Measuring Decision Confidence Levels from EEG Using a Spectral-Spatial-Temporal Adaptive Graph Convolutional Neural Network

Rui Li[1], Yiting Wang[1], and Bao-Liang Lu[1,2,3](✉)

[1] Center for Brain-like Computing and Machine Intelligence,
Department of Computer Science and Engineering,
Shanghai Jiao Tong University, Shanghai 200240, China
[2] Key Laboratory of Shanghai Education Commission for
Intelligent Interaction and Cognitive Engineering,
Shanghai Jiao Tong University, Shanghai 200240, China
[3] RuiJin-Mihoyo Laboratory, Clinical Neuroscience Center, RuiJin Hospital,
Shanghai Jiao Tong University School of Medicine, 197 RuiJin 2nd Rd.
Shanghai 200020, People's Republic of China.
{realee,bllu}@sjtu.edu.cn

Abstract. Decision confidence can reflect the correctness of people's decisions to some extent. To measure the reliability of human decisions in an objective way, we introduce a spectral-spatial-temporal adaptive graph convolutional neural network (SST-AGCN) for recognizing decision confidence levels based on EEG signals in this paper. The advantage of our proposed method is that it fully utilizes the knowledge from the spectral, spatial, and temporal dimensions of the EEG signals. The experiments based on a confidence text exam task within limited time are designed and conducted. The experimental results demonstrate that the SST-AGCN enhances the performance compared with the models without using the spatial or temporal information for classifying five decision confidence levels, achieving the average F1-score of 57.92% and the average accuracy of 58.16%. As for the two extreme confidence levels, the average F1-score reaches to 93.17% with the average accuracy of 94.11%. Furthermore, the neural patterns of decision confidence are analyzed in this paper through the brain topographic maps and the learned functional connectivities by the SST-AGCN. The experimental results indicate that the delta, theta and alpha bands may be critical in measuring human decision confidence levels with better recognition performance than other frequency bands.

Keywords: Decision confidence · Electroencephalogram · Graph convolutional neural network · Functional connectivity.

1 Introduction

Decision confidence is a subjective sense of correctness or optimization when making a decision, which reflects an internal estimation of the probability that a choice is correct [13]. Moreover, in spite of the rapid development of science nowadays, human involvement is still essential in our actual working lives. However, people do not always make reliable decisions since they can subjectively lie. So there needs to be an objective way to measure the reliability of people's decisions, such as measuring their decision confidence levels.

Due to the importance of decision confidence, it has been extensively investigated using different types of recorded physiological data, such as eye movement, functional magnetic resonance imaging (fMRI), and electroencephalogram (EEG), etc. There are many studies employing fMRI methods [11, 1] to explore the neural basis of the decision confidence, revealing that anterior cingulate cortex, prefrontal cortex, superior parietal lobule, posterior parietal cortex and ventral striatum might be the brain areas of great importance for human decision confidence. Electroencephalogram (EEG) data record the electrical activity in the brain, which can also contribute to the study of decision confidence. Several researches based on event-related potential (ERP) have been conducted to investigate the human decision confidence [17, 2, 7]. Electroencephalographic studies have confirmed that in the event related potential of the signal, the magnitude of the signal varies at different levels of confidence [17] and the two levels of confidence can be distinguished [7]. Nevertheless, the ERP experiment is usually have many experimental restrictions, such as the stimulus is usually needed to be presented in a rapid speed, which is not conducive to practical applications.

The majority of studies on decision confidence are based on psychological research techniques. To study decision confidence in a more realistic scenario, researchers [9, 8] have developed some new experiments in the visual perceptual tasks with infinite amount of time to simulate real-world situations, and deep neural networks are employed to measure the human decision confidence levels from multi-channel EEG recorded in decision-making process. Moreover, Liu *et al.* proposed an attentive simple graph convolutional networks to learn the topological knowledge of EEG in the spatial dimension and improved the performance of classifying the five decision confidence levels [10]. From those researches, EEG signals are proved to be able to recognize decision confidence levels in the visual perceptual tasks with deep learning algorithms.

