Estimation of SSVEP-based EEG Complexity using Inherent Fuzzy Entropy

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***Abstract*—This study considers the dynamic changes of complexity feature by fuzzy entropy measurement and repetitive steady-state visual evoked potential (SSVEP) stimulus. Since brain complexity reflects the ability of the brain to adapt to changing situations, we suppose such adaptation is closely related to the habituation, a form of learning in which an organism decreases or increases to respond to a stimulus after repeated presentations. By a wearable electroencephalograph (EEG) with Fpz and Oz electrodes, EEG signals were collected from 20 healthy participants in one resting and five-times 15 Hz SSVEP sessions. Moreover, EEG complexity feature was extracted by multi-scale Inherent Fuzzy Entropy (IFE) algorithm, and relative complexity (RC) was defined the difference between resting and SSVEP. Our results showed the enhanced frontal and occipital RC was accompanied with increased stimulus times. Compared with the 1st SSVEP session, the RC was significantly higher than the 5th SSVEP session at frontal and occipital areas ($p < 0.05$). It suggested that brain has adapted to changes in stimulus influence, and possibly connected with the habituation. In conclusion, effective evaluation of IFE has a potential EEG signature of complexity in the SSEVP-based experiment.**

Keywords— EEG, SSVEP, Complexity, Inherent Fuzzy Entropy

I. Introduction

The electroencephalogram (EEG), due to its broad availability and cost-effectiveness, is considered as a non-invasive mode to assess dynamic changes in brain electrical activity. With the rapid development of dry sensors and wearable devices [1-3], wireless wearable EEG with dry sensors leads to a reduction of required preparatory work for long-term monitoring. Moreover, it is possible to implement EEG-based models from laboratories to real-world applications.

Brain complexity reflects the ability of the brain to adapt to changing situations [4]. In recent times, time series of dynamic complexity have been investigated via several measures, e.g., approximate entropy [5] and sample entropy [6, 7]. To further address stable complexity, the concept of fuzzy sets [8] was proposed to investigate the fuzzy entropy measure [9, 10], relying on fuzzy membership functions, overcomes the weakness of approximate entropy [5] and sample entropy [6, 7]. However, physiological signals, such as EEG, usually exhibit complex fluctuations, uncertain disturbance and high levels of nonlinearity and nonstationarity, they often contain lots of dynamics information [12]. Additionally, we had recently applied the fuzzy entropy structure to develop a more accurate complexity, called Inherent Fuzzy Entropy (IFE) algorithm [11], which performed an improved evaluation of EEG complexity by eliminating trend oscillations in EEG signals.

Steady-state visual evoked potentials (SSVEPs) could trigger response to 3.5-100 Hz stimulus and reflects on the visual cortex [12]. The SSVEP-based experiment includes a display with target regions and flickering frequencies. By single periodic visual inputs, the evoked responses generated by that stimulus has an intermittent time course [13]. The previous studies described that SSVEPs motivated in EEG signals over occipital areas of the cortex are natural responses to flickering stimuli. The stimulus dynamics could extend to habituation [14, 15], attention, and brain-computer interface studies [16, 17]. Traditionally, habituation has been defined as "a response decrement as a result of repeated stimulations" based on the behavioural characteristics, which response to multifactorial events [14, 15]. According to the "dual-process" theory, motioned in a landmark habituation study [14], it proposed the "dual-process" conducted two opposing processes (depression vs. facilitation). The facilitation occurs in stimulus session in the beginning and performs the transient enhance of response amplitude at the initial condition, whereas habituation occurs the whole stimulus session and explains the delayed response decrease. Recently, the definition of habituation has been revised at a workshop [18], which offered a re-evaluation of the characteristics of habituation. It expands habituation description, relates to long-term habituation, and serves as a useful primer for stimulus repetition studies.

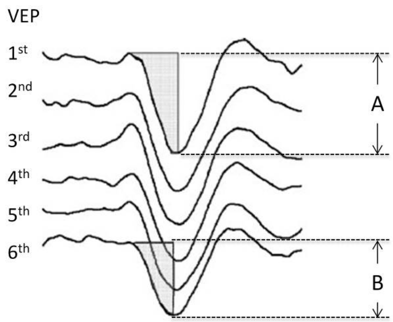

Fig. 1 VEPs habituation in a healthy subject. A: 1st VEP descend range; B: 6th VEP descend range.

As shown in Fig. 1, the potential characteristics of habituation performed the reduced amplitude (descend range: B<A) with repetitive visual evoked potentials (VEPs) [19]. Importantly, habituation was considered as the most useful phenomenon for studying the neuronal substrates of behaviour, the mechanisms of learning processes, or the treatment of information in the central nervous system [18]. Despite the fact that the characteristics of habituation phenomenon either by behavior (e.g., questionnaires) or amplitude-frequency analysis (e.g., EEG power) is well-known properties, the knowledge of their complexity characteristics is still limited. Exploring brain complexity might help us understanding more on human being's habituation.

