Investigating Emotion EEG Patterns for Depression Detection with Attentive Simple Graph Convolutional Network

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***Abstract*— Depression severely limits daily functioning, diminishes quality of life and possibly leads to self-harm and suicide. Noninvasive electroencephalography (EEG) has been shown effective as biomarkers for objective depression diagnose and treatment response prediction, and dry EEG electrodes further extend its availability for clinical use. Even though many efforts have been made to identify depression biomarkers, searching reliable EEG biomarkers for depression detection remains challenging. This work presents a systematic investigation of capabilities of emotion EEG patterns for depression detection using a dry EEG electrode system. We design an emotion elicitation paradigm with happy, neutral and sad emotions and collect EEG signals during film watching from 33 depressed patients and 40 healthy controls. The mean activation levels at frontal and temporal sites in the alpha, beta and gamma bands of the depressed group are different to those of the healthy group, indicating the impacts of depressive symptoms on the emotion experiences. To leverage the topology information among EEG channels for emotion recognition and depression detection, an Attentive Simple Graph Convolutional network is built. The deep depression-health classifier achieves a sensitivity of 81.93% and a specificity of 91.69% on the happy emotions, suggesting the promising use of the emotion neural patterns for distinguishing the depressed patients from the healthy controls.**

I. INTRODUCTION

Major depressive disorder (MDD), or major depression, is a common mental disorder that severely limits psychosocial functioning and diminishes quality of life [1], and has been one of the leading causes of the global health-related burden [2]. Clinical diagnosis of MDD mainly relies on patient interviews with symptom-based questionnaires, which may not be objective enough [3]. Biomarkers are measurable indicators that could help objectively diagnose MDD and/or effectively predict treatment response. In the last years, many efforts have been made to search and identify depression biomarkers, and reviews on promising biomarkers can be found in previous studies [3]–[5].

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We focus on the study of biomarkers for depression detection using noninvasive electroencephalography (EEG). There are mainly six types of quantitative EEG for depression, i.e., band power, alpha asymmetry, EEG vigilance, evoked potential, signal features and functional connectivity [5]. As one of the most consistent findings in recent decades, elevated alpha activities during rest were observed in depressed patients [6]. When compared to healthy subjects, increased high-alpha power at the left brain hemisphere and reduced beta power in the central-left side of depressed patients were reported [7]. Using convolutional neural network, EEG signals from the right hemisphere were discovered to be more distinctive in depression than those from the left hemisphere [8]. With graph analysis, right hemisphere function deficiency, symmetry breaking and randomized network structure were found in patients with MDD [9]. Activated regions associated with microstate generation were identified and alteration of brain activity patterns were found for depressed patients [10]. However, as claimed in the review [5], the findings are sometimes inconsistent due to the heterogeneous symptoms, unpredictable course and variable treatment responses. Finding reliable EEG biomarkers for depression remains important but challenging.

In this paper, we propose to investigate emotion neural patterns for depression detection using dry EEG electrodes. Popular resting state EEG has been shown effective but might not be able to capture complex cognitive dynamics for depression detection. Since depression is a mood disorder that causes a persistent feeling of sadness and loss of interest, emotion tasks have the potential to uncover the highly related alteration of brain activities with pertinence. Moreover, although wet EEG electrodes provide better quality signals, dry EEG electrodes are usually easy for setups and comfortable over long durations, extending the availability for large-scale depression detection into the real world (e.g., at home or clinics). Therefore, we resort to use a dry EEG electrode system to record neural signals during emotion experiences for depression detection.

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. Table I summarizes the demographic information.

Patients (16 males and 17 females; mean age: 30.75 ± 10.49 years) 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 HAMD-17 and BDI-II scores of the 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 (≥ 3 months) medical conditions and intense suicidal intention. Forty adults (12 males and 28 females, mean age: 23.05 ± 3.29 years) 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 for the HC group is 8.15 ± 6.66. All participants were informed with written consent forms and a local ethics committee approved the study.

TABLE I
DEMOGRAPHIC INFORMATION (MEANS ± S.D.) OF THE MDD PATIENTS AND THE HEALTHY CONTROLS.

