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Cognitive Load During Multitasking Can Be Accurately Assessed Based on Single Channel Electroencephalography Using Graph Methods

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ABSTRACT Mental workload has been widely estimated based on electroencephalography (EEG) in the frequency domain. However, simple frequency features are not entirely accurate indicators of the cognitive load because surface EEG signals are weak, nonstationary and randomness. We hypothesize that graph methods, which analyse the relationship between each point and other points of the EEG signals, may provide a more precise identification of the mental load. To investigate this hypothesis, we aim to identify the optimum graph features from 14 channel EEG recordings (sampling rate = 128 Hz) in order to detect the high cognitive load related to multitasking. Three graph features: mean degree $\overline{d}$, clustering coefficient $\overline{c}$, and degree distribution $p(k)$, are extracted from 48 subjects EEG records. Each experimental subject conducts two tasks: without tasks and with a simultaneous capacity task, respectively. After the experiment is completed, the feeling of the subject with the cognitive load tags in three types: low load, medium load, and heavy load. The optimal features of these three levels of the subject sensation and two types of cognitive load in different tasks are selected on the basis of statistical analysis. Then all graph features are forwarded into a support vector machine (SVM) and a decision tree to conduct objective scoring classification and a three subjective rating classification, respectively. Based on the present results,channels O2, T8, FC6, F8, and AF4 are considered optimal for a more efficiently estimation of the cognitive load. $\overline{c}$ associated with F8 and T8 during low cognitive load is significantly lower than those associated with high cognitive load ($p < 0.001$). Using three graph features, the accuracy of identifying two types of mental load is 89.6%. Current findings suggest that the mental workload associated with multi-tasks can be accurately assessed using the graph approaches to EEG data.

INDEX TERMS Mental load, fatigue evaluation, difference visibility graph, clustering coefficient, channel selection.

I. INTRODUCTION

The cognitive workload involves studying the dynamic relationships between the resources necessary to accomplish a task and the ability of the brain to adequately supply those resources [1], [2]. It is defined as the total mental activity imposed on a subject's cognitive system during a particular period of work. Measurement of cognitive load can be used to optimize the learning process, promote alertness, enhance work efficiency [3], [4], and improve driving performance. According to the literature, the cognitive load is not only depend solely on the complexity of the task, but also includes the skills of subjects in the given task [5]. The management of cognitive load is fundamental and is widely used in various

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fields, such as it applications in estimating the fatigue index experienced by professional drivers, and evaluating mental health, medical performance, and education effectiveness [6].

Cognitive load can be evaluated through subjective or objective measurements [7], [8]. The former assesses the causal relationship between various tasks using self-reporting to reduce human cognitive load. The latter mainly investigates the measurement function of physiological signals, such as electroencephalogram (EEG) [9], electrocardiogram (ECG), galvanic skin response (GSR), respiration, and heart rate variability (HRV) [10]. Among these signals, EEG has been widely used in the study of mental load due to its fast data acquisition and convenient usage in sport or driving cars.

Traditionally, the analysis of EEG data in evaluating cognitive load is either in the frequency domain or in the time domain. The frequency domain analysis is mainly based on δ wave (0.1-4Hz), θ wave (4-8Hz) α wave (8-12Hz), and β wave(12-30Hz) frequency bands. For instance, the power of α waves declined significantly on the channel FP1 and FP2 for driving tasks [11]. In an over-arousal state, the alpha activity is suppressed [12]. Compared with beta rhythm, alpha rhythm response more significantly to mental stress in the prefrontal cotex [13]. The perceived mental effort was in correlated with the beta frequency on F7 channels [14]. A robust decline in right posterior alpha power may be observed for higher arousal [15]. However, the frequency domain analysis might produce conflicting results as shown in [13] (alpha rhythm has more advantages than than beta) and [14] (beta is better than others).

Recently, complex network methods have been applied in social networks [15] and electromagnetic signal processing [16], especially used to evaluate cognitive load using multi-channel EEG as graph nodes [16]–[20]. For instance, it has been demonstrated that while driving, the graph degree in the frontal brain area increases [18]. The α wave has a higher graph degree and clustering coefficient $\bar{c}$ in arousal in driving state as compared to the eye-closed state [19]. Another study found that stress status (such as driving) has higher $\bar{c}$ features than normal status [20]. Therefore, these results [18], [19] differ from that decreased α waves in the case of a single-channel in the frequency domain [11], [12], [15]. Also, whether by car or outdoors, people always wear a comfortable EEG headset which has less than 16 channels in general, The 16 channels EEG could generate 16 nodes according to currently network constructing methods. Thus, existing network approaches could not obtain high accuracy results. It is necessary to investigate whether the graph features of the portable EEG could be effective in identifying cognitive load using a fewer channel EEG signals.