This paper proposed an SSVEP-based experiment to investigate brain complexity characteristics by Inherent Fuzzy Entropy measurement. The hypothesis is that EEG complexity performs the significant changes after repetitive SSVEP stimulus, as the brain has adapted to changes in stimulus influence, possibly closely related to habituation. It is hoped that our study provides a novel EEG bio-signature to describe complexity characteristics in the SSVEP-based experiment.

II. Complexity Analysis

Complexity has been posited as a potentially powerful explanation and applications for a broad range of emergent phenomena in human neuroscience and computer science. From a systemic perspective, complexity reflects the ability of the brain to adapt to constantly changing situations, and the complexity theories implicated varies nervous and mental diseases [20]. Brain complexity, popularly using the multi-scale inherent fuzzy entropy (IFE)-based algorithm [11], may provide a useful temporal bio-signature for evaluating habituation characteristics. Of note, the complexity algorithm based on IFE with four steps was shown as follows.

Step 1. Normalize the EEG signals $y(t)$.

$$y(t)^* = \frac{y(t) - mean(y(t))}{standard\ deviation} \tag{1}$$

Step 2. Multi-scale IFE measurement with 1-20 scales [11].

Step2.1 A "coarse-graining" process is applied to the time series. For a given time series, multiple coarse-grained time series are constructed by averaging the data points within non-overlapping windows of increasing length τ. Each element of the coarse-grained time series, $y_j^{(\tau)}$, is calculated according to the equation:

$$y_j^{(\tau)} = 1/\tau \sum_{i=(j-1)\tau+1}^{j\tau} x_i \tag{2}$$

where τ represents the scale factor and $1 \le j \le N/\tau$. The length of each coarse-grained time series is N/τ. For scale 1, the coarse-grained time series is simply the original time series.

Step2.2 Inherent FuzzyEn [11] is calculated for each coarse-grained time series, and then plotted as a function of the scale factor. Inherent FuzzyEn is a "regularity statistic." It "looks for patterns" in a time series and quantifies its degree of predictability or regularity.

The FuzzyEn considering the N sample time series $\{u(i) : 1 \le i \le N\}$, given m, n, and r, and a vector set sequences $\{X_i^m, i = 1, \dots N - m + 1\}$ is calculated as follows:

$$X_i^m = \{u(i), u(i+1), \dots, u(i+m-1) - u0(i)\} \tag{3}$$

Where $1 \le i \le N-m+1$, and X presents m consecutive u values, commencing with the i point and generalized by removing a baseline:

$$u0(i) = m^{-1} \sum_{j=0}^{m-1} \mathrm{u}(\mathrm{i}+\mathrm{j}) \tag{4}$$

Given a vector X, define the similarity degree D_{ij}^m between X_i^m and X_j^m by a fuzzy membership function:

$$D_{ij}^m = fm\,(d_{ij}^m, n, r) \tag{5}$$

Where fuzzy membership function is an exponential function:

$$fm\left(d_{ij}^m, n, r\right) = exp\left(-\frac{\left(d_{ij}^m\right)^n}{r}\right) \tag{6}$$

and d_{ij}^m is the maximum absolute difference of the corresponding scalar components of X_i^m and X_j^m.

Construct the function φ^m as

$$\varphi^m(n, r) = (N - m)^{-1} \sum_{i=1}^{N-m} ((N - m - 1)^{-1} \sum_{j=1, j\neq i}^{N-m} D_{ij}^m) \tag{7}$$

Similarly, for $m + 1$, repeat the above steps:

$$\varphi^{m+1}(n, r) = (N - m)^{-1} \sum_{i=1}^{N-m} ((N - m - 1)^{-1} \sum_{j=1, j\neq i}^{N-m} D_{ij}^{m+1}) \tag{8}$$

If the length of datasets N is finite, the parameter $FuzzyEn(m, n, r, N)$ of the sequence $\{u(i): 1 \le i \le N\}$ is defined as the negative natural logarithm of the deviation of φ^m from φ^{m+1} :

$$FuzzyEn(m, n, r, N) = \ln \varphi^m(n, r) - \ln \varphi^{m+1}(n, r) \tag{9}$$

For the parameter choices of FuzzyEn, the first parameter m, is the length of sequences to be compared. The other two parameters r and n determine the width and the gradient of the boundary of the fuzzy membership function, respectively.

Step 3. Calculating he individual complexity $\boldsymbol{C}_{baseline}$ and $\boldsymbol{C}_{SSVEP}$ were in the resting and SSVEP sessions, respectively.

