Brain-computer interface (BCI);Steady-state Evoked Potential (SSVEP);fast Fourier transform (FFT);Hilbert transform (HT);Phase-tagged trigger (PTT).

I. Introduction

Brain-computer Interfaces (BCI) is novel technology that established a communication channel between human-brain and external world environment. The users will pay His/her attention by gazing on stimulus LED flickers to extract a certain signal which is controlled on systems such as a computer, TV, machine, Etc. The controlling signals are expressed to external world based on brain response activity depend on stimulation of light flickers which evoked Steady-state Evoked Potential (SSVEP) paradigms. SSVEP is an induced electrical potential which recorded from human brain of nervous-system; appear by oscillatory on EEG signals after stimulus effect. The observation of visual instance stimuli rhythmic gives us growing oscillatory on EEG signals with major frequency component on the flicker stimuli within several harmonics [5]. Electroencephalography (EEG) studies are realizing flicker lights stimulation to real world activities by transferring rhythmic response signal. Typically SSVEP based BCI is involved repetitive visual stimuli to procurement brain response. Researches in BCI are identified that SSVEP based BCI needs less training time; and provide a faster response with higher information transfer rate [2-4]. The SSVEP theory constitute an explanation depending on: supplement of occurring changes in all EEG epoch trials based Baseline (BL) that expose a shifting signals and transient latency which are resetting of current response activity. Interpretation signal based on SSVEP responses are noisy affect with eye blink artifacts and other external noise such as power-line interference. Those noisy signals require a special efficient strategy to prevention unwanted signals. Utilize specific digital signal processing (DSP) technique to reduce undesired effects [6]. The favorite analysis and classify depending on a short period of EEG raw data which reducing time recording; although will increase the spectral resolution. As a common approach in BCI system is involved the lower stimuli frequency, which accommodate user behavioral more than higher stimuli frequency [5]. Further a bounding of higher frequencies obvious that limitation in SSVEP based BCI systems [7]. By evoke a multi-pattern of visual stimulus which elicited a multiple SSVEP paradigms; the BCI researchers are investigating which paradigms give a superior resolution and strongest SSVEP response. The multi-stimulus panel content of light emitting diode (LEDs) which are flickered based stimulation paradigms in multi-position, three-color, multi-patterns and varieties of frequencies band. The visual stimulator panel plays an important role, which present flickers with six-pattern type by a single LED. Each LED responding by connecting to the FPGA depth board crossing the computer in order to send individual instance patterns to change in each.

The motivation of this empirical study is provide a practical BCI system which render a multi-pattern stimulus that driven and produce a multi-control command signals. Whereas the number of choices available respect to different phases and amplitude extended by introducing multi-pattern. Taking in account the effect of stimulation parameter relying on patterns stimuli compared to that system. Conclude result using Analysis of Variance (ANOVA) and Hilbert transform (HT) to recognize the different between patterns respect to amplitude and phase shifting.

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II. MATERIALS AND METHODSOF

A. System Configuration

To inspect the different patterns stimuli effect in BCI systems respect to LED flicker. Prepare a low-cost SSVEP based on BCI close-loop system that illustrates in Figure 1 as main block diagram. In this empirical study result evaluating, by setting four LEDs, which are centered distributed between each other with equally distance. A multi-stimulus LED flicker presented by externally stimuli board, which is induced a fixed intervals light as Regular/Irregular flicker paradigms. These flickers are configured with unique frequency at 11.8Hz. The stimulus panel is horizontally fixed on eye level of participants with distance around 80 cm in between. Employed a Cyclone IV EP4CE115F29C7N core connected to personal computer via serial cable, where the Altera depth board full connected to the stimuli LED's panel. Complete hardware design of visual-stimuli board was powered by pure DC power supply of 9V battery source to avoid any A.C. component interference.

