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Smart home has been widely used to improve the living quality of people. Recently, the brain-computer interface (BCI) contributes greatly to the smart home system. We design a BCI-based smart home system, in which the event-related potentials (ERP) are induced by the image interface based on the oddball paradigm. Then, we investigate the influence of mental fatigue on the ERP classification by the Fisher linear discriminant analysis. The results indicate that the classification accuracy of ERP decreases as the brain evolves from the normal stage to the mental fatigue stage. In order to probe into the difference of the brain, cognitive process between mental fatigue and normal states, we construct multivariate weighted recurrence networks and analyze the variation of the weighted clustering coefficient and weighted global efficiency corresponding to these two brain states. The findings suggest that these two network metrics allow distinguishing normal and mental fatigue states and yield novel insights into the brain fatigue behavior resulting from a long use of the ERP-based smart home system. These properties render the multivariate recurrence network, particularly useful for analyzing electroencephalographic recordings from the ERP-based smart home system. Published by AIP Publishing. https://doi.org/10.1063/1.5018824

The brain-computer interface (BCI) enables users to interact with the environment without relying on neural pathways and muscles. We design an event-related potentials (ERP)-based smart home system, in which the ERP are induced by the image interface based on the oddball paradigm. As an unavoidable problem, the mental fatigue state occurs after a long use of the ERP-based smart home system. In this regard, characterizing brain fatigue behavior constitutes a problem of significant importance. The multivariate weighted recurrence network has established itself as a powerful tool for analyzing multivariate time series. In this paper, we first investigate the influence of mental fatigue on the ERP classification accuracy. Then we infer and analyze the multivariate weighted recurrence networks from electroencephalographic (EEG) recordings. The results suggest that our method allows effective characterizing of the brain fatigue behavior and representing distinct brain states of normal and mental fatigue. Due to the generality of the multivariate weighted recurrence network, we expect it to be useful for broader applications in BCI systems.

I. INTRODUCTION

Smart home undoubtedly makes our lives more convenient than ever, 12 which is controlled according to intentions of users or automated commands. In recent years, BCI has attracted much attention from the design of smart home systems, since it enables one to construct a bridge between the human brain and smart environment for communication and control. Electroencephalography (EEG) is one of the noninvasive techniques for acquiring brain signals, which has been universally used in BCI. Common ways to induce EEG include event-related potentials (ERP), steady state visual evoked potential (SSVEP), and motor imagery (MI). In particular, ERP, induced by lower frequency stimuli, is more comfortable for subjects than SSVEP. What is more, acquiring high-quality ERP needs less training than acquiring MI. 3 The signals acquired from ERP-based mind-control systems include a N200 potential component (a negative deflection occurring at 180–325 ms post-stimulus) 4 and a P300 potential component (a positive deflection occurring at 250–800 ms post-stimulus). 5 The ERP-based BCI system is competent in the task of controlling smart home. N200 and P300 potentials have been applied in many areas, e.g., the control of smart home, 6 the Internet browser, 7 robots, 8 wheelchair, 9 etc. The ERP-based smart home system has attracted a great deal of attention on account of its significant importance. Nataliya et al. 10 realized the interaction between the health or disabled subjects and the smart-home, including TV, toggle-light, water kettle, and shutters. Holzner et al. 11 used P300 to control the BCI-based virtual smart home system for the subjects, in which they can control TV, phone, and video camera intelligently. Achieving a high classification accuracy represents one of the most significant issues in the N200-based or P300-based mind control systems. Nevertheless, after a long use of the ERP-based BCI system, subjects may get fatigue easily due to the flickering visual stimulus in the repetitive cognitive task, and the classification accuracy decreases consequently. Fatigue is a functional state between normal and drowsy states, 12 and it is caused by physical activity or mental activity continuously. 13 Characterizing the fatigue behavior underlying the ERP-based smart home system is a challenging problem of significant importance.
In recent years, complex network theory\textsuperscript{14–24} has contributed significantly to our understanding of complex systems. In particular, complex network analysis of time series elicits a great deal of interest from different research fields.\textsuperscript{25–35} The recurrence network,\textsuperscript{36–42} one of the particularly useful networks, has been applied extensively in characterizing the dynamical property of complex systems. The recurrence network is derived from the recurrence plot (RP) and recurrence quantification analysis.\textsuperscript{43–50} More recently, the multivariate weighted recurrence network\textsuperscript{24} has been proposed to characterize complicated dynamical behavior from multivariate time series. For more details, see Ref.\textsuperscript{51}. Bridging recurrence network and ERP analysis can be an appealing approach for investigating the brain fatigue behavior, which has a broad application in the BCI-based smart home system.