In complex networks, degree distributions $p(k)$ has widely studied in EEG signals. Shang *et al.* [16] showed that $p(k)$ associated with EEG could be as features from multi-channel EEG signals to identify cognitive load. Zhu *et al.* [29] demonstrated that the clustering coefficient over degree distributions p(k) of DVG associated with sleep ECG satisfy the power law as well. However, no one studied whether p(k) of a complex network associated with multitasking met which type of distributions and p(k) of high stress satisfies the law of power or not.

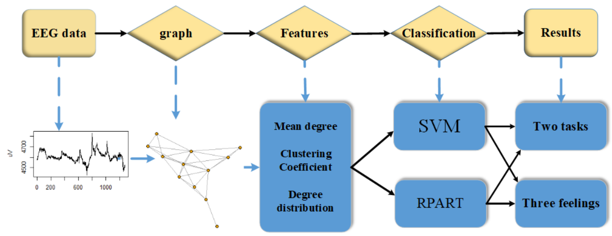

FIGURE 1. Flowchart of the proposed methods.

In this article, the cognitive load is evaluated based on subjective feeling ratio and objective task levels with graph methods, such as degree distributions and clustering coefficient, using comfort electroencephalography (EEG) signals without liquid gel injection. The 14 channel EEG data is collected using a wearable device from 48 subjects during Simultaneous Capacity (SIMKAP) task and as a reference during no task [21]. Meanwhile, the subjects labels three levels of feeling when conducting each task. Data on each EEG channel is converted into a graph through oblique visibility graph algorithms. Then three types of graph features: mean degree, $\bar{c}$, and degree distributions are extracted. To identify the difference between the simultaneous task and non-task, and the three emotional categories of subject, statistical analysis of graph degree, clustering coefficient between non-task and simultaneous task is applied. Lastly, a support vector machine and a decision tree are used to classify the cognitive load from those extracted graph features.

The main contribution of this work can be summarized in three main aspects. Firstly, it develops a graph approach from a single-channel EEG to estimate cognitive load different from existing graph methods that generally use multiple EEG channels (e.g. 14 channels). Secondly, it is found that the clustering coefficient can be identified the cognitive load efficiently than those of degree features. Lastly, it demonstrates that, combined with three graph features (mean degree, clustering coefficient, and degree distribution), the proposed method can achieve high accuracy compared to current time and frequency domain methods. The advantage of this graph method is to investigate the traditional graph feature degree and clustering efficient as well as estimates the degree distribution of the cognitive load.

II. METHODOLOGY

The EEG data analysis procedure is described in Fig 1, which mainly includes four steps.

- The EEG raw data of 48 subjects were collected from a 14-channel portable EEG, one channel of EEG is shown in the subfigures when they conducted tasks and label their feelings.

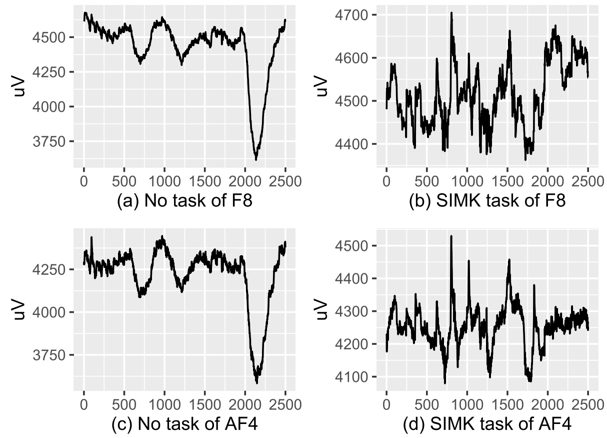

FIGURE 2. 20s EEG of the first subject (a) No tasks of F8 channel, (b) SIMK tasks of F8 channel, (c) No tasks of AF4 channel, (d) SIMK tasks of AF4 channel.

- Each channel of EEG signals was converted into an oblique visibility graphs (OVG) .
- Three typical features (mean degree, clustering coefficient, and degree distribution) were extracted from the OVG of each channel and each subject.
- The optimal features and EEG channels were selected through the non-parametric Wilcoxon test between two tasks and among three types of subject feelings, respectively.
- The extracted graph features were forwarded int to two classifiers, a support vector machine (SVM) technique and a decision tree classifier, to conduct binary classification, non-task and multi-task, as well as the classification of three self-reported feelings in different tasks, respectively.

A. EXPERIMENTAL DATA

The Simultaneous Task EEG Workload (STEW) EEG database (48 subjects) used in this article was obtained from the Nanyang Technological University [26]. Each subject performed the Simultaneous Capacity (SIMKAP) test. The recordings from each subject include 14 channel EEG signals from the Emotiv EPOC EEG headset: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 according to the 10-20 international system. The signal was sampled at 128 Hz, and the duration of each trial was 150 seconds. Fig 2 illustrates the EEG of F8 and AF4 channel time-domain waveforms for Non-tasks and SIMK-tasks.

