Deep Depression Detection with Resting-State and Cognitive-Task EEG

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***Abstract*— Depression is a common mental disorder that negatively affects physical health and personal, social and occupational functioning. Currently, accurate and objective diagnosis of depression remains challenging, and electroencephalography (EEG) provides promising clinical practice or home use due to considerable performance and low cost. This work investigates the capabilities of deep neural networks with EEG-based neural patterns from both resting states and cognitive tasks for depression detection. We collect EEG signals from 33 depressed patients and 40 healthy controls using wearable dry electrodes and build Attentive Simple Graph Convolutional network and Transformer neural network for objective depression detection. Four experiment stages, including two resting states and two cognitive tasks, are designed to characterize the alteration of relevant neural patterns in the depressed patients, in terms of decreased energy and impaired performance in sustained attention and response inhibition. The Transformer model achieves an AUC of 0.94 on the Continuous Performance Test-Identical Pairs version (sensitivity: 0.87, specificity: 0.91) and the Stroop Color Word Test (sensitivity: 0.93, specificity: 0.88), and an AUC of 0.89 on the two resting states (sensitivity: 0.85 and 0.87, specificity: 0.88 and 0.90, respectively), indicating the potential of EEG-based neural patterns in identifying depression. These findings provide new insights into the research of depression mechanisms and EEG-based depression biomarkers.**

I. INTRODUCTION

Major depressive disorder (MDD), or depression, is a common mental disorder that causes persistent feelings of sadness and loss of interest in previously rewarding or enjoyable activities [1]. MDD negatively affects physical health and personal, social and occupational functioning, and even leads to recurrent suicidal ideation and attempts [2]. According to the estimation of World Health Organization, globally, 5% of adults suffer from depression. Currently, clinical diagnosis of MDD relies on patient interviews with symptom-based questionnaires, which may be not accurate and objective enough. Biomarkers are measurable indicators that could help to objectively diagnose MDD and/or predict treatment response. In the last years, biomedical models conceptualize depression as a disorder of neural networks incorporating changes in widely distributed brain areas [3], and many neuroimaging-based efforts have been made to search promising depression biomarkers [4]–[6].

Among various neuroimaging methods for precision psychiatry, electroencephalography (EEG) measures electrical activities from neuronal populations via electrodes on the scalp, and is more appealing for clinical practice or home use due to considerable performance and low cost [7]. Alpha power differences, altered theta activities and gamma oscillations during rest for depressed patients were thoroughly discussed [6], [8]. When compared to euthymic subjects, increased high-alpha power at the left brain hemisphere and reduced beta power in the central-left side of depressed patients were reported [9]. With graph analysis, right hemisphere function deficiency, symmetry breaking and randomized network structure were found with resting-state EEG data from MDD patients [10].

Most of previous studies used wet electrodes to collect EEG data in a resting state or a task-related experiment. The wet sensors relying on electrolytic gels provide a clean conductive path for high quality signal collection. However, they could be uncomfortable and inconvenient for users and can be too time-consuming and laborious for daily use [11], which limits the use for real-world large-scale depression detection. In this paper, we use wearable dry electrodes to collect long-term and multi-stage EEG data with the benefits of comfort and stability, and develop deep neural networks to extract complex EEG patterns to distinguish the depressed patients from the healthy controls.

II. EXPERIMENT SETUP

A. Subjects

Thirty-three patients with MDD (DPs) and 40 healthy controls (HCs) took part in the experiment. All subjects were right-handed and had normal or corrected normal hearing and vision. The study was approved by the Ethics Committee from Ruijin Hospital, Shanghai Jiao Tong University School of Medicine, and all participants were informed of the study procedure and signed the consent forms.