In this paper, we design an ERP-based smart home system, which allows controlling TV, computer, curtain, lamp, water heater, and air-conditioner. We also carry out an experiment to acquire ERP from subjects under normal and mental fatigue states. We use Fisher linear discriminant analysis (FLDA) to probe the influence of fatigue on the ERP classification accuracy. We find that the FLDA performs well in the ERP classification and its average classification accuracy for the normal stage is 98.14\%, while it decreases to 94.65\% for the mental fatigue stage. Then we infer multivariate weighted recurrence networks from ERP for the subjects under normal and mental fatigue states. Specifically, we deem each channel signal as a node and determine the weighted connections in terms of the derived synchronization matrix. Furthermore, the average weighted clustering coefficient and weighted global efficiency are resorted to describe these brain networks. The results indicate that our method allows characterizing the difference of the brain cognitive process between normal and mental fatigue states.

II. EXPERIMENT SETUP AND SIGNAL PROCESSING

A. Interface of experiment

The experiments are conducted at the Laboratory of Complex Networks and Intelligent Systems at Tianjin University. The experiment is designed based on the classical “oddball” paradigm. The visual stimuli interface contains six image stimuli arranged in a $2 \times 3$ matrix. The interface is shown in Fig. 1(a). The duration of the stimulus onset asynchrony (SOA) is 200 ms; an image stimulus is presented for 160 ms, then shielded by a black square with a white solid circle in the center, as shown in Fig. 1(b). The interval between two stimuli is 40 ms. We apply the single character (SC) method to randomly activate the images one by one. A repetition is defined as a process in which each image is presented once, and eight repetitions compose a trial. In a trial, the subject is asked to gaze at only one specified image (target image). A session consists of six trials, the target image alternates from “stimulus 1” to “stimulus 6”. A sub-experiment contains two sessions, and each subject needs to compete 12 sub-experiments.

B. Subjects and experiment devices

Seven subjects (four females and three males, aged 24–25, right hand dominant) participated in our experiment, and their visual acuities were normal or corrected to normal. They all signed a written informed consent to participate in experiments. During the experiment, the subject sits in a comfortable chair, and the horizontal distance between the subject and the screen is about 70 cm. We use a 40-channel EEG cap manufactured according to “the international 10-20 system” to record EEG signals. The reference channel is arranged at mastoids behind the ears, and the channel AFz is the ground channel. We use the Neuroscan NuAmps amplifier to record the EEG signals, and the sampling frequency is 1000 Hz. All subjects are required to complete a validated questionnaire including 16 questions based on the Chalder Fatigue Scale (CFS) before every sub-experiment. The degree of fatigue is estimated by a 4-point Likert scale (0-3), and the scope of total points is 0-48. High CFS scores suggest high levels of fatigue. We choose datasets with higher CFS scores as the data acquired under fatigue status and datasets with lower CFS scores as data under normal status.

C. Signal preprocessing

We preprocess the origin data with EEGLAB using the following steps. First, we filter the data with bandwidth from 1.0 Hz to 40.0 Hz. And then, we apply the independent component analysis (ICA) method to eliminate artifacts including
eye blinks, eye movement, and muscle activity to obtain 30 channel EEG data without Electrooculogram components.

III. FEATURE EXTRACTION AND ERP CLASSIFICATION

Feature extraction includes six steps: (1) Selecting the data of 100 ms–800 ms post-stimulus as epochs. (2) Eliminating signal drift with the common average reference (CAR) method. (3) Filtering data of each epoch with a Butterworth band pass filter, and the cut-off frequency of the filter is set at 1.0 Hz and 10.0 Hz. (4) The average value of each epoch is subtracted to eliminate the direct component. (5) Data of three epochs induced by the same type of stimulus (non-target or target) are averaged. (6) The averaged data from the selected channels are downsampled from 1000 Hz to 20 Hz and then concatenated into feature vectors.

We use the FLDA\textsuperscript{52} method to distinguish whether the signals are elicited under target image stimulus. The FLDA method allows discovering a direction in which the projection of the same category is tightly clustered while maximizing the distance between two categories. The extracted data derived from the selected channels (including Fz, Cz, T5, P3, Pz, P4, T6, and Oz) are concatenated into feature vectors as the input of the FLDA-based classifier.

The basic idea of the FLDA is as follows: It classifies two classes of data by linearly projecting the training set on the axis that is defined by the difference between the center of mass for both classes, corrected for within-class correlations.