	MDD Patients (n = 33)	Healthy Controls (n = 40)
Age (Y)	30.75 ± 10.49	23.05 ± 3.29
Gender	16 M, 17 F	12 M, 28 F
Education (Y)	14.41 ± 2.04	16.15 ± 1.64
HAMD-17	14.39 ± 5.97	–
BDI-II	23.76 ± 12.17	8.15 ± 6.66

B. EEG Recording

We designed an emotion elicitation paradigm, where 9 film clips were chosen as happy (HAP), sad (SAD) and neutral (NEU) emotion stimuli and displayed in a sequence of HAP, NEU, SAD, SAD, NEU, HAP, HAP, NEU and SAD to the participants. The procedure was similar to that of the public emotion dataset SEED [11]. There were 5 seconds of hints before each clip, 1.5-3 minutes for each clip and then self-assessment after each clip. Every participant performed the experiment only once. EEG signals were recorded using a Dry Sensor Interface (DSI-24) and DSI-Streamer at a sampling rate of 300 Hz. The sensors were located according to the international 10-20 system, where Pz electrode was set as reference by default and other 18-channel signals were selected for data analysis. The DSI-24 EEG cap[1] and sensor layout for 18 channels are illustrated as Fig. 1.

III. METHODS

A. Feature Extraction

A bandpass filter from 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 1s Hanning window without overlapping for all channels, and the linear dynamic system approach was applied to further filter out components that were not associated with emotion states. Therefore, with 18 channels, there are a total of 18 × 5 = 90 dimensions of the DE features for emotion EEG pattern analysis.

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

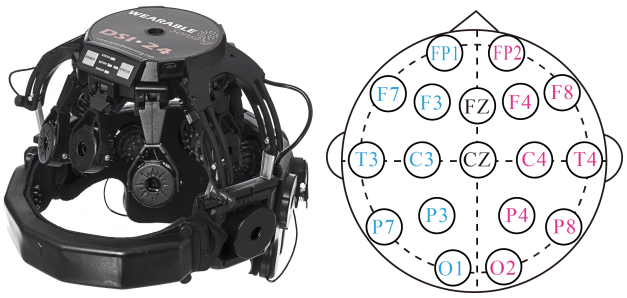

Fig. 1. The EEG cap and the sensor layout with 18 channels.

B. Classification

To investigate the emotion neural patterns for depression detection, Support Vector Machine (SVM) and Attentive Simple Graph Convolutional network (ASGC) [12] were built for two sub-problems, i.e., Emotion Recognition and DP-HC Classification. The former sub-problem helps to explore the EEG patterns of different emotions for both depressed and healthy groups. Subject-dependent and subject-independent experiments were conducted, and similarities and differences of the EEG patterns between the two groups were discussed. The latter sub-problem aims to distinguish the depressed patients from the healthy controls with the emotion EEG patterns. Together, the emotion EEG patterns and their capability of depressive emotion identification would provide insights towards reliable EEG biomarkers for depression detection.

As a basic model, an SVM classifier was trained to find a hyper-plane that creates a boundary between different classes (e.g., the happy, neutral and sad emotions or the DP and HC groups). Linear kernel function and a soft margin parameter were used. Taking the EEG channels as graph nodes and combining the attention mechanism with a graph convolutional network, an ASGC classifier was utilized to explore the topology information for classification. By learning both coarse-grained and fine-grained inter-channel relations, ASGC can capture more complex neural patterns and improve the predictive power. We adopted Adam optimizer, ReLU activation, a learning rate of $1e-2$ or $5e-3$, and a batch size of 16 for the subject-dependent setting and 64 for the subject-independent setting. The numbers of hidden nodes in the graph convolution network and the 2-layer multilayer perceptron were tuned within $\{6, 12, 18\}$.

IV. RESULTS AND DISCUSSION

A. Emotion EEG Patterns

The neural patterns with the averaged DE features in the five frequency bands for different emotions and groups are