Patients were diagnosed with MDD by psychiatrists according to the International Classification of Diseases, Tenth Revision (ICD-10). At the time of testing, the severity of symptoms was assessed with the Hamilton Rating Scale for Depression, 17-item version (HAMD-17) by psychiatrists and with the Beck Depression Inventory (BDI-II) from self-reports. The mean HAMD-17 and BDI-II scores of the

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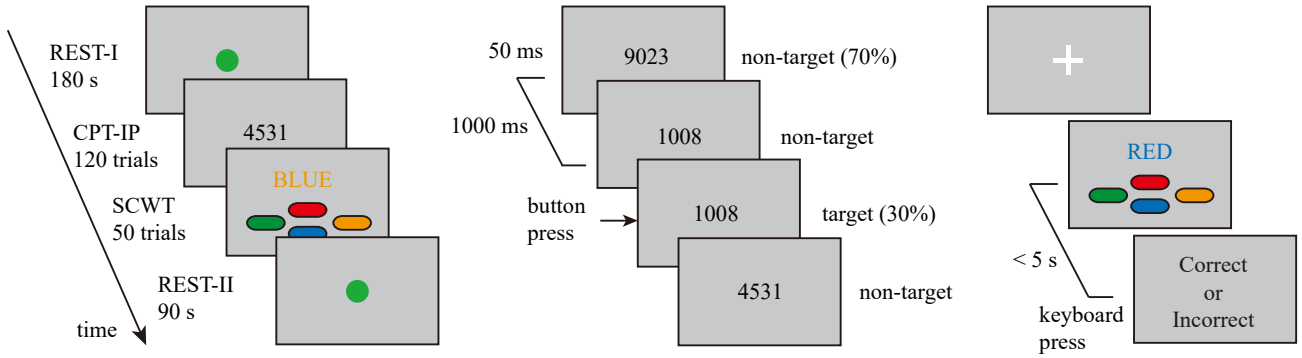

(a) Procedure (b) CPT-IP (c) SCWT

Fig. 1. The procedure, (a) including four stages: REST-I, CPT-IP, SCWT and REST-II. The detailed stimuli and time course of (b) CPT-IP and (c) SCWT.

DP group are 14.39 ± 5.97 and 23.76 ± 12.17, respectively. Exclusion criteria included: Bipolar Disorder, current ($<$ 6 months) drug/alcohol abuse or dependence, history of seizures or psychosis, unstable ($\geq$ 3 months) medical conditions and intense suicidal intention. The control group was recruited from the local community with advertisement. Forty adults with no psychiatric disorder, no alcohol/drug abuse or dependence, no history of seizures or brain trauma participated in the experiment. The mean BDI-II score of the HC group is 8.15 ± 6.66 ($p < 0.05$ with one-way ANOVA analysis between the two groups).

B. Experimental Procedure

As shown in Fig. 1, the experimental procedure includes four stages: REST-I, Continuous Performance Test-Identical Pairs version (CPT-IP), Stroop Color Word Test (SCWT) and REST-II. Hints about the progress and the expected options were given before each stage.

REST-I and REST-II were two independent eyes-open resting stages and were conducted before and after the two task stages, respectively. Participants were required to maintain a gentle fixation on a green point on the screen for 180 s in REST-I or 90 s in REST-II with their eyes open. The longer duration in REST-I was to help the participants get relaxed before facing challenging tasks.

CPT-IP and SCWT were two cognitive tasks. CPT-IP measures attention and requires identification of identical stimulus pairs within a continuously presented series of stimuli. Stimuli (e.g., four-digit numbers in this paper) in sequences of 120 trials were flashed on the screen at a constant rate of 1 per second, with a stimulus 'on' time of 50 ms. In each session, 30% of the trials were target trials (i.e., the second of a pair of two identical stimuli appeared) and expected a response (i.e., pressing once the 'Enter' key on the keyboard). The remaining trials were randomly distributed numbers. Responses to the trials were scored as 'correct' (for matched responses) or 'incorrect' (for missed responses or false alarms). SCWT evaluates the ability to inhibit cognitive interference that occurs when the processing of a specific stimulus feature impedes the simultaneous processing of a second stimulus attribute. Color-words in sequences of 50 trials were printed in a consistent or inconsistent color ink on the screen, and the participants were required to name the color of the ink instead of reading the word, using the arrow keys on the keyboard within 5 seconds. Responses to the trials were scored as 'correct', 'incorrect' or 'time out'.

