EEG Analysis of Working Memory Between Sober State and Intoxicated State

XIN DENG, (Member, IEEE), PENGFEI YANG, XIANGWEI LV, KE LIU, AND KAIWEI SUN

Key Laboratory of Data Engineering and Visual Computing, College of Computer Science and Technology, Chongqing University of Posts and Telecommunication, Chongqing 400065, China

Corresponding author: Pengfei Yang (yang_pf@163.com)

This work was supported in part by the Natural Science Foundation of Chongqing under Grant cstc2020jcyj-msxmX0284; in part by the Scientific and Technological Research Program of Chongqing Municipal Education Commission under Grant KJQN202000625; in part by the National Natural Science Foundation of China under Grant 61806033, Grant 61703065, and Grant 62101084; and in part by the Key Industry Core Technology Innovation Project of CQ under Grant cstc2017rzyy-zydyx0012.

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethical Committee of the Chongqing University of Posts and Telecommunications and performed in line with the Declaration of Helsinki, in 1964.

ABSTRACT More and more people are exposed to drinking and in addicted. In recent years, Electroencephalography (EEG) technology has been used to diagnose the effects of alcohol on brain structure and functions. Since the brain contains a variety of different functions, it is difficult to explore the effects of alcohol on a certain cognitive function by single tasks to induce EEG signals. Additionally, alcohol has an effect on the performance of the working memory (WM) which is particularly susceptible to external stimulus and recovering in the short-term. This study investigates the differences of the EEG signals on the WM-load before and after alcohol intake by using the working memory tasks. Ten participants take part in the N-back experiments with taking alcohol. After preprocessing the EEG signals, seven different features are selected to classify the different WM-load levels, and these features are also used to distinguish the states whether in drinking or not. At last, the support vector machine (SVM) is applied for the classification and the accuracies for some subjects can achieve 100% in the time domain. This work not only provides a new way to explore the effects of alcohol on the specific functions of the brain but also indicates that mild alcohol consumption could alter the perception of the brain on working memory load and reduce the WM-load level.

INDEX TERMS Alcohol, working memory, N-back, EEG.

I. INTRODUCTION

The Working Memory (WM) represents a process of maintaining the information in short time and psychologically manipulating information with limited capacity. The process of WM can be divided into three different phases (update, maintenance, and readout) [1]. By studying the WM, we can analyze the brain’s ability to extract and process information. Electroencephalography (EEG), as a technique for measuring electrical activity, can analyze the changes in brain functions and mental activities by neuroelectric signals [2]. Therefore, the researchers record the EEG signals stimulated by repeated events under the WM tasks and averaged the EEG signals to obtain the relatively small changes in neural activities of the brain, which are caused by the specific WM events, named WM event-related potentials (ERPs) [3]–[6].

Some related researches have demonstrated that the P300 is an ERP that is associated with the cognitive functions such as the attention and the WM [7], [8]. Reference [9] has analyzed the correlation of P300 amplitudes and latencies by single trial ERP variability measures and observed an amplitude increase and latency decrease in the P300 component with increasing WM-load. Reference [10] has found the differences of amplitudes by comparing the P300 between different experimental tasks. In parallel, the activation of multiple cerebral cortexes is strongly associated with P300, including prefrontal, frontal, and parietal [11], [12].

The differences in WM-load are a significant part of the WM studies. The N-back paradigm is one of the tasks frequently mentioned in WM, which is used to manipulate the high and low cognitive WM-loads [13]. By utilizing
the subjective assessment based on different task difficulties under the N-back experiments, it has been found that the tasks with the high-load levels are more suitable for assessing WM capacity [14]. Reference [15] use the spatial N-back and arithmetic tasks to explore mental workload assessment, and propose a structure of neural networks for binary classification of low and high mental workload, which achieves an average accuracy of 88.9%.

In daily life, we could face many people to drink and increase drinking subsequently. The individuals’ behaviors are vulnerable to external stimuli such as alcohol intake. No matter how much alcohol intake is, it will affect the changes of EEG [16], [17]. By analyzing the changes in different rhythms, some studies have found that the alcohol has significant effects on EEG. Reference [18] has been investigated the effects on EEG signals of heavily drinking students, and the results show that the EEG has more synchronization in the theta (4-8 Hz) and gamma (30-45 Hz) bands during eyes closed, both with and without a mental-rehearsal task. It has also shown the differences in functional connectivity compared with the light-drinking controls. Reference [19] has found that the binge drinking displayed a lower oscillatory response than the age-matched controls in the delta and theta frequency ranges during Go and NoGo task conditions. From the above, the existing studies are aimed at analyzing EEG differences of habitual alcohol consumption or acute alcohol consumption. However, two problems exist in the above studies. On one hand, the select of research object has been too limiting, on the other hand, the stimulus type of the experimental task is relatively simple and single.

To address the above two problems, we attempt to analysis the EEG differences of healthy subjects, and investigate the effects of alcohol on EEG signals under the WM tasks. We compare the differences between the sobriety and the intoxication under the WM tasks. We use the N-back paradigm to induce the EEG signals, which are recorded by using a non-invasive equipment. Firstly, the reaction time (the duration between stimulus onset and the response of the subjects) and response accuracies (the value of response correctly during the task period) are calculated under different tasks. Secondly, we calculate the P300 latencies and amplitudes which are compared differences under different tasks. Thirdly, the ERS/ERD of power spectrum are analyzed. Finally, we have trained a SVM classifier to classify the different WM-load levels among high-level, meddle-level, and low-level from the time and frequency domain of EEG. And the classifier has also been classified the state of sober or intoxicated based on the features extracted of EEG under the same task. The classification accuracy distribution in different brain regions and in the different features are plotted to facilitate our analysis. To sum up, the present study aims to analyze the impact of intoxication on EEG signals under WM tasks.

The structure of the remainder of this paper is as follows. Materials include participants, experimental procedures, data acquisition, and preprocessing are in Section II. The methodology behind each feature is explained in Section III. Results are presented in Section IV. Section V and VI provide a final discussion and conclusion, respectively.

II. MATERIALS
A. PARTICIPANTS
Ten right-handed students (10 males, mean age: 23.5 years) get paid for participating in the experiments, who recruit from the College of Computer Science and Technology, Chongqing University of Posts and Telecommunications. All of them have the normal auditory acuity and normal or corrected-to-normal vision. None of the participants have a previous history of cognitive impairment, the mental or neurological problems. The results indicate that they have no symptoms of abuse of alcohol and excessive drinking when we piloted questionnaires to all participants. The study is approved by the ethical committee of Chongqing University of Posts and Telecommunications.