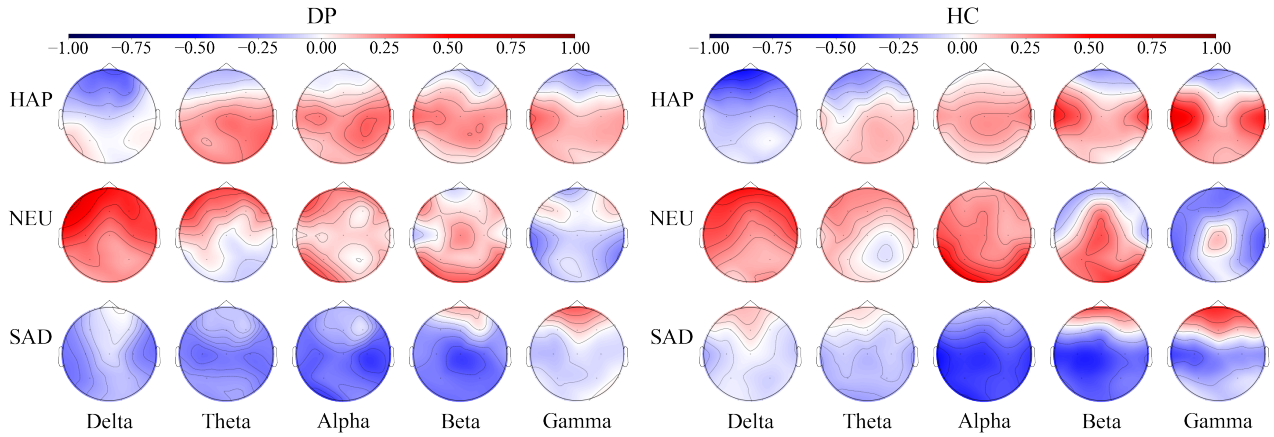

Fig. 2. Average neural patterns for emotions within the depressed patients (left) and the healthy controls (right), respectively. Blue colors indicate low energy levels, and red colors indicate high energy levels. Abbreviations: HAP-Happiness, NEU-Neutral, SAD-Sadness.

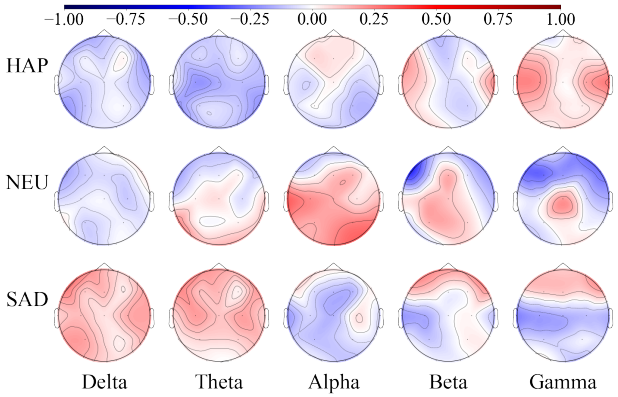

Fig. 3. Differences of emotion EEG patterns between the healthy controls and the depressed patients.

depicted in Fig. 2, and Fig. 3 illustrates the differences of emotion patterns between HCs and DPs. As summarized in [13], while delta and theta waves are more associated with the unconscious and subconscious mind, alpha waves are typically associated to an aware but relaxed mental state, beta waves are prominent in the frontal cortex during intense focused mental activity and gamma waves are associated with a hyper brain activity. Therefore, we concentrate on the neural patterns in the alpha, beta and gamma bands.

The emotion patterns of HCs are in consistency with previous studies [11]. In the beta and gamma bands, there is high activation at the temporal sites and low activation at the frontal site for happy emotions, and completely opposite activation for sad emotions. For neutral emotions, While low activation at the temporal and frontal sites in the beta and gamma bands is observed, there is high alpha power across the whole brain, especially at the parietal and occipital sites.

Compared to the patterns of HCs, the patterns of DPs show similar trends of activation for the three emotions except some details: (1) In the beta and gamma bands, there is less frontal activation for sad emotions and less temporal activation for happy emotions, and thus the neural responses to happy and sad emotions of MDD patients are much moderate (which may indicate their depressed mood or dysfunctional emotion regulation); and (2) For neutral emotions, the energy levels at the frontal site are higher in the beta and gamma bands (which are similar to the neural patterns of sad emotions), the alpha power is higher at the frontal site but lower at the parietal and occipital sites (which may reflects their sleep disturbance).

B. Emotion Recognition

1) Individual Stability: We first train subject-dependent models with 3-fold cross validation for emotion recognition. Table II presents the results, which demonstrate the stability of emotion EEG patterns of depressed and healthy individuals. The ASGC model achieves the high accuracies (i.e., 85.92% for DPs and 88.48% for HCs) and significantly outperforms the SVM model (i.e., $p < 0.05$ with one-way ANOVA analysis), suggesting that the inter-channel relations captured by ASGC contain key information for depression detection. Fig. 4(a) shows the confusion matrices. For individuals, (1) the HCs have experienced more consistent emotions than the DPs; and (2) Among the three emotions, the neural patterns of happy emotions are the most stable (i.e., the accuracies are 90.05% for DPs and 92.12% for HCs, respectively).

TABLE II
ACCURACIES (MEANS ± S.D., %) OF SVM AND ASGC FOR SUBJECT DEPENDENT AND INDEPENDENT EMOTION RECOGNITION.

Exp.	Model	MDD Patients	Healthy Controls
Subject Dependent	SVM	68.22 ± 23.04	80.28 ± 18.05
	ASGC	$\mathbf{85.92 \pm 14.78}^{a}$	$\mathbf{88.48 \pm 13.35}^{a,b}$
Subject Independent	SVM	63.24 ± 16.08	71.59 ± 14.51
	ASGC	$\mathbf{75.91 \pm 10.81}^{a}$	$\mathbf{79.22 \pm 8.56}^{a,b}$

For MDD patients $n = 33$, for healthy controls $n = 40$.
[a] $p < 0.05$ (ASGC significantly outperforms SVM).
[b] $p > 0.05$ (No significant difference of the ASGC performance between DPs and HCs).