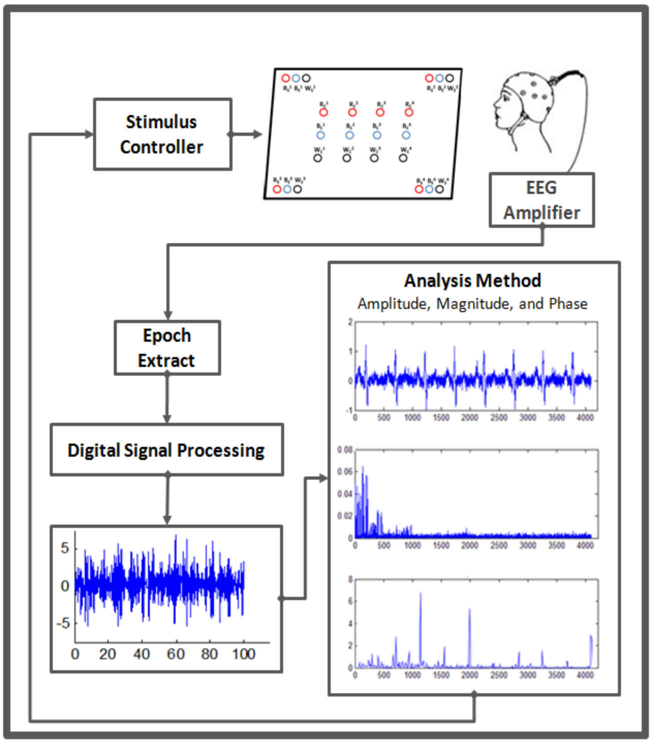

Figure 1: The main block diagram proposed Multi-pattern LED's stimuli as a low-cost SSVEP based BCI, Analysis methods extract feature from EEG-Data base on amplitudes and phases

The experiment is companion to extract the influence of brain responses, which exploits different patterns, based SSVEP paradigms. Assessment flicker frequency is configured with single frequency, since (4 LEDs × 6 patterns) are distributed in surround and centre with distance in between for each row-group. Set all light emitting diodes (LEDs) flickered with main four shift-phases respect to Phase-tagged trigger (PTT) of $(\mathrm{i,e.}, 0^0, 360^0, 720^0, 1080^0)$ respectively according to the setup configuration of pattern. The stimuli are separated into six-different patterns arranged with WHITE LED. The EEG signal was measured by a single electrode placed at O_z position on scalp occipital region.

B. Visual Stimuli

Explore the multi-pattern visual stimulus panel using an LED flicker under fixed frequency respect to different patterns. The amplitude of lumens must large enough to evoke SSVEP response. The different patterns respect to phase is induced in each stimulus which separated into groups, which are covered all experiment setup condition; in order to find out the behavioral and effectuation of brain activity response in all circumstances patterns. The stimuli cycle is divided into five segments of rhymester on LED as onset of (on/off _ LED) of stimulation. Provoke the SSVEP paradigm depending on flickers besides the Phase-shift (PS) for each cycle according to Eq. (1):

$$\theta_i = (i-1).90^{\circ} \quad ; i = 1, 2, \ldots, N \qquad (1)$$

When flickering LED_i is shifted respect to phase angle distributed over full-phase of 360°, and $N = 5$ incremented by 90°.

Taken in account of each LED stimulus flicker that considered pulse trigger at same time of LED flicker event, in each cycle; implicit control delay signal that consider on Eq. (2): Expected phase delay θ_i evaluate by extract t_i to indicate event of LED flicker respect to time domain.

$$t_i = \theta_i / 360^{\circ} \qquad (2)$$

Consider t_i which indicates the time trigger event.

In Table 1, illustrates different patterns, which are consider by Regulars and Irregular paradigms respect to different phases based SSVEP. Generate patterns depending on θ° in each stimulus as functional of flicker LED.

Table 1: Six patterns regular / irregular paradigms with flickering sequence on a single LED into four cycles, which include the different phases

Stimuli LEDs Position	Pattern Numbers	Generate Patterns	Phase Different θ°	Pattern Type
LED_1	1	**1000,0000,0000,0000**	0^0	Regular
LED_1	2	**1000,1000,1000,1000**	0^0 360^0 720^0	Regular
LED_1	3	**1110,1110,1110,1110**	0^0 360^0 720^0	Regular
LED_1	4	**1000,0100,1000,0010**	0^0 450^0 720^0 1260^0	Irregular
LED_1	5	**1000,0100,1000,0100**	0^0 450^0 720^0 1170^0	Irregular
LED_1	6	**1110,0111,1110,0111**	0^0 450^0 720^0 1170^0	Irregular

The patterns numbers (2 and 3) / (5 and 6) are same phases but with a high duty cycle, indeed to discernment the brain activity when increased the duty cycle effects by referring to same stimulus patterns. Nonetheless, in this experiment considered single LED, to evoke and extract SSVEP response. The flicker frequency represented by θ_i as a flicker sequence on four LEDs, in the other hand t_i represent the iteration time request that compacting into Eq. (3):

$$T = 1/f \tag{3}$$

Where, T is flicker cycle duration, and f is the flicker frequency, indeed setting one stimulus frequency at 11.8Hz which is surround by Alpha (α) brain response range of (8-13Hz) [15].