B. OBLIQUE VISIBILITY GRAPH METHOD

The oblique visibility graph (OVG) [27] is a powerful method for transferring a time series into a graph $G(V, E)$. A time point x_i is mapped into a node v_i. The relation between any two points v_i, v_j is represented as an edge e_{ij}. The value is defined as

$$\frac{x_j - x_k}{j-k} > \frac{x_j - x_i}{j-i} \wedge (x_k \leq x_i) \vee (x_k \leq x_j) \wedge i \neq j-1 \quad (1)$$

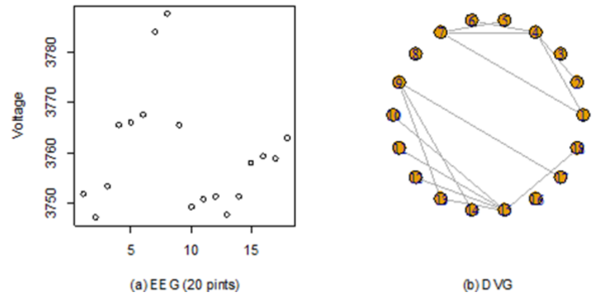

FIGURE 3. 20 points of (a) EEG in F8 and (a) the example of OVG, where the first point of (a) is the node v1 of (b) .

Fig 3 shows an OVG associated with a time series, which was collected from subject Sub03 recorded in the STEW EEG data set.

The number of time points in Fig 3 (a) are 20, the first 7 values are $Y = (3751.79, 3747.18, 3753.33, 3765.64, 3766.15, 3767.69, 3784.10)$. The first to the seventh node in Fig 3 (b) is associated with the first to seventh value in Y in Fig 3 (a) respectively. A node degree is one of the basic features to measure graphs. The degree d_i is the number of edges from node v_i. For example, in Fig 3 (b), $d_1 = 2$ and $d_3 = 0$.

C. MEAN DEGREE AND CLUSTERING COEFFICIENT

Besides degree, there are several measuring parameters in complex networks, such as clustering coefficient, average path, etc [28]. The average degree $\overline{d}$ of a graph with n nodes is defined as:

$$\overline{d_i} = \frac{1}{n}\sum_{j=1}^{n} d_j \quad (2)$$

The clustering coefficient (c) is another typical property of the graph, the c_i of a node v_i is the number of edges between the neighbors of v_i divided by all possible edges between the neighbors of v_i. The average $\overline{c}$ of a graph G with n nodes is defined as:

$$c_j = \frac{\sum_{k=1}^{d_j}\sum_{s=1}^{d_j} a_{jk}a_{sj}a_{ks}}{d_j * (d_j - 1)} \quad (3)$$

$$\overline{c} = \frac{1}{n}\sum_{j=1}^{n} c_j \quad (4)$$

where a is the adjacency matrix of G. Similar to the graph clustering algorithm in [27] for a $n > 3000$ points EEG series, the d_i is always less then 30 as shown in previous work [27]. Thus, we could always calculate equation 3 within constant times (30×30 repeat time). Therefore, the computational complexity of the $\overline{c}$ could assume within $O(n)$.

D. DEGREE DISTRIBUTION

The degree distribution $(p(k))$ is a probability that a node has a degree of k. It is obtained by counting the number of nodes having degree k divided by the total number of nodes. Let $p(k)$ be denoted as the proportion of degree k of an OVG.

The total number of nodes in Fig 3 is 20, the $p(k)$ of degree from 0 to 6 is $p(k) = (\frac{3}{20}, \frac{10}{20}, \frac{2}{20}, \frac{2}{20}, \frac{1}{20}, \frac{1}{20})$.

E. DECISION TREE

One of the classification methods in this article is to use a decision tree model to conduct cognitive classification. It is also called binary decomposition technique. The tree splited from a root node (represent a choice of a graph feature) to grow into two nodes, each nodes represent another graph feature and is split again into another sub tree. This article used the R package RPART [30] to implement this decision tree.

F. SUPPORT VECTOR MACHINE

To measure the performance of the cognitive load classification, a support vector machine (SVM) [31] is selected to conduct the binary classification. The SVM has been successfully used in alcoholic EEG classification [32] and fatigue identification [27], [33]. It can perform both the linear space discrimination and nonlinear classification by choosing different "kernel" functions which can be linear, polynomial kernel, radial basis function (RBF) and sigmoid. In this article, the SVM algorithm with RBF kernel [34] is implemented in R package e1071.

III. EXPERIMENTAL RESULTS

To evaluate the performance of the methods in Section II, the DVG algorithm is implemented in C program language, while the SVM and statistical analysis are implemented by R. The experiments include three parts: (1) analysis clustering coefficient, degree distribution and mean degree of DVG associated with two tasking EEGs; (2) analysis clustering coefficient, degree distribution and mean degree of DVG associated with three feelings of self-reported; (3) evaluating classification accuracy of the DVG features by different lags on two different sizes of data sets. The SVM and RPART involve the training stage and the testing stage, with the size of training data equals to the size of testing sets.