B. EXPERIMENTAL PROCEDURES
The experiments are conducted in a comfortable and quiet environment. The behavioral experiments consist of four N-back WM tasks: 1-back, 2-back before drinking, 2-back after drink, and 3-back. The drinking test is only completed under the 2-back task. Participants are seated approximately 50 cm from the screen. A series of numbers (0-9), which are used as stimulus materials, are visually randomly presented in sequence in the middle of the computer screen with a black background. In N-back tasks, participants are asked to decide whether the current stimulus presented is the same as the one presented N trials before. Each task is divided into two sessions with the first part used for training and the second part for recording the EEG signals. Each subject is required to practice at least five times in the training session to ensure that the response accuracies could be achieved a high accuracy of over 70%.

A 500ms blank is presented before stimuli presentation, and each stimulus appears on screen for 500ms followed by a 2000ms fixation point (Fig. 2a). The subjects are required to respond with a button press when the currently presented
X. Deng et al.: EEG Analysis of Working Memory Between Sober State and Intoxicated State

FIGURE 2. Experiment paradigm of N-back. The time series is presented for the N-back in a trial in (a). Each block includes 20 trials in (b). And the different blocks is set for a task based on its difficulties in (c).

letter corresponded to the one presented by N trials earlier. When the letter is same as the one presented N trials before (Target stimulus), participants are asked to press the ‘F’. Vice versa, ‘J’ is pressed (Standard stimulus). Each block includes 20 trials (Fig.2b), and the ratio of target stimulus to the standard stimulus is 3:7 in a block. The number of blocks varies from task to task (Fig.2c). The number of blocks is 30 for both 1-back and 2-back before drinking, and the other is 35 for both 2-back after drinking and 3-back.

Two different alcohol concentrations (45%, 53%) of Chinese Baijiu are selected for drinking. The moderate consumption of liquor is based on the participants’ unique situation and needs. The BAC (blood alcohol concentration) measurement is compared with a criterion measure of Chinese drink-driving: when the BAC is greater than or equal to 80mg/100ml, the participants are considered as a state of intoxication. In this paper, we use the expiratory-hold method to make an approximate measurement of BAC by alcohol tester. The BAC is measured after 20 minutes of the end of drinking, which ensures that the alcohol would be absorbed in the stomach and the small intestine as much as possible. Through three alcohol testing before, during, and after the experiments, all the participants are in a state of intoxication during the experiment. In addition, we use a test of standing on one foot after drinking to determine whether alcohol causes a severe impact on the balance ability. The test is also repeated for a total of three times. It is worth mentioning that all participants can stand for a long time which is taken over 30 seconds intervals.

C. DATA ACQUISITION AND PREPROCESSING

The EEG signals are collected by using a 32-channel Ag/AgCl electrodes recording system (actiCHamp, Brain Products) with electrodes arranged according to the standard international 10-20 system. In the WM-related studies, it is found that the most of cognitive function areas of human beings are concentrated in the frontal and parietal regions [20], [21]. The occipital is mainly used to process visual information, and ERPs of P100 and P200 in parietal lobe are induced by visual stimuli at the experimental interface. Although there is also a relationship between occipital and cognitive function, We decide not to select the channels of parietal in order to prevent other ERPs effect the feature information of P300. Therefore, the 23 channels (Fp1, Fp2, Fz, F3, F4, F7, F8, FC1, FC2, FC5, FC6, Cz, C3, C4, CP1, CP2, CP5, CP6, Pz, P3, P4, P7, P8) are chosen in the frontal and parietal lobes, and horizontal and vertical electrooculograms (EOG) are recorded from left and right eyes for further identification and removal of ocular-related artifacts. EEG is recorded at 1000Hz sampling frequency and is internally downsampled to 500Hz. The electrode impedances are kept under 10 KΩ.

The bilateral mastoids (TP9, TP10) are used as the reference electrodes, and the ground electrode is Fpz. The experimental interface is compiled by the software Eprime 2.0, and the Software BrainVision Analyzer is used for the offline EEG preprocessing. The data are internally band-pass filtered between 0.5Hz and 40Hz using a 5th order Finite Pulse Response (FIR). The independent component analysis (ICA) is used to identify and manually remove ocular-related artifacts. The ERPs are plotted based on the Python MNE software package.

III. FEATURE SELECT AND ANALYSIS

In this section, we introduce and analyze the features that we selected in our work. These features are adopted to classify the subjects’ states based on the differences of EEG between the time-domain and frequency-domain according to the different WM-load levels. And then we analysis whether these features could be used to classify the subjects’ states of the sober or the intoxicated under tasks of the same WM-load level.

A. METHODS

1) STANDARD DEVIATION

The standard deviation is a statistic that measures the dispersion of a dataset relative to its mean and is widely used in the evaluation of EEG signals. The standard deviation is defined as

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^2},$$

where $\mu$ is the mean, and $\sigma$ stands for the standard deviation of signal $X$. The $i$ is the index of the sample points of signal $X$. 
2) DIFFERENTIALS
The differentials are useful for approximating certain values of the derivative of a function in mathematics, and the differentials can also be used to approximate changes in non-stationary signals. In this paper, the differentials of different order are extracted. The average value of the first-order differentials absolute value is
\[
|\delta| = \frac{1}{N-1} \sum_{i=1}^{N-1} |x_{i+1} - x_i|,
\]
and the second-order differentials absolute value is
\[
|\gamma| = \frac{1}{N-2} \sum_{i=1}^{N-2} |x_{i+2} - x_i|,
\]
The normalized first-order differentials and second-order differentials are computed by
\[
\delta' = \frac{\delta}{\sigma}, \quad \gamma' = \frac{\gamma}{\sigma},
\]
where \( \delta \) stands for the first-order differential, and \( \gamma \) represents the second-order differential.

3) HJORTH PARAMETERS
The Hjorth parameters have been introduced firstly in [22], which assess the complexity of the signal in the time domain. There are three different definitions of activity, mobility, and complexity of the Hjorth parameters, defined respectively as the following.
\[
\text{Activity} = \frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^2 = \sigma^2,
\]
\[
\text{Mobility} = \sqrt{\frac{\sigma^2}{\sigma^2}} = \frac{\sigma_d}{\sigma},
\]
\[
\text{Complexity} = \sqrt{\sigma^2 - \sigma^2} = \frac{\sigma_c}{\sigma},
\]
where \( \sigma^2 \) represents the variance of signal \( X \). The \( \sigma_d \) and \( \sigma_c \) indicate the standard deviation of the first derivative and the second derivative.