Two additional trigger signals occur in each cycle; first trigger is produced in each LED Pulse-On; and a second trigger is produced with each new cycle sequence to indicate that a new segment is begin. Each stimulus cycle have T period; include T_{on} stand-on-time and T_{off} stand-off-time, as one duty cycle represents on-time of stimulus. Create square wave of onsets as one certain group, within events triggers. Produce four phases of lagging control signal to induce time delay of t_i in each stimulus. These triggers called Phase-tagged (PTT) is assist to extract Data in analysis such as epoch-average process. Typically, we considered a 25% duty cycle light flicking technique, which attains high SSVEP amplitude with comfortable view. However, we induced 75% as high duty cycles in some patterns to distinguish the brain responded.

C. *Signal Analysisi*

This empirical study investigates whether different between patterns respect to flicker LEDs that motive the change of brain activity based SSVEP paradigms. Adopt offline analysis, were accumulated EEG-Data raw into epochs according to the time-shift signals and onsets stimulus in flickering sequence in each pattern groups. The different between phases and amplitudes into brain-wave activity, depend on two analysis methods to distinguish brain response. Firstly; utilize the Analysis of Variance (ANOVA) method to discriminate brain influence respect to different patterns with stimuli frequency at 11.8Hz. As well we consider a Hilbert Transform (HT) as second analysis method; to achieve different phases between patterns according to multi-pattern stimulation.

Extracting epochs in each recode level of EEG raw, which are collected as templates to analyze; as mentioned before utilized Analysis of Variance (ANOVA), to compare a significant hypothesis. ANOVA caliber F-tests is used to examine a pre-specified set of standard effects, (e.g. 'main effects' and 'interactions'), as described in [11]. Several stimuli depending on six patterns are support to find out the change in brain activity corresponding to the SSVEP response. The "Mean-Values" are accumulating from brain responses which represent the influencing of different patterns stimulus. Accumulated templates reveal SSVEP amplitude in each pattern stimulus by extract FFT to detect the maximum spectral power [10]. Comparisons between independent groups utilize ANOVA to determine whether, any of those groups are significantly different from each other. Indeed, the test of null hypothesis H_0 according to alternative hypothesis H_1. Statically all stimulus-tests condition in each pattern are equal without restrict common value. Alternative hypothesis H_1 signify "Pattern means" which are not equal, and hypothesis H_0 signify equal entire patterns group which are significant different according to Eq. (4) and (5) denote by:

$$H_0\colon\ \mu_1 = \mu_2 = \mu_3 \ldots = \mu_k \tag{4}$$

$$H_1\colon\ \mu_1 \neq \mu_2 \neq \mu_3 \ldots \neq \mu_k \tag{5}$$

Since, the groups are individual and different values of Mean Squares, which are observe individually from each patterns respect to the estimate value Eq. (6) [11].

$$SS_{\text{within}} = \sum_{j=1}^{n_i} (Y_{ij} - \overline{Y_i})^2, \quad df_{\text{within}} = n_i - 1 \tag{6}$$

Where df represent "degrees of freedom", according to the definition [11].

Distinguish a null hypothesis, respect to F statistic ratio tend on non-rejection region; assumption that alternative hypothesis is true, lead to neglect null hypothesis. Finally, prepare all epochs from accumulated Data based flickering onsets to obtain SSVEP response respect to hypothesis discriminate.

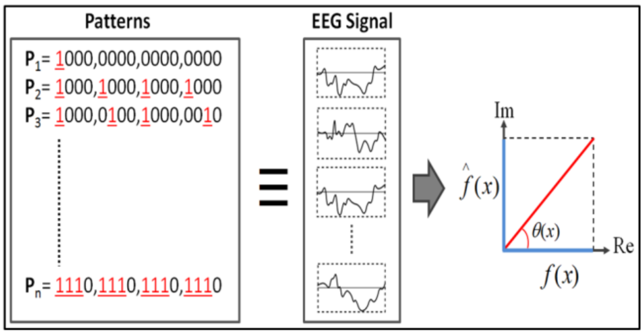

Figure 2: Exactest the patterns feature from EEG signals according to stimulus, subsequent to the Hilbert Transform (HT) of brain activity responded between a different patterns