A. STATISTICAL ANALYSIS ON NON-TASK VS SIMK-TASK

The mean degree ($\bar{d}$) and Average clustering coefficient ($\bar{c}$) of 14-channel EEG signals are drawn in Figs 4 and 5 respectively. In relation to the status of the Non-task, the SIMK-task has higher values of $\bar{c}$ and $\bar{d}$. The optimal channels are selected by the following two tests: Firstly, Shapiro-Wilk tests show that the c, d of both groups do not satisfy normal distributions [35]. Then non-parametric Wilcoxon tests are applied to test the difference k between two tasks among different EEG channels. There are only two channels, FC6 and T8, which shows a significant difference between the two tasks (p $<$ 0.05).

However, non-parametric Wilcoxon tests indicate that every channel shows a significant difference ($p < 0.05$) except FC5 ($p = 0.221$) during two tasks. More importantly, channels on the right hemisphere: $O2, T8, FC6, F8$, and $AF4$ show a very significant difference in two tasks ($p < 0.0001$).

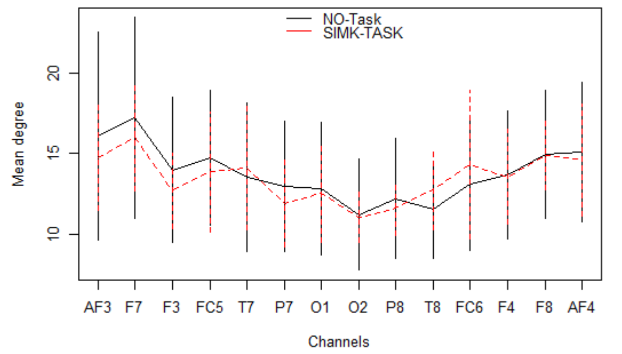

FIGURE 4. Mean degree associated with the two tasks at 14 channel EEGs.

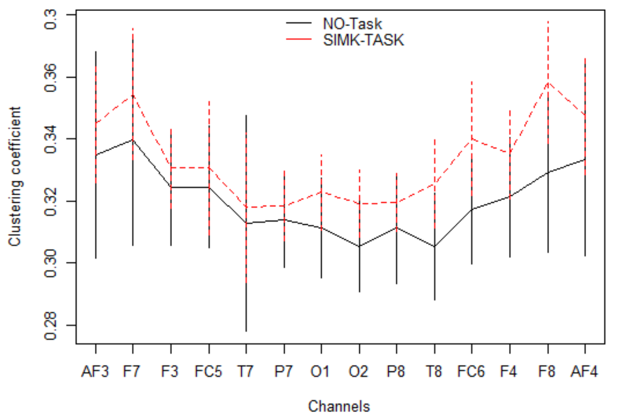

FIGURE 5. The clustering coefficient associated with the two tasks at 14 channel EEGs.

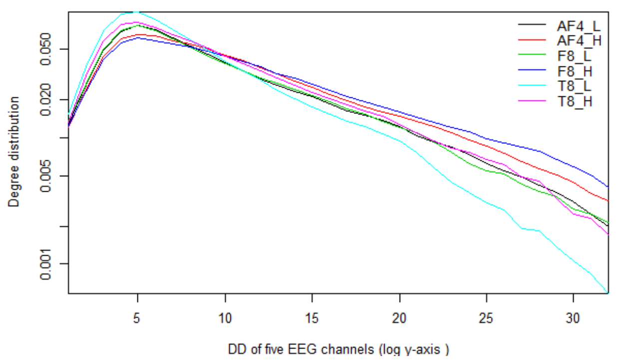

FIGURE 6. The degree distribution of three optimal channels associated with the two tasks (the difference occurred after degree larger than 13).

Based on the mean degree and clustering coefficient plots in Figs 4 and 5, channel T8 can potentially be the optimal channel for classification of two types of tasks with two features degree and clustering coefficient. Next, then the Degree distribution ($p(k)$) of the optimal channels F8 and T8 are drawn in Fig 6. Obviously, it is difficult to use $p(k)$ between degrees 0 and 10 to identify those two tasks.

B. STATISTICAL ANALYSIS ON SUBJECTS FEELING

Mean degree ($\bar{d}$) and average clustering coefficient ($\bar{c}$) of 14-channel EEG signals based on subjects' feelings

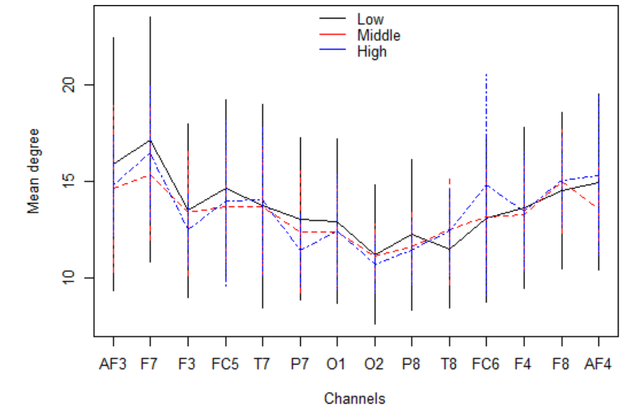

FIGURE 7. Mean degree associated with 14 channel EEG with three type feelings.