III. METHODS

A. EEG Recording and Feature Extraction

EEG signals were recorded using a Dry Sensor Interface (DSI-24)[1] and DSI-Streamer at a sampling rate of 300 Hz. The sensors were located according to the international 10-20 system. In this study, 18-channel signals were for data analysis, and the Pz electrode was set as reference. A bandpass filter between 1-45 Hz was applied to the raw EEG data to filter out noise and artifacts, and then the EEG data were processed in the five frequency bands (i.e., delta: 1–4 Hz, theta: 4–8 Hz, alpha: 8–14 Hz, beta: 14–31 Hz and gamma: 31–45 Hz). Specifically, differential entropy (DE) features of EEG signals were calculated using short-term Fourier transforms with a 1 s Hanning window without overlapping for all channels, and the linear dynamic system approach was applied for further denoising.

B. Classification Models

Three classifiers were applied for depression detection: Support Vector Machine (SVM), Attentive Simple Graph Convolutional network (ASGC) [12] and Transformer neural network [13]. For generalization, the split of training data and test data was subject-independent, and a three-fold cross validation strategy was used for all classifiers.

As a basic model, an SVM classifier was trained to find an optimal hyperplane that separates the EEG features from the two groups. Linear kernel function and a soft margin parameter was used.

Taking the EEG channels as graph nodes and combining the attention mechanism with a simple graph convolutional network, an ASGC classifier was adapted to explore the topology information between EEG features for classification. By learning both coarse-grained and fine-grained inter-channel relations, ASGC can capture more complex neural

[1]https://wearablesensing.com/dsi-24/

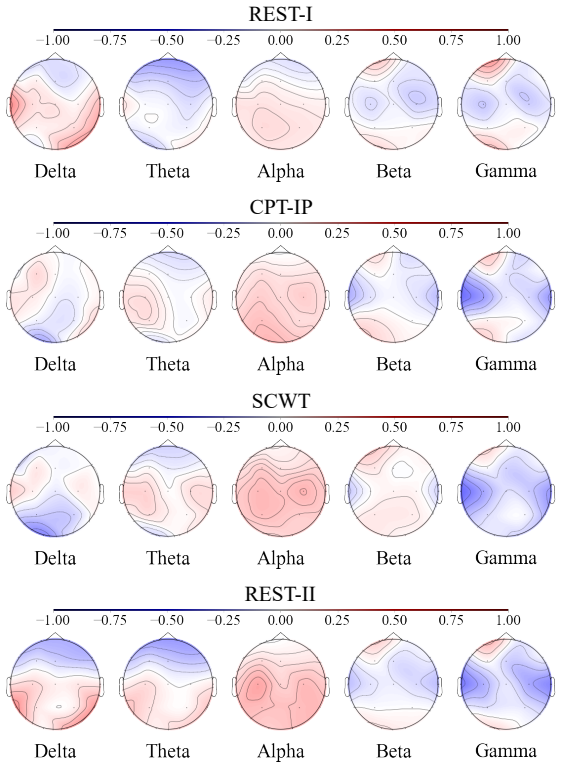

Fig. 2. Differences of the neural patterns between HCs and DPs in different stages. Blue colors indicate higher energy levels from DPs, while red colors indicate higher energy levels from HCs.

patterns and improve the predictive power. We adopted Adam optimizer, ReLU activation, a learning rate of $5e{-}3$ or $1e{-}2$, and a batch size of 64 or 128. The numbers of hidden nodes in the graph convolution network and the 2-layer multilayer perceptron were tuned within $\{6, 12, 18\}$.

For the Transformer neural network, after position encoding with the channels, the EEG features were fed into a Transformer encoder to learn deep feature representations for classification. The encoder is composed of a stack of multiple identical blocks. Each block has two sub-layers (i.e., a multi-head self-attention and a fully connected feed-forward network), and a residual connection is around each of them. We adopted Adam optimizer, GELU activation, a learning rate of $1e-3$ or $1e-2$, and a batch size of 64 or 128. The number of blocks, number of heads, dimension of head and weight decay rate are empirically tuned within $\{2, 3\}$, $\{2, 4\}$, $\{4, 8\}$ and $\{1e-4, 1e-3\}$, respectively.