Subsequently, implemented a Hilbert Transform (HT) to substantiate the brain activity responded between a different patterns. Decomposition EEG signals in HT give a relative state variable for each frequency band. Distinguishing and compare the different in pattern parameters by extracting data according to the brain response, as shown in Figure 2. Fast Fourier transform (FFT) methods give a proximate result when applied to signals [12-13]; FFT and wavelet (WT) transformation are relatively need long executing time. In other word Hilbert Transform (HT) is differ than FFT, where FFT is more transaction with linear operator, since EEG signal is non-stationary signals; HT expressing frequency as a rate of change in phase [12]. Therefore Hilbert Transform (HT) is offered a high temporal resolution and rapid in analytic state variables for frequency based on the phases and amplitudes according to incoming signals. In each state variable is defining on axis in space of dynamic model, that present a finite bulge from infinite brain state space [9]. Ranges of possible observed as values (*Im*) and (*Re*). Incoming brain signals (EEG) depict on $V(t)$[9], which is extracted by applying HT on accumulated templates as complete session of each stimulus patterns. Transformed into series of complex part and a real part, of $v(t)$ and $u(t)$ according to Eq. (7):

$$V(t) = v(t) + u_i(t) \quad (7)$$

Real part of $v(t)$ represent the amplitudes as normal FFT filter [9] and [10], while the imaginary part is $u_i(t)$ depicting a phase difference according to Eq. (8):

$$u_i(t) = \frac{1}{\pi}\ PV \int_{-\infty}^{\infty} V_i(\acute{t})\ /\ (t - \acute{t})\ d\acute{t} \quad (8)$$

Where PV signifies Cauchy Principal Value [9].

The independent variable will not effect on result of transformation, so that the output of $u_i(t)$ is dependent on input function in time domain. Therefore perform inverse Fourier Transform to get desired result. Consequently, the original functions of $V(t)$ represents the harmonic conjugate respect to Hilbert transform (HT) [8]. The arctangent angles of bulge vector depict the state variable of phase in each pattern according to (9):

$$P(t) = \tan^{-1}(u_i(t)\ /\ v(t)) \quad (9)$$

In order to track $P(t)$ over arbitrarily long time intervals, the disjoint phase sequences are straightened by adding π to $\tan^{-1}$ function.

III. Result

Performed this empirical study based on EEG signal to exploit the brain responses; utilizing two offline analysis methods to indicate a difference between multi-patterns. Apply pre-processing on accumulates templates in each session with Low-Pass-Filter (LPF) and High-Pass-Filter (HPF) to deduct and remove unwanted signals. Adding to process a computational parameters for each template, were depending on time interval of PTT trigger windows and Baseline (BL). Determine time interval windows by setting Pre-Frame with 250ms.and Post-Frame 500ms. Artifacts of eye blinking are removed by setting a threshold value of 100µV, to reject any artifacts over limit. Since, different subjects respect to our experiment configuration of multiple pattern, recording each session under the same stimulus condition. Average sessions after accumulation as six patterns individually and stored as template. Referring to multi-patterns recognizing based SSVEP paradigms of stimuli, since the configuration of experiment is steady in all sessions.

A statistical inference of null and alternative hypothesis is used to distinguish the difference between patterns. As preliminary results of ANOVA are representing into six mean values of brain signals which are accept (α) band. The scheme in ANOVA result demonstrated different of brain response into six patterns that estimate from flicker. The particular events occur according to the influences of brain response, which is pragmatic different in each stimulus respect to SSVEP paradigms. Figure 3 illustrates result of brain activity only with WHITE LEDs stimulus within a six patterns. A different SSVEP response based multi-pattern with fixed flicker frequency at 11.8Hz. Statistical results contain a significant effect according to equation (5), whereas all mean values are not equal, that lead to different quantity respect to different patterns. In other hand, reject the null hypothesis for a pre-specified level of significance. Consequently, extract P-Value and F-ratio depending on two standards of freedom degrees that clarify in SS, which is (405.07, 213.21, 668.72) respectively. However the probabilities P - Value of all tests were approximately near to zero and less than threshold value of 0.005.

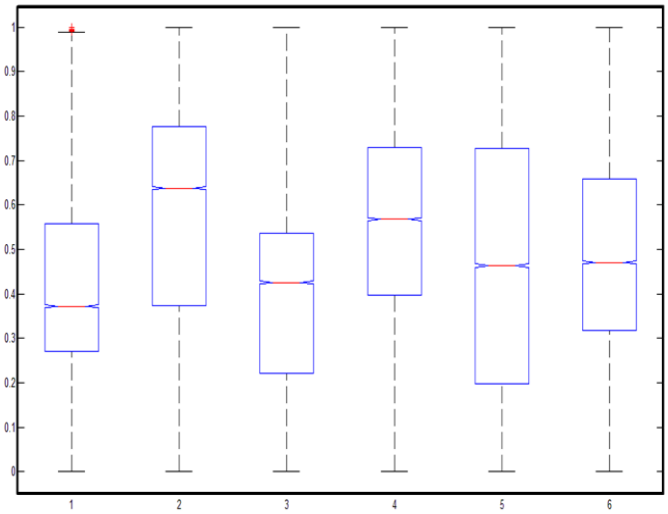

Figure 3: Six patterns regular / irregular paradigms of (1, 2, 3, 4, 5, and 6) correspondingly to Table 1 with flickering sequence of 11.8Hz; on a single LED into four cycles according to experiment configuration setup, which extract the brain response activities by utilizing the Analysis of variance (ANOVA), to indicate the mean values difference in phases of each patterns