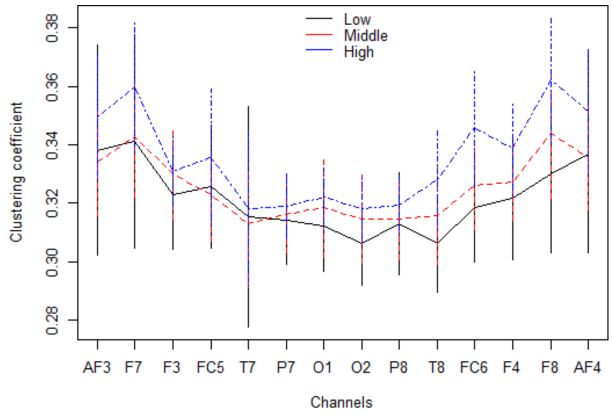

FIGURE 8. The mean clustering coefficient of OVG at each channel with three type feelings.

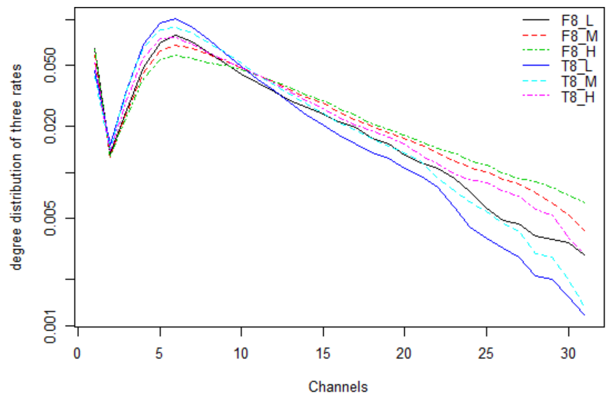

FIGURE 9. The degree distribution of the optimal channels associated with three feelings.

associated with two tasks are drawn in Figs 7 and 8. Compared to the low and middle self-reported feeling, the high self-reported feeling has higher $\bar{c}$. The optimal channels are selected by two tests: firstly, Shapiro-Wilk tests show that the $\bar{d}$ and $\bar{c}$ of three groups does not satisfy normal distributions. Secondly, non-parametric pairwise Wilcoxon tests are applied to compare two graph features between low, middle, and high workload feeling.

Unlike the two task cases in Fig 4, there has no significant difference among low, middle and high workload feeling using mean degree features (the smallest $p = 0.058$ between low load feeling and high load feeling in AF6 channel) in Figs 7 and 8. On the mean clustering coefficient case, the channels F8, FC6, and T8 show a significant difference between low feeling, middle and high workload feeling ($p < 0.05$). In the three types of feeling, only three channels can be selected based on statistical analysis. The Degree distribution ($p(k)$) of two optimal channels F8 and T8 are drawn in Fig. 9. It is clear that the degree between middle and high workload feelings is not significantly differed among all degrees.

C. EVALUATING THE CLASSIFICATION ACCURACY WITH TWO TYPES OF CLASSIFIERS

Two types of classification are conducted using the above optimal selected features and channels in this section. The first type is to identify the simultaneous task from non-task subjects. The second one is to classify the subject's feelings after they complete the tasks. The results for the first type of classification are shown in Table 1.

It can be seen the two classes are based on mean degree, clustering coefficient and degree distribution appear using optimal channels in Table 1. The feature candidates $\bar{c}$ and $\bar{d}$ of F8 and T8 has no significant difference between SVM and PRART. When the number of optimal channels increased from single channel to two channels: F8 and T8, and the number of features increases from 1 to 3, the classification accuracy of SVM is improved to 87.5% of ACC and with 0.75 Kappa. When the epoch length is 384, the graph features from three optimal channel F8, T8, and AF4 achieve 89.6% of ACC and with 0.79 kappa accuracy by the SVM method. The expected two tasks classification accuracy by random chance is 83.77% of ACC and with 0.67 Kappa accuracy by the SVM method.

TABLE 1. Accuracy for two tasks cognitive load classification.

Channels	Features	SVM ACC	SVM Kappa	RPART ACC	RPART Kappa
F8	$\bar{c}$	77.1%	0.54	75.0%	0.50
T8	$\bar{c}$	72.9%	0.46	75.0%	0.50
F8	$\bar{c}, \bar{d}$	77.1%	0.54	75.0%	0.50
T8	$\bar{c}, \bar{d}$	75.0%	0.50	75.0%	0.50
F8, T8	$\bar{c}, \bar{d}, p(20)$	87.5%	0.75	75.0%	0.50
F8, T8, AF4	$\bar{c}, \bar{d}, p(14)$	) 89.6%	0.79	79.1%	0.58

Table 2 shows the accuracy of three self-reported feelings of classification using SVM and RPART classifies. Firstly, all features are observed on three group classification with two classifiers in Table 2. Secondly, the performance are poor than those of two tasks classification if the features are from the same channels. However, it is possible to obtain a high performance by picking the highest optimal combined channels and features.