4) SHANNON ENTROPY
The Shannon entropy provides a single quantity that reflects the uncertainty of the signals [23]. The greater is the entropy, the greater are the uncertainties of the signals.
\[
H = - \sum_{i=1}^{N} p_i \log (p_i),
\]
where \( p_i \) denotes the probability of \( x_i \) on signal \( X \).

5) SAMPLE ENTROPY
Richman and Moorman [24] proposed the sample entropy (SampEn) estimator as an improvement over the approximate entropy (ApEn) estimator. The sample entropy does not generate self-comparison bias and is not affected by the length of the input time series.

**Step 1:** A time series of \( N \) sample \( \{X(i), 1 \leq i \leq N\} \) is divided into \( N - m + 1 \) \( m \)-dimensional vectors, where \( m \) is the embedding dimension. And then the distance is calculated as the maximum absolute value of the element corresponding from the current vector to other vectors. It is defined as
\[
d_{ij} = d[X^m(i), X^m(j)] = \max|u(i + k) - u(j + k)|,
\]
where the \( k \) takes the rank of 0 to \( m - 1 \).

**Step 2:** Define \( B^m_i(r) = (N - (m + 1)r)^{-1} \) times the number of vector \( X^m(i) \) within \( r \), which remain close to \( X^m(j) \), where \( j \) takes the rank of 1 to \( N - m \), and \( j \neq i \) to exclude the auto matches, it is defined as
\[
B^m_i = \frac{1}{N - (m + 1)r} \sum_{j=1,j \neq i}^{N-m} \theta (r - d[X^m(i), X^m(j)]).
\]

And then \( B^m(r) \) is defined as
\[
B^m = \frac{1}{N-m} \sum_{i=1}^{N-m} B^m_i.
\]

**Step 3:** Change the embedding dimension from \( m \) to \( m + 1 \), and repeat Step 2, then get \( A^m \).
\[
A^m = \frac{1}{N-m} \sum_{i=1}^{N-m} A^m_i
\]
Define \( \text{SampEn}(m, r) = \lim_{N \to \infty} \frac{A^m}{B^m} \) where \( N \) tends to be positive infinite, and define \( \text{SampEn}(m, r, N) = \ln \left( \frac{A^m}{B^m} \right) \) where \( N \) is a finite number.

In this paper, \( r \) is set to 1, and the classification accuracies of sample entropy performs the best when \( m = 2 \) and \( r = 0.1 \times \sigma \).

6) DIFFERENTIAL ENTROPY
Differential entropy is used to measure the complexity of continuous random variables and depends on the minimum description length [25]. The formula can be described as
\[
h(X) = - \int f(x) \log(f(x)) dx.
\]
Reference [25] has proved that the probability of sub-band signals meeting the Gaussian distribution \( N(\mu, \sigma^2) \) by Kolmogorov-Smirnov test method. Therefore, in a fixed frequency band \( i \), the differential entropy is defined as
\[
h(X) = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi} \sigma_i^2} e^{-\frac{(x-\mu)^2}{2\sigma_i^2}} \log \left( \frac{1}{\sqrt{2\pi} \sigma_i^2} e^{-\frac{(x-\mu)^2}{2\sigma_i^2}} \right)
\]
\[
= \frac{1}{2} \log \left( 2\pi \sigma_i^2 \right),
\]
where \( h_i \) and \( \sigma_i^2 \) denote the differential entropy of the corresponding EEG signals in frequency band \( i \) and the signal variance, respectively.
7) MULTITAPER POWER SPECTRUM

The Multitaper (MT) is first proposed by Thompson, which can increase spectrum estimation by enhancing leakage and deviation in the assessment [23]. It is widely used in EEG signals processing.

The standard MT spectral estimator of the \( \hat{S}^{(mt)}(f) \), is the average of the \( K \) eigenspectra,

\[
\hat{S}^{(mt)}(f) = \frac{1}{K} \sum_{k=1}^{K} \hat{S}^{(mt)}_{k}(f), \quad (15)
\]

where the \( k \)th \((k = 1, \ldots, K)\) eigenspectrum is defined by \( \hat{S}^{(mt)}_{k}(f) = |J_k(f)|^2 \), with

\[
J_k(f) = \sum_{r=1}^{N} h_{k,r}X_{t}e^{-j2\pi f_{t}}. \quad (16)
\]

B. FEATURE ANALYSIS

In our work, we need to complete two classification tasks. One is three-classification task among different WM-load levels, the other is binary classification task of different state of the sober and the intoxicated under tasks of same WM-load level.

We divide different features into two categories: time domain features or frequency domain features. On one hand, it is assumed that the alcohol intake could increase the complexity of the EEG signals in the time and frequency domain. Since different entropy can be used to calculate the complexity of the EEG data, the sample entropy, the differential entropy, and the Shannon entropy are categorized into time domain features and frequency domain features, which are extracted from each EEG segment and used to compute the randomness of the EEG signals algebraically. On the other hand, some features are used only in one aspect, not both in two aspects of time and frequency domain. The standard deviation and Hjorth parameters are only categorized into time domain features, and the power mean is only categorized into frequency features. Meanwhile, we find that there is a linear correlation between the differential entropy and the standard deviation in Eq.14. In order to verify the correlation between them, we categorize the standard deviation into time domain feature and frequency domain feature.

Next, we use the EEG signals to train classifier both in the time domain and the frequency domain. In the temporal domain, the EEG signals are partitioned into 2.2-s-long segments from 200ms before stimulus onset to 2000ms after onset. We select the first 140 trials of each task to assure the balance of sample distribution of different tasks. However, we fail to read enough data for the subject 8 due to errors in EEG data format in a task. The subject 8 is only selected the first 120 trials in different tasks. In the spectral domain, we select a specified segment of raw data from 100ms to 600ms after stimulus onset for further power features analysis of P300. And then the MT is utilized to obtain power features in eight frequency bands (i.e., \( \delta \), 2-4 Hz; \( \theta \), 4-8 Hz; \( \alpha_1 \), 8-10 Hz; \( \alpha_2 \), 10-13 Hz; \( \beta_1 \), 13-16 Hz; \( \beta_2 \), 16-20 Hz; \( \beta_3 \), 20-25 Hz; and \( \beta_4 \), 25-30 Hz).