Given class $C_1 (x_1, x_2, \ldots, x_{n_1})$ with $n_1$ samples and class $C_2 (x_1, x_2, \ldots, x_{n_2})$ with $n_2$ samples, the task is to find the linear mapping, $y = \omega^T x$, that maximizes

$$F(w) = \frac{|m_1 - m_2|^2}{\sigma_1^2 + \sigma_2^2},$$

where $m_i$ denotes the mean of class $C_i$ and $\sigma_i$ denotes the variance of class $C_i$. In conclusion, this corresponds to finding the line that provides the maximum separation. The criterion function, $F(w)$, can be rewritten as an explicit function of $w$ as

$$F(w) = \frac{w^T S_B w}{w^T S_W w}.$$

where $S_B$ is the between class scatter matrix and $S_W$ is the within class scatter matrix. The within class scatter matrix $S_W$ is defined as

$$S_W = S_1 + S_2,$$

where $S_1$ and $S_2$ are

$$S_i = \sum_{x \in C_i} (x - m_i)(x - m_i)^T$$

$$m_i = \frac{1}{n_i} \sum_{x \in C_i} x$$

The between class scatter matrix $S_B$ is defined as

$$S_B = (m_1 - m_2)(m_1 - m_2)^T.$$

According to the formulas above, $w$ that maximizes $F(w)$ can then be written as

$$w = S_W^{-1} (m_1 - m_2).$$

For each subject, 140 target epochs and 700 non-target epochs are used in normal and mental fatigue states for the calculation, respectively; we calculate ERP classification accuracy of the FLDA under normal and fatigue states, respectively. In particular, the 10-fold cross validation is employed. We present the results in Fig. 2. We can see that the classification accuracy of different subjects in the state of normal is higher than that in the state of fatigue. Specifically, the average classification accuracies of FLDA in normal and fatigue states are 98.14\% and 94.65\%, respectively. These findings demonstrate that the mental fatigue state can lead to a decrease in ERP classification accuracy. Next, we will probe into the fatigue mechanism in terms of the multivariate weighted recurrence network analysis.

IV. MULTIVARIATE WEIGHTED RECURRENCE NETWORK ANALYSIS OF FATIGUE BEHAVIOUR UNDERLYING ERP-BASED SMART HOME SYSTEM

Our proposed multivariate weighted recurrence network has established itself as a powerful tool for characterizing dynamical behavior from multichannel signals.\textsuperscript{24} In order to capture synchronization, here the joint recurrence plot (JRP)\textsuperscript{53} technique is considered. The construction of the weighted recurrence network can be described as follows: For a multichannel signal $\{x_{k,l}\}_{l=1}^{p}$, $k = 1, 2, \ldots, p$, which contains $p$ sub-signal of equal length $L$, we first perform the phase-space reconstruction by using a suitable dimension $m$ and a proper time delay $\tau$ (determined by false nearest neighbors (FNN)\textsuperscript{54} and C-C\textsuperscript{55} methods, respectively) as follows:

$$\tilde{x}_k(t) = (x_{k,t}, x_{k,t+\tau}, \ldots, x_{k,t+(m-1)\tau}), \quad t = 1, 2, \ldots, N,$$

where $m$ is the number of vector points in the reconstructed phase space trajectory. For any generated phase space trajectories $\tilde{x}_m(i)$ originated from any sub-signal $x_m$, an $N \times N$ recurrence plot (RP) can be achieved:

$$R_{ij}^{\tilde{x}_m}(\varepsilon) = \Theta \left( \varepsilon - \| \tilde{x}_m(i) - \tilde{x}_m(j) \| \right), \quad i = 1, \ldots, N, \quad j = 1, \ldots, N.$$
Thus, for a multi-channel signal \( \{x_{ik}\}_{k=1}^{p}, k = 1, 2, \ldots, p \), containing \( p \) sub-signal, the number of obtained recurrence plots is \( p \). For pair-wise RPs, in order to look for the times when both of them recur simultaneously, we can obtain the joint recurrence plot (JRP) as follows:

\[
JRP_{ij}^{m,n}(e^{\vec{x}_m}, e^{\vec{x}_n}) = R_{ij}^{m}(e^{\vec{x}_m})R_{ij}^{n}(e^{\vec{x}_n}).
\]

Thereafter, we can use the joint recurrence rate (JRR) to quantify the density of recurrence points in each JRP as follows:

\[
JRR(x_m, x_n) = \frac{m}{100} \sum_{p=1}^{100} N_{m,n}.
\]

Then we can characterize the synchronization of pair-wise time series as follows:

\[
S(x_m, x_n) = \frac{JRR(x_m, x_n)}{RR},
\]

where RR represents the recurrence rate of each recurrence plot which is 0.1. Thus, for a multi-channel signal \( \{x_{ik}\}_{k=1}^{p}, k = 1, 2, \ldots, p \), containing \( p \) sub-signal, we can obtain a synchronization matrix \( S(x_m, x_n) \) of the size \( p \times p \). Finally, we can infer a multivariate weighted recurrence network by regarding each sub-signal as a node and deeming the synchronization \( S(x_m, x_n) \) as the weight of the edge connecting node \( m \) and node \( n \).