TABLE 2. Accuracy for the three self-reported cognitive load classification.

Channels	Features	SVM ACC	SVM Kappa	RPART ACC	RPART Kappa
F8	$\bar{c}$	60.0%	0.38	57.8%	0.33
T8	$\bar{c}$	53.3%	0.23	60.0%	0.38
F8	$\bar{c}, \bar{d}$	64.4%	0.42	57.8%	0.33
T8	$\bar{c}, \bar{d}$	53.3%	0.23	60.0%	0.38
AF4, F8, T8	$\bar{c}, p(14)$	60.0%	0.37	57.8%	0.30
F8, P8, T8	$\bar{c}, p(13), p(16)$	) 79.5%	0.67	57.8%	0.32

It can be seen that high performance are based on three graph features, the clustering coefficient $\bar{c}$ and two degree distribution $p(13)$, $p(16)$ as shown in Table 2. When the epoch length is 384, the classification accuracy between SVM and PRART shows that features of DVG in channels F8, T8, f8, AF4 have no significant difference. However, using the graph features ($\bar{c}$, $p(13)$ and $p(16)$) from three optimal channel (F8, P7, and P8), features of the classification accuracy increase to 79.5%, and 0.67 kappa by the SVM method. The expected three self-reported feelings classification accuracy by random chance is 75% of ACC and with 0.5 Kappa accuracy by the SVM method.

IV. DISCUSSION

The study examines the impact of cognitive load based on graph features on EEG data. This study's findings suggest that the clustering coefficient has an effective performance in identifying the cognitive load using EEG signals. The accuracy can achieve 77.1% by just using a single feature: clustering coefficient of F8 channel. Previous results [26] on the same database have obtained 75% using 5-fold cross-validation for the tasks classification, whereas 80% as training and 20% as testing. Thus, the graph feature has high performance for identifying the cognitive load based on objective rating. The accuracy of the proposed method is 89.6% using SVM (50% as training and 50% as testing), which is 14.6% higher than those previous results on the same datasets for the tasks classification.

TABLE 3. Compared with existing cognitive load classification on two level arousal.

Authors	Signals	Features	Tasks	Accuracy
Mazher et al. [19]	EEG	Graph	Learning	85.77%
Lim et al. [26]	EEG	Frequency	SIMKAP	79.5%
Proposal methods	EEG	Graph	SIMKAP	89.6%

Table 3 compares the existing mental load classification based on tasks. The subjective sentiment classification results using the proposed method achieved 79.5% accuracy with only three features, which is also 10.3% higher than those of the previous methods [26]. Regarding the three types of classification of feeling, we also obtain 69.2% accuracy with 28 features [26]. It should be noted that the expected classification accuracy by random chance in the previous studies is 41.7% [26].

The other contribution of this article is to find that the optimal EEG channels of cognitive load measurement are not only related to the frontal area (F8 and AF4) but also related to temporal regions(T8). Channels (F8, T8 and AF4) with the three features ($\bar{c}$, $\bar{d}$ and $p(14)$) have the highest classification accuracy for different tasks. In addition, we suggest that the clustering coefficients of both F8 and T8 channels are the optimal channels for discriminating cognitive load from individual tasks. These findings also reveal that the channels on the right hemisphere: F8 and T8 show a very significant difference from two tasks ($p < 0.0001$), where F8 are similar to the findings of the previous work. Working cognitive load measures are significant predictors of multitasking [26]. For the "No task" condition, the delta activity is concentrated around the AF4 and F8 position, and the theta activity is present in AF4, F8, and T8 along with alpha and beta activity. For "SIMKAP" condition, FC5, AF4, and F8 are activity in the bands of the delta, theta, alpha and theta [26]. Also, So *et al.* [25] discovered that the frontal area was sensitive to cognitive loading. However, this study shows that the right temporal region T8 can also be efficiently applied in cognitive load detection.

Regarding the complexity of the proposal method, the degree and clustering coefficient features can be calculated in $O(n)$ respectively, where n is the number of points in the time series. Other contribution is to find that the optimal EEG channels of cognitive load measurement and related to the frontal area (F8 and AF4). It is slightly slower than those of power spectrum methods; the latter has the same computational complexity as that FFT speed. Excluding EEG sampling time, the process time of the proposed method is within one second on a PC with Intel®Core™ i7-4790 @ 3.60 GHz CPU to complete extracting three graph features and classification verification (see Tables 1 and 2).

This study's limitation is that the only two graph topology, degree and clustering coefficient, are applied in features extraction. There has many other graph topology, such as path, community or strength. Furthermore, it is unclear whether the gender, age or patients can affect the cognitive load recognition. In the feature, the accuracy of cognitive load identification could be improved by increasing the number of graph features. In addition, it is also possible to measure the cognitive load to differentiate mental diseases better and improve the operator efficiency of the brain-computer interfaces, especially on fatigued driving detection.