Finally, based on classification accuracies, we evaluate these features whether can be used in both classification tasks. If the classification accuracy performance is similar between the two classification tasks in EEG signals, it may indicate that these selected features can not only be used at the three-classification task of different WM-load levels, but also distinguish between different states of the sober and the intoxicated.

IV. RESULTS

A. RESPONSE ACCURACY AND REACTION TIME

We analyze the behavioral data of the N-back tasks and calculate the reaction time and mean accuracies of the correct responses for each task. With the increase of WM-load, the reaction time also increases, and the mean accuracies of the correct responses decrease. We also calculate the average accuracies of all subjects for each N-back task at Fig.3.

The values of response accuracies of 1-back are the first highest, followed by the value of accuracies of 2-back, while the ones of 3-back are the lowest. Meanwhile, a discrepancy also exists in the response accuracies before and after drinking under 2-back task. The effects of alcohol intake increase the rate difference by almost one percentage points between sober and intoxicated.

The tasks of 1-back and 3-back were finished in one period, and the tasks of 2-back under different state were finished in another. Therefore, we compare the reaction time of the N-back tasks that are at the same period of time to avoid interference of other factors in the results of comparison.

In Fig.3, we can find different phenomena by comparing the reaction time of different tasks. Exception for subject 1 and subject 3, there is one phenomenon in the other subjects that the reaction time of 3-back is observably greater than the one in 1-back. On the contrary, however, there is the other phenomenon that the reaction time in the intoxicated state under 2-back is significantly smaller than the one in the sober state. And the phenomenon is present in seven participants (3, 4, 5, 7, 8, 9, 10). Besides, in the rest three participants (1, 2, 6), the reaction time in the intoxicated state under 2-back
is slightly greater than or equal to the one in the sober state. Since the tasks are completed over different periods, there is a possible situation where the reaction time in 1-back is greater than the one in 2-back.

**FIGURE 4.** The comparison of P300 amplitudes of Fz and Pz electrodes under different tasks. The different colors in the figure represent the P300 waveforms deviation among different tasks. Three different tasks of 1-back, 2-back and 3-back are divided into one group, such as (a) and (c), and the other two tasks of the state of the sober and the intoxicated under 2-back are divided into another group, such as (b) and (d).

**B. P300**

The latencies and amplitudes of the P300 are recorded for each participant under different tasks at Tab.1. We find that the averages of latencies and amplitudes of the intoxication under 2-back are greater than the ones in the sobriety, and the averages of latencies and amplitudes in 1-back are greater than the ones in 3-back. All group-average ERPs potentials are compared of different tasks, and then the ERP potentials of Fz and Pz electrodes are visualized in Fig.4. For all four experimental tasks, the P300 is found on channel Fz, but is not found on channel Pz. However, the N400 is found on channel Pz. Additionally, we find that the amplitudes of P300 and N400 decreases with the increasing of MW-load except the ones of N400 on channel Pz between the sober and the intoxicated state.

**C. ERD AND ERS**

The ERD or ERS is defined as a percentage of energy decrease or increase [26]. We use the ERS or ERD to characterize the power changes. The ERD/ERS% formula is defined as follows,

$$ ERD/ERS\% = \frac{A - R}{R} \times 100\% $$

The ERD/ERS% can calculate the changes from baseline as a power sample point minus the baseline value. Base on the baseline, the ERD% indicates a decrease of energy, and the ERS% indicates a increase of energy. We use the power mean of the baseline from 200ms before the stimulus onset as R for each task. The different rhythmic power sample point is used as A. We plot the Beta ERD and Theta ERS maps of all channels between different tasks (Fig.5). Compared with the other tasks, the differences of ERDs are more obvious in comparison of sobriety and intoxication under 2-back. And it is not obvious by comparing ERSs differences between different tasks.

**FIGURE 5.** The ERD/ERS map. The red indicates an increase in energy and the blue indicates a decrease in energy. The vertical axis denotes different channels and the horizontal one denotes power sample point in each rhythm. The channel numbers are incremented from small to large, and the channel order are consistent with the order specified in subsection II-C. Beta ERDs (a) and Theta ERSs (b) are shown of three tasks of 1-back, 2-back and 3-back. And the other of Beta ERDs (c) and Theta ERSs (d) are shown of two tasks of the state of sober and intoxicated under 2-back.

In ERD/ERS maps, the greater the color changes are, the greater the ERD/ERS effects are. So the EEG signals can be found the power changes not only in tasks of different WM-load levels’ tasks but also in tasks of different state of the sober or intoxicated. We analyze the ERD/ERS of all eight rhythms. The stronger alpha and beta ERDs are observed, and ERSs are observe in the rhythms of delta, theta, and alpha.

**D. CLASSIFICATION ACCURACY ANALYSIS**

A SVM with a linear kernel function is utilized for classification. The ten-folded cross-validation is adopted to compute classification accuracies of the classifier. And then the average values of the ten runs are regarded as the final classification accuracies in different tasks.

In our work, it is the first classification task (T1) that the three-classification task of three different WM-load levels’ tasks but also in tasks of different state of the sober or intoxicated. We analyze the ERD/ERS of all eight rhythms. The stronger alpha and beta ERDs are observed, and ERSs are observe in the rhythms of delta, theta, and alpha.
TABLE 1. The P300 information of latencies (ms) and amplitudes (mV). The latencies and amplitudes of different subjects are recorded under each task. The average of latencies and amplitudes are bold, and the amplitudes are marked red specifically.