Step 4. Calculate relative complexity $\boldsymbol{RC}$ in individual, where i is the stimulus times.

$$\boldsymbol{RC}_i \quad = \boldsymbol{C}_{SSVEP(i)} - \boldsymbol{C}_{baseline} \tag{10}$$

III. Experiment

A. Wearable EEG

EEG signals were recorded at a sampling rate of 500 Hz by a "Mindo" EEG device, which is a wearable EEG device with dry sensors developed by our research center [1]. The new dry-contact EEG device with spring-loaded sensors [21] was proposed for possible operations, and each probe was designed to include a probe head, plunger, spring, and barrel. The probes were inserted into a flexible substrate using a one-time forming process via an established injection molding procedure. Using dry sensors are more convenient than conventional wet electrodes in measuring EEG signals avoiding any conductive gel usage or skin preparation. Besides, two dry-contact electrodes (Fpz and Oz) were placed according to the International 10–20 system. A1 and A2 were used as the reference channels.

B. Experimental Paradigm

This experiment was performed at a static and lightless room in National Chiao Tung University, Taiwan. To avoid light source interference, we turned off the fluorescent lamps during the whole experimental procedure. Moreover, the repetitive visual stimulus was presented on display using alternating graphical patterns.

SSVEP was considered as the repetitive visual stimulus in this study. The experiment consisted two parts in which one was the resting session, and the other was the SSVEP sessions (Fig. 2). Furthermore, a wearable EEG device fits on the head of the participant to record EEG in resting and SSVEP sessions. The resting session contained two epochs for 1 min of open eyes and three epochs for 1 min of close eyes, and the SSVEP sessions involved in 5-times 15Hz closed-eyes SSVEP with 10s resting intervals.

C. Participants

Participants were recruited from students and staffs from National Chiao Tung University, and they did not have past or family histories of disease during the past year. All subjects had normal vision and no acute or chronic diseases. The Institutional Review Board of the Taipei Veterans General Hospital approved the study project. Informed consent was obtained from all subjects before their entering this study.

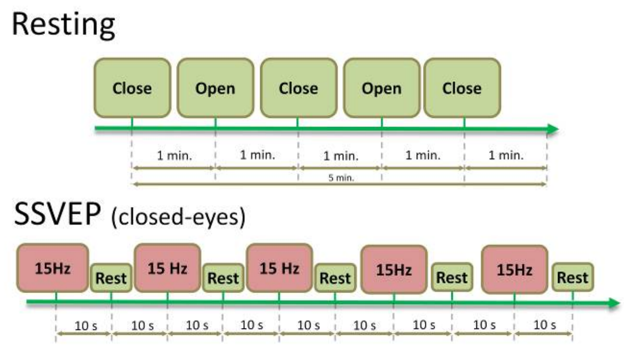

Fig. 2 Experimental paradigm: Resting and SSVEP sessions.

D. EEG Pre-processing

The original EEG was reviewed by an experienced EEG specialist. Segments contaminated with non-physiological artifacts, including movement artifacts, electrode pop, sweating artifacts, and 60 Hz noises, were marked and discarded. All of EEG data were analyzed by Matlab software (The Mathworks, Inc.). EEGLAB is an open source Matlab toolbox for electrophysiological signal processing (http://sccn.ucsd.edu/eeglab/), which consists of artifact signal rejection, time/frequency analysis, and several visualized models for EEG signal.

The raw EEG signals were filtered through 1 Hz high-pass and 30 Hz low-pass FIR filters. EEG activities were sampled at 500 Hz as the recording sampling rate. The three 1-min closed-eye resting and 5-times SSVEP trials were extracted from Fpz and Oz channels, respectively. The epoch EEG data were then inspected to the MSE-based complexity analysis (Section II).

E. Statistical Analysis

For the independence of different relative complexity (RC) variables after repetitive SSVEP stimulus (e.g., 1st SSVEP vs. 5th SSVEP) in the individual participant, the paired t-test was calculated to evaluate the RC trends and temporal characteristics of habituation. The statistical significance was set at $p < 0.05$.

IV. Results

A. Demographic Characteristics

Twenty participants (2 men and 18 women, mean age 36.2 ± 8.7 years) were recruited as healthy subjects with no disease history. All involved participants have the normal or corrected-to-normal vision with no vision impairment, and 5 participants were excluded as they had diseases in personal or family history. Furthermore, each participant was confirmed to have no uncomfortable experience with flashing lights.

B. Relative Complexity (RC)

Figure 3 displays the relative complexity (RC) profiles in response to 15 Hz repetitive (5-times) stimulus at Fpz and Oz electrodes. As shown in Fig. 3A, enhanced EEG RC was accompanied with increased stimulus times in most long scales (scale range: 7-19) at the frontal area. Similarly, for occipital RC changes (Fig. 3B), EEG RC increased accompanied with incremental stimulus times in most long scales.