IV. RESULTS AND DISCUSSION

A. Neural Patterns

The differences of the averaged neural patterns between the healthy controls and the depressed patients during the four experiment stages are depicted in Fig. 2. Consistent trends are observed in the four stages. Compared to HCs, (1) in the delta and theta bands, DPs have higher activation at the frontal site and lower activation at the temporal sites; (2) in the alpha band, DPs have lower activation across the whole brain except the frontal lobe; and (3) in the beta and gamma bands, DPs have higher activation at the temporal sites and lower activation at the left frontal and left parietal sites. Besides, there are pattern differences between stages: (1) in the delta and theta bands, the neural activations are prominently different in the frontal and parietal areas in resting states, while the differences triggered by cognitive tasks are more related to the temporal sites; (2) in the alpha band, the energy differences between HCs and DPs are larger during REST-II (after the tasks) than those during REST-I (before the tasks); and (3) during SCWT, DPs show a larger brain area of low activation in the beta band and high activation in the gamma band.

We can infer from the pattern differences that: (1) since alpha waves typically reflect an aware but relaxed state and wide-spread frontal theta is more often a reflection of drowsiness, the healthy controls were more relaxed, while the depressed patients may be a little disturbed or tired during the whole experiments, irrespective of resting or tasking stages; (2) differences in the theta and alpha waves between REST-I and REST-II may result from the exacerbated fatigue of patients after challenging tasks; and (3) differences especially at the frontal and temporal sites during CPT-IP and SCWT may suggest the deficits in sustained attention and response inhibition of the depressed patients.

B. DP-HC Classification

Table I lists the accuracies of SVM, ASGC and Transformer on the stages of REST-I, CPT-IP, SCWT and REST-II, and Table II details the performance of Transformer in terms of accuracy, F1-score, AUC, sensitivity and specificity. On each stage, all models can distinguish the depressed patients from the healthy controls, and the deep neural networks, ASGC and Transformer, outperform the traditional SVM classifier. Especially, Transformer with a high discriminative capacity successfully extracts the deep complex features for depression detection, achieving a sensitivity of 0.93 and a specificity of 0.88 on SCWT, and 0.87 and 0.91 on CPT-IP, respectively. The AUCs for the REST-I, CPT-IP, SCWT and

TABLE I
ACCURACIES (MEANS ± S.D., %) OF SVM, ASGC AND TRANSFORMER FOR DP-HC CLASSIFICATION.

Exp	SVM	ASGC	Transformer
REST-I	66.63 ± 2.84	83.39 ± 1.98	**86.66** ± 2.55
CPT-IP	74.46 ± 6.99	83.33 ± 6.11	**89.04** ± 1.92
SCWT	76.05 ± 7.16	81.92 ± 2.88	**90.27** ± 1.66
REST-II	70.67 ± 1.63	84.55 ± 6.76	**88.52** ± 5.65

TABLE II
DP-HC CLASSIFICATION PERFORMANCE (MEANS, %) OF TRANSFORMER ON RESTING STATES AND COGNITIVE TASKS.

Exp	Acc	F1	AUC	Sens	Spec
REST-I	86.66	86.65	88.86	84.76	88.29
CPT-IP	**89.04**	**89.01**	**93.62**	**87.01**	**90.80**
SCWT	**90.27**	**90.27**	**93.75**	**92.93**	**87.96**
REST-II	88.52	88.52	90.44	87.00	89.75