| Subjects | 1-back | 2-back Sober | 2-back Intoxicated | 3-back |
|----------|--------|--------------|--------------------|--------|
|          | Latency | Amplitude   | Latency            | Amplitude |
| S1       | 470     | 12.51        | 406                | 13.06   | 468            | 12.59 | 470            | 8.91 |
| S2       | 446     | 12.6         | 240                | 8.38    | 428            | 14.74 | 432            | 5.88 |
| S3       | 428     | 9.58         | 546                | 7.64    | 394            | 3.86  | 416            | 6.39 |
| S4       | 296     | 7.77         | 302                | 6.54    | 316            | 9.86  | 202            | 5.66 |
| S5       | 560     | 9.3          | 268                | 6.63    | 554            | 9.35  | 262            | 5.71 |
| S6       | 524     | 8.28         | 216                | 11.73   | 214            | 13.2  | 208            | 11.76 |
| S7       | 222     | 5.36         | 252                | 9.58    | 242            | 9.27  | 236            | 7.14 |
| S8       | 220     | 10.4         | 424                | 6.06    | 470            | 10.28 | 498            | 13.67 |
| S9       | 566     | 8.76         | 264                | 5.35    | 264            | 7.18  | 550            | 9.89 |
| S10      | 398     | 12.4         | 511                | 10.16   | 600            | 13.6  | 368            | 6.55 |
| Avg      | 413     | 9.692        | 343.2              | 8.513   | 395            | 10.393| 364.2          | 8.156 |
| Std      | 128.90  | 2.35         | 119.97             | 2.56    | 132.88         | 3.29  | 128.45         | 2.81 |

TABLE 2. The classification accuracies of different features under T1 in frontal.

| Subjects | Differentials | Hjorth | SampEn | Std | DiffEn | shannonEn |
|----------|---------------|--------|--------|-----|--------|-----------|
| S1       | 0.986         | 0.888  | 0.975  | 0.794 | 0.81   | 0.812     |
| S2       | 0.983         | 0.799  | 0.972  | 0.848 | 0.906  | 0.923     |
| S3       | 0.969         | 0.9    | 0.983  | 0.731 | 0.769  | 0.848     |
| S4       | 0.991         | 0.981  | 0.998  | 0.942 | 0.942  | 0.951     |
| S5       | 0.961         | 0.929  | 0.949  | 0.86  | 0.871  | 0.915     |
| S6       | 0.99         | 0.886  | 0.98   | 0.678 | 0.737  | 0.759     |
| S7       | 0.997         | 0.946  | 0.983  | 0.912 | 0.912  | 0.919     |
| S8       | 0.956         | 0.804  | 0.859  | 0.741 | 0.755  | 0.749     |
| S9       | 0.995         | 0.975  | 0.986  | 0.913 | 0.923  | 0.911     |
| S10      | 0.974         | 0.843  | 0.878  | 0.732 | 0.727  | 0.741     |

TABLE 3. The classification accuracies of different features under T2 in frontal.

| Subjects | Differentials | Hjorth | SampEn | Std | DiffEn | shannonEn |
|----------|---------------|--------|--------|-----|--------|-----------|
| S1       | 0.983         | 0.875  | 0.987  | 0.862 | 0.869  | 0.862     |
| S2       | 1             | 0.9   | 1      | 0.962 | 0.972  | 1         |
| S3       | 0.863         | 0.83   | 0.757  | 0.78  | 0.79   | 0.77      |
| S4       | 0.994         | 0.925  | 0.988  | 0.837 | 0.855  | 0.855     |
| S5       | 0.967         | 0.983  | 0.948  | 0.948 | 0.969  | 0.886     |
| S6       | 1             | 0.922  | 1      | 0.858 | 0.896  | 0.886     |
| S7       | 1             | 1      | 1      | 0.983 | 0.986  | 0.983     |
| S8       | 1             | 0.968  | 1      | 0.838 | 0.884  | 0.902     |
| S9       | 0.98          | 0.865  | 0.882  | 0.674 | 0.687  | 0.711     |
| S10      | 0.977         | 0.977  | 0.99   | 0.832 | 0.876  | 0.902     |

* Bold font of each row indicates the highest accuracy in different feature in a subject. The accuracies equal to 100% are marked in red.

There are obvious differences in the classification accuracies of different brain regions in the time domain of Fig.6. The classification accuracies of T1 and T2 are recorded in Tab.2 and Tab.3. To explore the effect of the number of frontal channels on classification accuracies, we also divide the frontal into three parts: frontal, left frontal, and right frontal. The classification accuracies of the three parts are shown in Fig.7.

There are obvious differences in the classification accuracies of different brain regions in the time domain of Fig.6(a) and Fig.6(b). On one hand, the classification effects of the frontal lobe are similar in the whole-brain’s, even yielding the accuracies as high as 100%. The frontal lobe contains half the number of channels of the whole-brain and achieve high accuracies as same as the whole-brain. On the other hand, the classification accuracies in the parietal are slightly lower than the ones in the frontal. The phenomena are clearly visible among different features in both T1 and T2 tasks.

There are also subtle differences in the classification accuracies among three different frontal regions in the time domain in Fig.7. In both T1 and T2 tasks, when the number of channels increases, the classification accuracies increase significantly. The classification accuracies of frontal are greater than both the left frontal and right frontal. At the same time, the classification accuracies of right frontal are greater than the left frontal under T1 in Fig.7(a). The lines of classification accuracies almost overlap between the left and right regions of frontal under T2 in Fig.7(b).

However, the classification effects are not obvious among three brain regions in the frequency domain of Fig.6(c)(d) and Fig.7(c)(d). From the results in frequency domain, the power mean value feature achieve better classification accuracies in T1 compared with the T2 in Fig.6(c). Except the power mean value, the other entropy features exist lower accuracies, even...
lower than 50%. We can only find differences in classification accuracies on the power mean value feature among different regions in Fig.6(c) and Fig.7(c). Thus, the EEG signals have more obvious complexity changes in the time domain rather than the frequency domain. Additionally, we can find that the power changes are more obvious in the samples ranged from 100 to 200 among different rhythms in ERD/ERS analysis. So the interval is used to calculate the power mean value in order to achieve better results of classification.

Two three-dimensional (3D) bar graphs are visualized to better compare the classification accuracies in different features in frontal lobe in Fig.8. The results show these features perform better under T2 than T1. At Fig.9, we divide the brain into ten different regions, while the number of electrodes in different regions can be obtained from Tab.4. The “Symbol” attribute of Tab.4 will be used in Fig.10.
TABLE 4. Ten brain regions. The abbreviated letters are used to represent different brain regions. The “Channels” attribute represents the number of electrode channels in different brain regions.

| Brain Regions     | Channels | Symbols |
|-------------------|----------|---------|
| Whole-brain       | 23       | A       |
| Left Hemisphere   | 10       | LH      |
| Right Hemisphere  | 10       | RH      |
| Frontal           | 11       | F       |
| Left Frontal      | 5        | LF      |
| Right Frontal     | 5        | RF      |
| Parietal          | 9        | P       |
| Left Parietal     | 4        | LP      |
| Right Parietal    | 4        | RP      |
| Center            | 3        | C       |

We use the multivariate analysis to compare the scatter distribution of accuracies of different features pairs among ten brain regions. The different colors represent the different brain regions. The scatter distribution between T1 and T2 are similar among all feature pairs. We find that there are significant correlations among three features (the standard deviation, the differential entropy, and the Shannon entropy) both T1 and T2. The scatter distribution of the other feature pairs is approximately similar in the time domain both T1 and T2. The scatters are concentrated in the upper right area among six brain regions (whole-brain, left hemisphere, right hemisphere, frontal lobe, left frontal, and right frontal).