Especially, comparing EEG RC changes between the first (1^{st}) and last (5^{th}) SSVEP sessions, it indicated that EEG RC performed significant ($p < 0.05$) enhancement after 5-times SSVEP stimulus in the majority of long scales. Apparently, consistent with the above-observed results, long scales were more efficient to distinguish RC changes than that in the short scales.

C. *Characteristics of Complexity*

From a systemic perspective, complexity reflects the ability of the brain to adapt to constantly changing situations [20]. Addressed the performances of EEG RC in this study, it suggested brain has adapted to changes in stimulus influence. Moreover, the potential observation from temporal domain confirmed the habituation phenomenon exists in the study. Therefore, the enhanced EEG complexity might perform the characteristics of habituation.

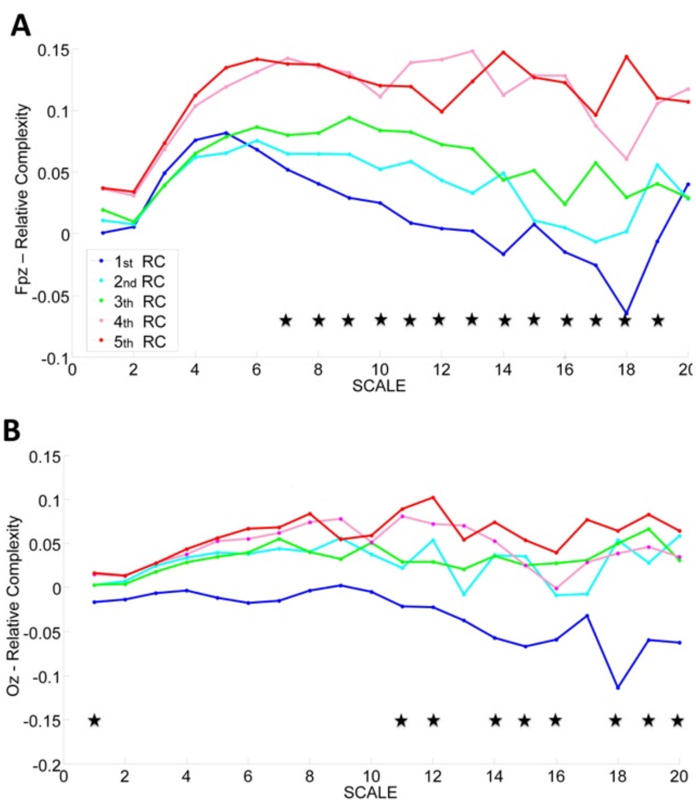

Fig. 3 The performances of EEG relative complexity (RC) in Fpz (A) and Oz (B) electrodes. For denotation, the blue, cyan, green, peach, and red lines are the mean EEG relative complexity from 1st to 5th SSVEP, respectively. The asterisk denotes the significant difference of relative complexity between 1st and 5th SSVEP.

V. Discussion

Despite sufficient progress of habituation studies achieved in recent years, the topic of complexity characteristics in SSVEP studies is still limited. Our study presented the individual changes of EEG RC in repetitive SSVEP stimulus via a wearable EEG device. The experiment results indicate that EEG RC significantly increases after the visual stimulus. These findings demonstrate the enhanced RC is closely connected with habituation, as brain complexity reflects the ability of the brain to adapt to changing situations. Seemingly, complexity features by IFE measurement with the wearable EEG, is potential for cognitive control, disease prevention, and stimulus studies, etc. It has a potential novel bio-signature for real-world applications.

Interestingly, it should be noted that the increased EEG RC can be observed the frontal area. It suggested the visual stimulus not only influenced in the occipital area, but also in the frontal area. Moreover, it seems exists the particular connection between these two curial brain areas on complexity or habituation. Additionally, temporal characteristics of habituation possibly responses to changes of EEG RC after repetitive stimulus with a particular frequency. We will apply the connectivity analysis to investigate the relationship in the further work.

VI. Conclusion

This study is a large-scale collect physiological signal to investigate the temporal characteristics of complexity by Inherent Fuzzy Entropy measurement under repetitive SSVEP and wearable EEG basis. We presented a robust evidence that EEG relative complexity performed aggressive trend after repetitive SSVEP sessions. As brain complexity reflects the ability of the brain to adapt to changing situations, it implied the enhanced RC is highly connected with characteristics of habituation. In summary, it shows a promising wearable EEG-based complexity model with Inherent Fuzzy Entropy algorithm to apply in future brain-computer interfaces.

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