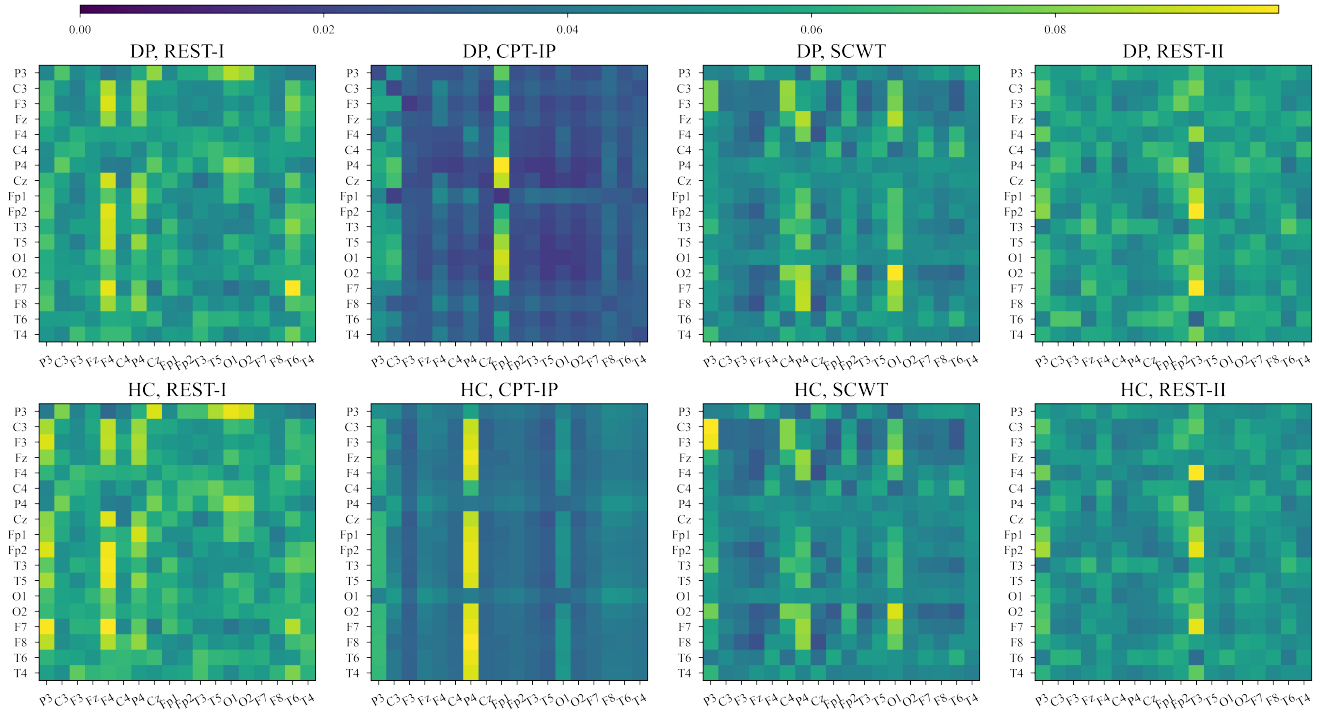

Fig. 3. The attention maps of the trained Transformers for the depressed patients and the healthy controls.

REST-II are about 0.89, 0.94, 0.94 and 0.90, respectively, suggesting that the depressed patients suffer from decreased energy and cognitive dysfunction.

Multi-head self-attention of a Transformer jointly obtains information from different representation subspaces at different positions and allows the interpretation of inter-channel relations via attention distributions. Fig. 3 visualizes the averaged attention maps of multiple heads and blocks of the trained Transformers on the four experiment stages, respectively. The models draw much attention to the electrodes $F4$, $T3$, $P3$ and $P4$ on the resting states, and to the electrodes $FP1$, $FP2$, $P3$, $P4$ and $O1$ on the cognitive tasks.

V. CONCLUSIONS

In this paper, we have investigated EEG-based neural patterns on both resting states and cognitive tasks for depression detection. We have collected EEG signals from 33 MDD patients and 40 healthy controls and built SVM, ASGC and Transformer classifiers for four experiment stages including REST-I, CPT-IP, SCWT and REST-II. The Transformer neural networks achieve an AUC of 0.89, 0.94, 0.94 and 0.90, respectively, indicating the potential of EEG patterns in identifying depression. The alteration of the neural patterns in the depressed patients may reflect their decreased energy and impaired performance in sustained attention and response inhibition. This work provides potential quantitative and objective approaches for depression detection and new insights into the research of mechanisms for mood disorders.

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