However, there are significant differences at the scatter distribution both T1 and T2 in the frequency domain. The scatter distribution of T1 is following a uniform distribution on all subplots, and the one of T2 is presenting a clustering distribution.

V. DISCUSSION

The present study proposes to use new experimental tasks to find out the effects of the alcohol intake on EEG signals. It has been found that the alcohol impacts the biological processes in the brain and the alcohol intake could further interfere with the cognitive process and decision-making [27], [28]. As the WM is one of the cognitive functions of the brain, we use the N-back tasks to evoke the EEG signals associated with the WM. To probe the influences of alcohol intake on the EEG signals, we analyze them into two aspects. For one aspect, we need to compare the differences on behaviors of subjects before and after alcohol intake. For the other aspect, we analyze some features used for classification of WM-load whether are used to classify the EEG signals between the sober and intoxicated state.

In our work, we find that the reaction time increases while the response accuracies decrease with increasing WM-load. By comparing the reaction time between the sobriety and the intoxication, the latter is lower than the former in most cases. Questionnaires before and after tasks are conducted, and the

FIGURE 8. The 3D bar graphs of classification accuracies in frontal of T1 and T2. The x-axis represents different features, and the y-axis represents different subjects. The z-axis is used to represent classification accuracies. The different colors represent different values of classification accuracies.

FIGURE 9. The channels are divided into ten different regions. The Regions are divided based on the cerebral cortexes. There are five regions in the figure, and the other five regions are the whole brain, left hemisphere, right hemisphere, frontal lobe, and parietal lobe.

FIGURE 10. The multivariate analysis between T1 and T2 in time domain and frequency domain. (a) and (b) represent the scatter distribution of multivariate analysis among different features in time domain. (c) and (d) represent the scatter distribution of multivariate analysis among different features in frequency domain. The different colors are used to represent different brain regions in (e).
results have shown that the attentions are more focused on drinking during experiments via self-report of all subjects. Since alcohol has stimulating effects on the nervous system, it might motivate the subjects’ brains to make them excited [29], thereby influencing the attentions. Some studies indicate that the alcohol has the positive effects on the working memory and the attentional functions [30], [31]. And then we have verified this hypothesis in our study.

The P300 firstly reported by [32] is regarded as an ERP index to assess the neurocognitive effects. The P300 component can sensitively reflect the cognitive function [33], [34]. Additionally, the P300 may be underpinned by activities in several distributed regions including prefrontal, frontal, and parietal [35], [36]. Therefore, we use the P300 as a probe to explore differences in WM-related EEG signals before and after drinking. We not only find that the latencies and amplitudes of the intoxication are greater than the one in the sobriety under 2-back, but also find that the latencies and amplitudes in 1-back are greater than the one in 3-back. Reference [10] has found that the increasing of the WM-load leads to a decreasing P300 amplitude. They propose that the P300 amplitude turned out as a good measure of changes in the overall WM-load. We suppose that the alcohol intake would decrease the WM-load level, when the changing trend of P300 amplitude is toward an increase from sober state to intoxicated state at Fig. 4. Reference [37] has been pointed out that a shorter P300 latency reflects a shorter stimulus evaluation time, while a larger P300 amplitude indicates more attentional resources devoted to a given task. Under the influence of alcohol intake, it could be increased the stimulus evaluation time, and the brain could have to allocate relatively more resources to respond to specific-tasks.

The ERD/ERS effects in an N-back task paradigm have been consistently observed in several studies [10], [38]. The ERD/ERS effects of all rhythms in tasks are analyzed. The contrast of ERD/ERS effects are obvious based on two different tasks both in T1 and T2. We find that the ERD/ERS significantly increases among different rhythms between the sobriety and the intoxication.

Next, the SVM is utilized to classify the multiple features of the different brain regions, and different feature selection can lead to different classification performances. We select seven features to classify the WM-load two different tasks. The entropy can illustrate the changes of underlying neural processes more specifically, and explain the behavioral variance in different WM tasks more clearly. There are three features of the entropy (the sample entropy, the differential entropy, and the Shannon entropy) to evaluate the complexity changes of EEG signals especially. In the time domain, the overall classification accuracies are high, focusing mainly on ranging from 70% to 100%. But the accuracies of entropy features are very poor when applying to classify EEG signals in the frequency domain.

The WM functions are associated with multiple brain regions which contribute to different functions. Although the frontal and parietal cortex which support high level of cognitive processes are involved in WM [39], [40], there are differences of WM functions between frontal and parietal. The frontal involves in many verbal expression processes, including verbal WM [41], and the parietal mediates the brain functions such as spatial WM [42]. The classification accuracies of the frontal are significantly higher than the parietal in WM tasks. The number symbols involve some semantic processes, which is more correlated with verbal WM. This may be the reason why the classification accuracies are significantly different in the frontal and parietal regions both in T1 and T2. At the same time, to explore the effect of the number of channels on classification accuracies, we also divide the frontal into three regions (frontal, left frontal, and right frontal) for comparison. The differences of classification accuracies of frontal can be found whether time domain or frequency domain under T1. The performance of right frontal is better than the left frontal. It is possible that the left hand is used less frequently than right hand in N-back tasks and the P300 characteristics of right frontal (contralateral regions) are more obvious than left frontal. Three tasks with different workload levels need to be classified in T1 and the same workload level tasks are classified in T2. This phenomenon of differences of classification accuracies is more pronounced in T1 than T2. It is possible that feature information under T1 is more abundant than that of T2.

Finally, the similarities are confirmed by the multivariate analysis among different features. We have plotted the scatter distribution which are applied for analyzing the correlation and similarity among the pairwise combination of all features. We find that the T1 and T2 tasks are classified using these features, performing well in the time domain and poorly in the frequency domain. And on the whole, these features are better in binary classification task than the three-classification task.