2) Within-group Similarities: Subject-independent models are constructed with leave-one-subject-out cross validation.

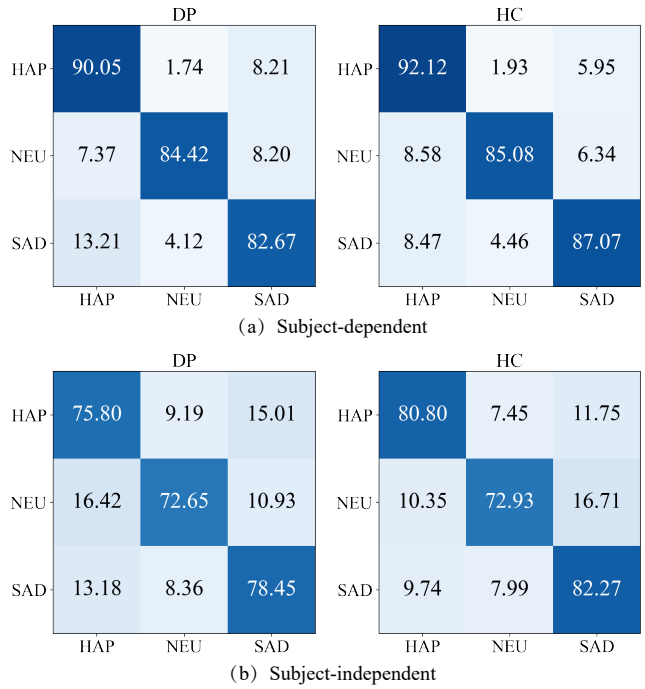

Fig. 4. Confusion matrices of ASGC for subject-dependent and subject-independent emotion recognition.

Specifically, for every subject in the DP or HC group as a test, the emotion recognition model is trained with data of other group members. As Table II shows, the mean accuracies of ASGC are 75.91% for DPs and 79.22% for HCs, respectively. Despite individual differences, the members within the same group still share lots of similarities of emotion neural patterns. As Fig. 4(b) demonstrates, group members show more resemblance for sad and happy emotions (i.e., the true sad rates are 78.45% for DPs and 82.27% for HCs, respectively, while the true happy rates are 75.80% for DPs and 80.80% for HCs, respectively).

C. DP-HC Classification

Classification models are built with 3-fold cross validation to evaluate the capability of the neural patterns in distinguishing the depressed patients from the healthy controls. Table III presents the classification results in terms of accuracy, F1-score, AUC, sensitivity and specificity. The mean AUCs of ASGC are 89.20%, 84.69% and 84.02% for detecting depression under happy, neutral and sad emotions, respectively. The experimental results indicate that the EEG patterns of all three emotions do contain potentially promising information for depression detection. With a threshold probability of 0.5, the discriminative capability of happy emotions achieves a sensitivity of 81.93% and a specificity of 91.69%, suggesting that the depressed patients do suffer from depressed mood and loss of interest or pleasure (which are the major depressive symptoms for diagnostic purposes).

V. CONCLUSIONS

We investigated the emotion EEG patterns for depression detection using Attentive Simple Graph Convolutional network. The EEG signals were collected from MDD patients and healthy controls with a dry EEG electrode system. The mean activation levels at the frontal and temporal sites in the alpha, beta and gamma bands of the depressed group were different to those of healthy group, and the promising capability of emotion EEG patterns in distinguishing depressed patients from healthy controls was evaluated. This work would contribute to the research of EEG-based depression biomarkers and extend the availability for large-scale and objective depression detection into the clinical scenarios.

TABLE III
PERFORMANCE (MEANS, %) OF SVM AND ASGC FOR THE DP-HC CLASSIFICATION BASED ON EMOTION EEG PATTERNS.

Exp.	Model	Acc	F1	AUC	Sens	Spec
HAP	SVM	65.85	65.38	73.52	62.54	68.94
	ASGC	**87.22**	**87.11**	**89.20**	**81.93**	**91.69**
NEU	SVM	69.49	68.85	76.45	58.08	79.06
	ASGC	**82.92**	**82.92**	**84.69**	**81.23**	**84.50**
SAD	SVM	70.29	69.60	77.60	60.26	78.91
	ASGC	**82.67**	**82.64**	**84.02**	**80.77**	**84.27**

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