V. CONCLUSION

In this article, three graph features are applied to identify cognitive load tests based on differences tasks and feeling of subjects. The clustering coefficient features are higher during the multi-task compared to those of the rest states. The F8, P8, T8, and AF4 channels in the right hemisphere of high cognitive load are significantly different from those of low cognitive load (*p-value* < 0.0001). It is the first time investigating mental EEG with graph methods and showing that both the temporal and the frontal area are sensitive to high cognitive load. In contrast, the previous work only found in the frontal area [25], [26]. Meanwhile, these results show that the graph features of EEG on tasks satisfy the exponential distributions. The proposed methodology is helpful in identifying fatigue and optimizing learning.

REFERENCES

[1] F. Paas, A. Renkl, and J. Sweller, "Cognitive load theory and instructional design: Recent developments," *Educ. Psychol.*, vol. 38, no. 1, pp. 1–4, Mar. 2003.

[2] K. A. Bernhardt, D. Poltavski, T. Petros, F. R. Ferraro, T. Jorgenson, C. Carlson, P. Drechsel, and C. Iseminger, "The effects of dynamic workload and experience on commercially available EEG cognitive state metrics in a high-fidelity air traffic control environment," *Appl. Ergonom.*, vol. 77, pp. 83–91, May 2019.

[3] J. Sweller, "Cognitive load during problem solving: Effects on learning," *Cognit. Sci.*, vol. 12, no. 2, pp. 257–285, Apr. 1988.

[4] N. Friedman, T. Fekete, K. Gal, and O. Shriki, "EEG-based prediction of cognitive load in intelligence tests," *Frontiers Hum. Neurosci.*, vol. 13, p. 191, Jun. 2019.

[5] C. D. Conrad and M. Bliemel, "Psychophysiological measures of cognitive absorption and cognitive load in E-learning applications," in *Proc. 37th Int. Conf. Inf. Syst.*, P. Agerfalk, N. Levina, and S. S. Kien, Eds. Dublin, Ireland: Springer Dec. 2016, pp. 1–9.

[6] M. Bannert, "Managing cognitive load—Recent trends in cognitive load theory," *Learn. Instruct.*, vol. 12, no. 1, pp. 139–146, 2003.

[7] F. Paas, J. E. Tuovinen, H. Tabbers, and P. W. M. Van Gerven, "Cognitive load measurement as a means to advance cognitive load theory," *Educ. Psychol.*, vol. 38, no. 1, pp. 63–71, Mar. 2003.

[8] R. Brunken, J. L. Plass, and D. Leutner, "Direct measurement of cognitive load in multimedia learning," *Educ. Psychol.*, vol. 38, no. 1, pp. 53–61, Mar. 2003.

[9] Z. Chen, Y. He, and Y. Yu, "Enhanced functional connectivity properties of human brains during *in-situ* nature experience," *PeerJ*, vol. 4, p. e2210, Jul. 2016.

[10] K. Gupta, R. Hajika, Y. S. Pai, A. Duenser, M. Lochner, and M. Billinghurst, "In AI we trust: Investigating the relationship between biosignals, trust and cognitive load in VR," in *Proc. 25th ACM Symp. Virtual Reality Softw. Technol.*, Nov. 2019, pp. 1–10.

[11] D. He, B. Donmez, C. C. Liu, and K. N. Plataniotis, "High cognitive load assessment in drivers through wireless electroencephalography and the validation of a modified N-back task," *IEEE Trans. Human-Machine Syst.*, vol. 49, no. 4, pp. 362–371, Aug. 2019.

[12] M. Lohani, B. R. Payne, and D. L. Strayer, "A review of psychophysiological measures to assess cognitive states in real-world driving," *Frontiers Hum. Neurosci.*, vol. 13, p. 57, Mar. 2019.

[13] F. Al-Shargie, M. Kiguchi, N. Badruddin, S. C. Dass, A. F. M. Hani, and T. B. Tang, "Mental stress assessment using simultaneous measurement of EEG and fNIRS," *Biomed. Opt. Exp.*, vol. 7, no. 10, pp. 3882–3898, Oct. 2016.

[14] Ö. Örün and Y. Akbulut, "Effect of multitasking, physical environment and electroencephalography use on cognitive load and retention," *Comput. Hum. Behav.*, vol. 92, pp. 216–229, Mar. 2019.

[15] S. Koelstra *et al.*, "Single trial classification of EEG and peripheral physiological signals for recognition of emotions induced by music videos," in *Proc. Int. Conf. Brain Inform.* Berlin, Germany: Springer, 2010, pp. 89–100.

[16] J. Shang, W. Zhang, J. Xiong, and Q. Liu, *Cognitive Load Recognition Using Multi-channel Complex Network Method*. Cham, Switzerland: Springer, 2017, pp. 466–474.