VI. CONCLUSION

In this work, we propose a method to evoke the EEG signals based on the WM tasks by using the N-back paradigm, and we also analyze the EEG signals differences before and after drinking. In the experiment, we choose the healthy subjects to record the EEG signals in order to distinguish the effects of alcohol intake based on the WM. Our results indicate the significant P300 and ERD/ERS phenomena in the EEG signals among all experimental tasks. After that, we explore some specific features to classify the EEG signals of different WM-load, and these features are also used to classify the EEG signals before and after drinking.

We verify that these specific features can be used either for classification of tasks under different WM-load or for classification of the state of sober and intoxicated. Alcohol may affect the brain’s perception of experimental tasks, leading to subtle changes of EEG both in the time domain and frequency domain, but the task-related feature information has not been changed in the EEG. We compare the classification accuracies of different brain regions. The results show that the performances of frontal are better than the parietal in classification tasks, and there are also differences in the
performances of classification between the right frontal and left frontal. In addition, the experiment results show that the features in the time domain can achieve better classification results than frequency domain.

In conclusion, our work suggest that the effects of alcohol on EEG signals can be studied based on some specific experimental tasks, and some task-related features can be used to classify the EEG signals whether the subjects are in drink or not. On one hand, the N-back has the better interactivity and can focus on specific brain cognitive functions, which compared with the Go/NoGo paradigm in traditional studies. On the other hand, it is easier to analyze the effects of alcohol intake on some specific brain functions through the comparison in different WM-load levels. In future work, we will explore how the alcohol intake could reduce the WM-load for human in being artificial intelligence point view.

REFERENCES

[1] R. W. Engle, S. W. Tuholski, J. E. Laughlin, and A. R. A. Conway, “Working memory, short-term memory, and general fluid intelligence: A latent-variable approach,” J. Exp. Psychol., Gen., vol. 128, no. 3, pp. 309–331, 1999.

[2] E. Basar, C. Basar-Eroglu, J. Roschke, and A. Schutt, “The EEG is a quasi-deterministic signal anticipating sensory-cognitive tasks,” in Brain Dynamics (Springer Series in Brain Dynamics), vol. 2, Berlin, Germany: Springer, 1989, pp. 43–71.

[3] T. W. Picton, S. Bentin, P. Berg, E. Donchin, S. A. Hillyard, R. Johnson, G. A. Miller, W. Ritter, D. S. Ruchkin, M. D. Rugg, and M. J. Taylor, “Guidelines for using human event-related potentials to study cognition: Recording standards and publication criteria,” Psychophysiology, vol. 37, no. 2, pp. 127–152, 2000.

[4] M. Semprini, G. Bonassi, F. Barban, E. Pesolin, R. Iandolo, M. Chiappalone, D. Mantini, and L. Avanzino, “Modulation of neural oscillations during working memory update, maintenance, and readout: An hEEG study,” Hum. Brain Mapping, vol. 42, no. 4, pp. 1153–1166, Mar. 2021.

[5] C. Kang, Y. Li, D. Novak, Y. Zhang, Q. Zhou, and Y. Hu, “Brain networks of maintenance, inhibition and disinhibition during working memory,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 28, no. 7, pp. 1518–1527, Jul. 2020.

[6] Y. Chen and X. Huang, “Modulation of alpha and beta oscillations during an n-back task with varying temporal memory load,” Frontiers Psychol., vol. 6, p. 2031, Jan. 2016.

[7] I. Kätner, S. C. Wiesnet, G. R. Müller-Putz, A. Kübler, and S. Halder, “Effects of mental workload and fatigue on the P300, alpha and theta band power during operation of an ERP (P300) brain–computer interface,” Biol. Psychol., vol. 102, pp. 118–129, Oct. 2014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0301051114001616

[8] R. Portin, T. Kovala, P. Polo-Kantola, A. Revonsuo, K. Müller, and E. Matikainen, “Does P3 reflect attentional or memory performances, or cognition more generally?” Scand. J. Psychol., vol. 41, no. 1, pp. 31–40, Mar. 2000.

[9] D. W. Shucard, T. J. Covey, and J. L. Shucard, “Single trial variability of event-related brain potentials as an index of neural efficiency during working memory,” in Foundations of Augmented Cognition: Neuropsychonomics and Operant Neuroscience (Lecture Notes in Computer Science), vol. 9743, D. Schmorrow and C. M. Fidopiastis, Eds. Cham, Switzerland: Springer, 2016, pp. 273–283.

[10] C. Scharinger, A. Soutschek, T. Schubert, and P. Gerjets, “Comparison of the working memory load in N-back and working memory span tasks by means of EEG frequency band power and P300 amplitude,” Frontiers Hum. Neurosci., vol. 11, p. 6, Jan. 2017.

[11] R. T. Knight, M. F. Grabowecky, and D. Scabini, “Role of human prefrontal cortex in attention control,” Adv. Neurol., vol. 66, pp. 21–34, 1995.

[12] L. Li, C. Gratton, D. Yao, and R. T. Knight, “Role of frontal and parietal cortices in the control of bottom-up and top-down attention in humans,” Brain Res., vol. 1344, pp. 173–184, Jul. 2010.

[13] M. A. Shalchty, V. Pergher, A. Pahor, M. M. Van Hulle, and A. R. Seitz, “N-back related ERPs depend on stimulus type, task structure, pre-processing, and lab factors,” Frontiers Hum. Neurosci., vol. 14, Oct. 2020, Art. no. 549966.

[14] C.-Y. Yang and C.-K. Huang, “Working-memory evaluation based on EEG signals during N-back tasks,” J. Integr. Neurosci., vol. 17, nos. 3–4, pp. 695–707, Sep. 2018.

[15] P. Zhang, X. Wang, W. Zhang, and J. Chen, “Learning spatial–spectrum–temporal EEG features with recurrent 3D convolutional neural networks for cross-task mental workload assessment,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 27, no. 1, pp. 31–42, Jan. 2019.

[16] J. Sorbel, S. Morzorati, S. O’Connor, T.-K. Li, and J. C. Christian, “Alcohol effects on the heritability of EEG spectral power,” Alcoholism, Clin. Exp. Res., vol. 20, no. 9, pp. 1523–1527, Dec. 1996.

[17] M. A. Shalchty, V. Pergher, A. Pahor, M. M. Van Hulle, and A. R. Seitz, “N-back related ERPs depend on stimulus type, task structure, pre-processing, and lab factors,” Frontiers Hum. Neurosci., vol. 14, Oct. 2020, Art. no. 549966.