The generated network is a fully connected network whose inherent topological structure and property are difficult to depict, and the integrals of the network measures over the sparsity range (corresponding to the areas of the network measure curve within the sparsity range) are taken into account. Specifically, the sparsity ranges from 10% to 35% with step 1%, and then we calculate the integrals of the average weighted clustering coefficient and weighted global efficiency. Specifically, the average weighted clustering coefficient \( C_w \) (Ref. 56) can be calculated by

\[
C_w = \frac{\sum_{i\in N} C_w^i}{n},
\]

\[
C_w^i = \frac{\sum_{j,h\in N} w_{ij}w_{jh}w_{hi}^{1/3}}{k_i(k_i-1)},
\]

where \( C_w^i \) is the weighted clustering coefficient of node \( i \) and \( k_i \) is the degree of node \( i \). \( w_{ij}, w_{jh}, \) and \( w_{hi} \) represent the weight between node \( i \) and \( j \), \( i \) and \( h \), and \( j \) and \( h \), respectively, and the weighted global efficiency \( E_w \) (Ref. 56) is defined as

\[
E_w = \frac{\sum_{i\in N} E_w^i}{n},
\]

\[
E_w^i = \frac{\sum_{j,h\in N, j\neq i} (d_{ij}^{-1})}{n-1},
\]

where \( N \) is the set of all nodes in the network and \( n \) is the number of nodes. \( E_w^i \) is the weighted efficiency of node \( i \). \( d_{ij}^{-1} \) is the shortest weighted path length between nodes \( i \) and \( j \).

For each subject, we construct numbers of networks from the normal state and the mental fatigue state, respectively. And then, we calculate the average weighted clustering coefficient and the weighted global efficiency for all generated networks. The \( t \)-test is employed to obtain the \( p \)-values of the network measures between normal and fatigue states. We show the results in Figs. 3 and 4. We can see that, for different subjects, the \( p \)-values are all much smaller than 0.05, indicating the existence of statistical significance. In addition, we find that, for all subjects, both the average weighted clustering coefficient and the weighted global efficiency of the mental fatigue stage are significantly higher than that of the normal stage. An increase in the weighted clustering coefficient suggests that the clustering of synchronization among different brain regions becomes stronger as the brain state changes from normal to mental fatigue. Actually, the clustering coefficient has a connection with the local efficiency of information transfer. Usually, a high clustering of the brain network is associated with low wiring costs. The mental fatigue can lead to an increase of brain regional synchronous activities, which can be reflected by the network clustering coefficient. These also account for why our network measures increase as the brain evolves from the normal stage to the mental fatigue stage. Sengupta et al. have indicated that an increasing trend in the clustering coefficient is indicative of tight coupling between the corresponding electrode regions that increasing in successive stages with an increase in fatigue. These existing results well support our interesting findings in the study of fatigue behavior underlying the ERP-based smart home system. In this regard, our method has a capacity to explore the variety of brain dynamical properties from the normal state to the mental fatigue state.
V. CONCLUSION

Investigating the fatigue behavior generating from a continuous use of ERP is of particular importance for the design of the ERP-based smart home system. We have designed an ERP-based smart home system and carried out experiments to acquire the EEG recordings from different subjects under normal and mental fatigue stages. Then, we use the FLDA to probe the influence of fatigue on the ERP classification accuracy. The results indicate that the average classification accuracy decreases as the brain changes from the normal stage to the mental fatigue stage. Furthermore, we have articulated a novel methodology for inferring the multivariate weighted recurrence network from EEG recordings. We introduce the average weighted clustering coefficient and weighted global efficiency to characterize the derived brain networks. Our results suggest that for all subjects, the two network measures of the mental fatigue stage are larger than that of the normal stage, suggesting that the synchronization among different brain regions becomes stronger as the brain state changes from normal to mental fatigue. Our recurrence network-based method allows effective characterizing of mental fatigue behavior and representing distinct brain states of normal and mental fatigue. A broad application of the recurrence network in the BCI-based smart home system is expected.

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