[17] F. Wang, X. Zhang, R. Fu, and G. Sun, "EEG characteristic analysis of coach bus drivers based on brain connectivity as revealed via a graph theoretical network," *RSC Adv.*, vol. 8, no. 52, pp. 29745–29755, 2018.

[18] H. Wang, X. Liu, J. Li, T. Xu, A. Bezerianos, Y. Sun, and F. Wan, "Driving fatigue recognition with functional connectivity based on phase synchronization," *IEEE Trans. Cognit. Develop. Syst.*, early access, Apr. 13, 2020, doi: 10.1109/TCDS.2020.2985539.

[19] M. Mazher, A. Qayyum, I. Ahmad, and M. O. Alassafi, "Beyond traditional approaches: A partial directed coherence with graph theory-based mental load assessment using EEG modality," *Neural Comput. Appl.*, pp. 1–16, Oct. 2020, doi: 10.1007/s00521-020-05408-2.

[20] D. Rodenburg, P. Hungler, S. A. Etemad, D. Howes, A. Szulewski, and J. Mclellan, "Dynamically adaptive simulation based on expertise and cognitive load," in *Proc. IEEE Games, Entertainment, Media Conf. (GEM)*, Aug. 2018, pp. 1–6.

[21] W. L. Lim, O. Sourina, and L. Wang, "STEW: Simultaneous task EEG workload dataset," *IEEE Dataport*, Jul. 2018, doi: 10.21227/44r8-ya50.

[22] Z. Zhang, S. Wei, G. Zhu, F. Liu, Y. Li, X. Dong, C. Liu, and F. Liu, "Efficient sleep classification based on entropy features and a support vector machine classifier," *Physiol. Meas.*, vol. 39, no. 11, Nov. 2018, Art. no. 115005.

[23] U. R. Acharya, S. V. Sree, P. C. A. Ang, R. Yanti, and J. S. Suri, "Application of non-linear and wavelet based features for the automated identification of epileptic EEG signals," *Int. J. Neural Syst.*, vol. 22, no. 2, Apr. 2012, Art. no. 1250002.

[24] N.-Y. Liang, P. Saratchandran, G.-B. Huang, and N. Sundararajan, "Classification of mental tasks from EEG signals using extreme learning machine," *Int. J. Neural Syst.*, vol. 16, no. 1, pp. 29–38, Feb. 2006.

[25] W. K. Y. So, S. W. H. Wong, J. N. Mak, and R. H. M. Chan, "An evaluation of mental workload with frontal EEG," *PLoS ONE*, vol. 12, no. 4, Apr. 2017, Art. no. e0174949.

[26] W. L. Lim, O. Sourina, and L. P. Wang, "STEW: Simultaneous task EEG workload data set," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 11, pp. 2106–2114, Nov. 2018.

[27] G. Zhu, Y. Li, and P. P. Wen, "Analysis and classification of sleep stages based on difference visibility graphs from a single-channel EEG signal," *IEEE J. Biomed. Health Inform.*, vol. 18, no. 6, pp. 1813–1821, Nov. 2014.

[28] M. E. J. Newman, "The structure and function of complex networks," *SIAM Rev.*, vol. 45, no. 2, pp. 167–256, 2003.

[29] G. Zhu, C. Wang, F. Liu, L. Tang, and J. Zheng, "Age-related network topological difference based on the sleep ECG signal," *Physiol. Meas.*, vol. 39, no. 8, Aug. 2018, Art. no. 084009.

[30] T. M. Therneau, B. Atkinson, and B. Ripley, "rpart: Recursive partitioning," *R Package Version*, vol. 3, no. 3.8, pp. 1–34, 2010.

[31] C.-W. Hsu and C.-J. Lin, "A comparison of methods for multiclass support vector machines," *IEEE Trans. Neural Netw.*, vol. 13, no. 2, pp. 415–425, Mar. 2002.

[32] G. Zhu, Y. Li, P. Wen, and S. Wang, "Analysis of alcoholic EEG signals based on horizontal visibility graph entropy," *Brain Informat.*, vol. 1, nos. 1–4, pp. 19–25, Dec. 2014.

[33] Z. Yang and H. Ren, "Feature extraction and simulation of EEG signals during exercise-induced fatigue," *IEEE Access*, vol. 7, pp. 46389–46398, 2019.

[34] J. A. K. Suykens, L. Lukas, P. Van Dooren, B. De Moor, and J. Vandewalle, "Least squares support vector machine classifiers: A large scale algorithm," in *Proc. Eur. Conf. Circuit Theory Design*, vol. 10, 1999, pp. 839–842.

[35] C. Liu, C. Liu, P. Shao, L. Li, X. Sun, X. Wang, and F. Liu, "Comparison of different threshold values r for approximate entropy: Application to investigate the heart rate variability between heart failure and healthy control groups," *Physiol. Meas.*, vol. 32, pp. 167–180, Feb. 2011.

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