Second step of analysis was effort a phase detection using Hilbert Transform (HT), which is a rapid efficient tool to extracting phase. Basically filtering EEG signal via particular band filters, then convert the EEG signal to the dataset. Calculate instantaneous phases of each pattern by accumulated dataset for each pattern as epochs. Applying Hilbert transform (HT) to quantify the rising and falling of dataset waveforms, which exploit all phases (θ).

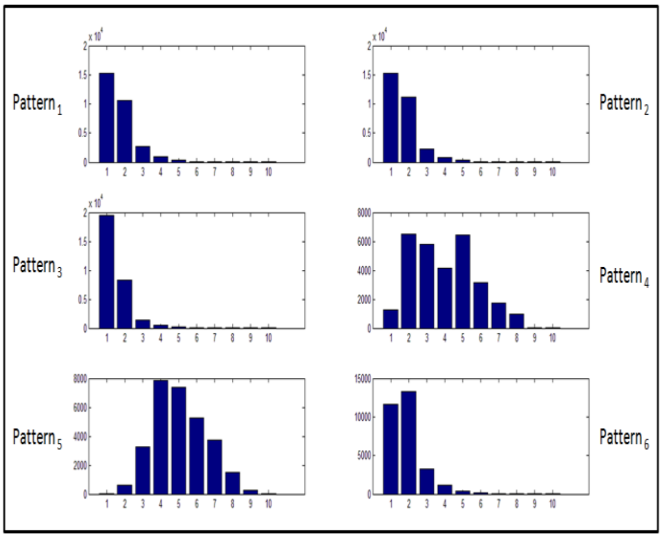

Figure 4: Observing brain response of six patterns respect to regular/irregular paradigms with flickering sequence on a single LED into four cycles based on flicker frequency at 11.8Hz, by utilizing the Hilbert Transform (HT), which extract the phases in each pattern, that discriminate the differences in multi-patterns based on SSVEP

The Dataset has high density of information which contain varying phase degrees array relying a spatial coherence among incoming signals of EEG waveforms. Add a global constant to avoid time-lag correlation in phase θ distribution of multiple frequencies by giving ratio between $\pm\pi$. The EEG features had been extracted at same time that corresponds to associated stimuli flicker phase for every peak of one stimuli cycle. Figure 4, illustrate six different patterns according to Regular/Irregular paradigms stimulus procedure as elucidate in Table 1. According to the experiment setup, represents all phases (θ) accumulating respect to each pattern. Observing brain responses of multi-patterns respect to SSVEP response paradigms by extract the phases in each pattern, which discriminate the differences between patterns.

IV. CONCLUSIONS

This study is successfully demonstrated aspect to inquire an offline analysis of SSVEP based BCI system. The present results indicate that outlined as assessment of a multi-patterns, which are define by visual stimulus depends on SSVEP response paradigms.

Structured of the Regular and Irregular stimuli flicker and handmade stimulation panel to evoke brain signals; His/her gaze on flickering at different patterns stimuli according to experiment setup configuration. Through the experiment preferred different flicker paradigms to observe the brain response.

In fact we conclude two methods as offline analysis, firstly; Analysis of variance (ANOVA), which realized the behavioral brain responses respect to a multi-pattern stimulus by extracting the FFT to detect the maximum spectral power. Second; the Hilbert transform (HT) to recognize the different patterns respect to phase shifting signal of brain-waves.

Summary for the pattern recognition study of multi-patterns sequence, we found a different brain activities response between six patterns respect to Regular / Irregular stimulus paradigm. A multi-patterns paradigms present numbers of available choices reached to 2^{16}, depending on each pattern slot, which are prepared a different phase in each pattern. Consequently, increased number of control signals commands based SSVEP paradigms, which are the stability and reliability to distinguishing with relying detecting in phase of patterns raw. Compare the results of ANOVA with phase detection of HT to discriminate patterns, we found they have varieties of brain responding activities levels in each pattern. This lead to create new applications based BCI systems by increasing control commands depending on numbers of patterns. Although, attractive with external environments and making objective comparisons between BCI systems. A multi-pattern paradigm will introduce a different protocol for different applications. Finally; this gave us the advantages to exploit this method as a future applications work in SSVEP based BCI system fields since it is adapted, optimized, and configured with support as real time experiments.

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