[18] C.-Y. Yang and C.-K. Huang, “Working-memory evaluation based on EEG signals during N-back tasks,” J. Integr. Neurosci., vol. 17, nos. 3–4, pp. 695–707, Sep. 2018.

[19] P. Zhang, X. Wang, W. Zhang, and J. Chen, “Learning spatial–spectral–temporal EEG features with recurrent 3D convolutional neural networks for cross-task mental workload assessment,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 27, no. 1, pp. 31–42, Jan. 2019.

[20] J. Sorbel, S. Morzorati, S. O’Connor, T.-K. Li, and J. C. Christian, “Alcohol effects on the heritability of EEG spectral power,” Alcoholism, Clin. Exp. Res., vol. 20, no. 9, pp. 1523–1527, Dec. 1996.

[21] S. Kähkönen, “MEG and TMS combined with EEG for mapping alcohol effects,” Alcohol, vol. 37, no. 3, pp. 129–133, Nov. 2005.

[22] E. A. de Bruin, S. Bilj, C. J. Stam, K. B. E. Böcker, J. L. Kenemans, and M. N. Verbaten, “Abnormal EEG synchronisation in heavily drinking students,” Clin. Neurophysiol., vol. 115, no. 9, pp. 2048–2055, Sep. 2004. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1388245704001531

[23] X.-S. Chen, Y.-Z. Lu, J.-J. Wang, H.-X. Wang, M.-D. Zhang, F.-Y. Lou, W. Gu, B. Wu, Z. Li, and X. Deng, “EEG Analysis of Working Memory Between Sober State and Intoxicated State,” Chin. Med. J., vol. 134, no. 9, pp. 742–749, Sep. 2021.

[24] J. S. Richman and J. R. Moorman, “Physiological time-series analysis using approximate entropy and sample entropy,” Amer. J. Physiol.-Heart Circulatory Physiol., vol. 278, no. 6, pp. H2039–H2049, Jun. 2000.

[25] C.-Y. Yang and C.-K. Huang, “Working-memory evaluation based on EEG signals during N-back tasks,” J. Integr. Neurosci., vol. 17, nos. 3–4, pp. 695–707, Sep. 2018.
[35] C. Bledowski, D. Prvulovic, K. Hochstetter, M. Scherg, M. Wirbal, R. Goebel, and D. E. J. Linden, “Localizing P300 generators in visual target and distractor processing: A combined event-related potential and functional magnetic resonance imaging study,” J. Neurosci., Off. J. Soc. Neurosci., vol. 24, no. 42, pp. 9353–9360, 2004.

[36] V. Singh-Curry and M. Husain, “The functional role of the inferior parietal lobe in the dorsal and ventral stream dichotomy,” Neuropsychologia, vol. 47, no. 6, pp. 1434–1448, May 2009.

[37] K. Kamijo, Y. Nishihira, T. Higashiura, and K. Kuroiwa, “The interactive effect of exercise intensity and task difficulty on human cognitive processing,” Int. J. Psychophysiol., vol. 65, no. 2, pp. 114–121, Aug. 2007. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0167876007000694

[38] J. Palomaki, M. Kivikangas, A. Alafuzoff, T. Hakala, and C. M. Krause, “Brain oscillatory 4–35 Hz EEG responses during an n-back task with complex visual stimuli,” Neurosci. Lett., vol. 516, no. 1, pp. 141–145, May 2012.

[39] F. Darki and T. Klingberg, “The role of fronto-parietal and fronto-striatal networks in the development of working memory: A longitudinal study,” Cerebral Cortex, vol. 25, no. 6, pp. 1587–1595, Jun. 2015.

[40] T. B. Singh, A. Aisikaer, C. He, Y. Wu, H. Chen, H. Ni, Y. Song, and J. Yin, “The assessment of brain functional changes in the temporal lobe epilepsy patient with cognitive impairment by resting-state functional magnetic resonance imaging,” J. Clin. Imag. Sci., vol. 10, p. 50, Aug. 2020.

[41] T. Kambara, E. C. Brown, B. H. Silverstein, Y. Nakai, and E. Asano, “Neural dynamics of verbal working memory in auditory description naming,” Sci. Rep., vol. 8, no. 1, p. 15868, Dec. 2018.

[42] E. Save and B. Poucet, “Hippocampal-parietal cortical interactions in spatial cognition,” Hippocampus, vol. 10, no. 4, pp. 491–499, 2000.

XIN DENG (Member, IEEE) received the bachelor’s degree from the Department of Computer Science and Technology, Jilin University, Changchun, China, in 2004, the master’s degree from the Department of Computer Science, Chongqing University, Chongqing, China, in 2007, and the Ph.D. degree in computer engineering from the National University of Singapore, Singapore, in 2013. He is currently an Associate Professor with the College of Computer Science and Technology, Chongqing University of Posts and Telecommunications, China. His research interests include brain–computer interface, electrophysiological signal processing, data engineering, and machine learning.

PENGFEI YANG received the B.Sc. degree from the College of Information Science and Engineering, Shanxi Agricultural University, Jinzhong, China, in 2019. He is currently pursuing the master’s degree with the Chongqing University of Posts and Telecommunications, Chongqing, China. His research interests include brain–computer interface, brain science, machine learning, and working memory.

XIANGWEI LV received the B.S. degree in engineering from China West Normal University, Nanchong, China, in 2014. He is currently pursuing the master’s degree with the Chongqing University of Posts and Telecommunications, Chongqing, China. His research interests include brain computer interface, cognitive neuroscience, machine learning, and affective computing.

KE LIU received the B.S. degree in automatic control from Southwest University, Chongqing, China, in 2011, and the Ph.D. degree in pattern recognition and intelligent systems from the South China University of Technology, Guangzhou, China, in 2016. He is currently an Associate Professor with the College of Computer Science and Technology, Chongqing University of Posts and Telecommunications, Chongqing. His research interests include pattern recognition, and Bayesian inference and their applications in EEG data analysis.

KAIWEI SUN received the bachelor’s degree in information security and the master’s degree in computer technology from the Chongqing University of Posts and Telecommunications, China, in 2010 and 2013, respectively, and the Ph.D. degree in information and communication engineering from Inha University, South Korea, in 2017. He is currently an Associate Professor with the School of Computer Science and Technology, Chongqing University of Posts and Telecommunications. His research interests include machine learning, big data analysis, computer vision, and natural language process.