In this paper, we employ a spectral-spatial-temporal adaptive graph convolutional neural network (SST-AGCN) to recognize different levels of decision confidence from EEG data, which fully utilizes the information from spectral, spatial and temporal domains of EEG signals. We construct a confidence graph of the brain, in which the vertices of the graph represented by EEG channels are connected by functional brain connections to serve as the topology of graph. Furthermore, the decision confidence associated functional brain connectivities can be learned by the model in an adaptive manner. Moreover, we design a novel confidence experimental paradigm where subjects perform a text-based exam task with limited time, which simulates the real scenarios in exams, to investigate the discrimination ability of EEG signals for measuring decision confidence levels in the situation of text-based exam. Extensive experiments on this text-based exam confidence dataset demonstrate the superior performance of

SST-AGCN compared with other models missing the knowledge from the spatial or temporal domains. Finally, we investigate the neural patterns of decision confidence in the text-based exam task.

2 Methodology

To fully utilize the knowledge related to decision confidence from spectral, spatial and temporal dimensions of EEG signals, we adopt a spectral-spatial-temporal adaptive graph convolutional neural network to measure human decision confidence levels. Fig. 1 illustrates the overall architecture of the spectral-spatial-temporal adaptive graph convolutional neural network. The preprocessed EEG features are passed to a stack of L basic SST-AGCN blocks where we apply the spectral-temporal convolution and spectral-spatial convolution in parallel to extract the confidence-related features.

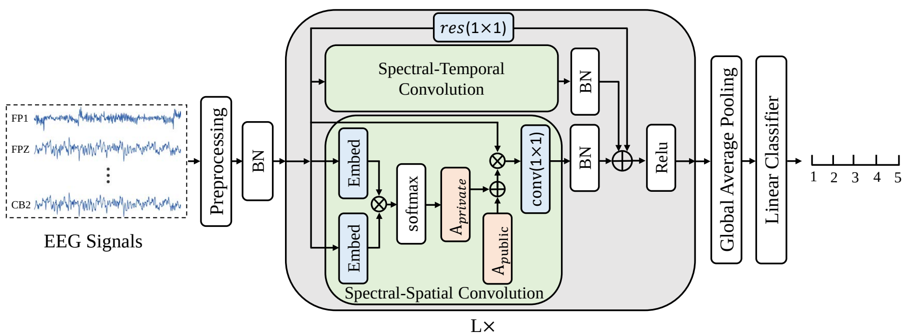

Fig. 1. The overall process of the spectral-spatial-temporal adaptive graph convolutional neural network (SST-AGCN), which consists of L basic SST-AGCN blocks, a global average pooling layer and a linear classifier to discriminate the decision confidence levels. Each SST-AGCN block contains a spectral-temporal convolution layer and a spectral-spatial convolution layer in parallel to extract the confidence-related features.

2.1 Data Preprocessing

To investigate the decision confidence levels, we extract the differential entropy (DE) features from the multi-channel EEG data in the spectral domain [4], as the DE feature has been proved to have excellent performance in decision confidence recognition tasks [9, 8]. The EEG data were first preprocessed with curry 7 and baseline corrected. Eye movement artifacts were removed using the signals of EOG and FPZ channels and the noise were filtered out by a 0.3 - 50 Hz band-pass filter. Then only the EEG segments during the decision-making process were extracted, and the segments were divided into the same-length epochs of 1 second without overlapping.

The short-time Fourier transform (STFT) of 1-second Hanning window was conducted on each epoch of the preprocessed EEG data to extract the DE features of five frequency bands (delta: 1-3 Hz, theta: 4-7 Hz, alpha: 8-13 Hz, beta: 14-30 Hz, gamma: 31-50 Hz). In addition, the linear dynamic system method [15] was employed for feature smoothing in order to filter rapid fluctuations.

The extracted spectral EEG features are defined as $\mathrm{X} = (\mathrm{x}_1,\ \mathrm{x}_2, \ldots, \mathrm{x}_N) \in R^{N\times F\times C}$, where N denotes the number of samples in time series after preprocessing, F denotes the five frequency bands of EEG feature, and C denotes the number of EEG channels. In addition, X is further transformed into $\tilde{\mathrm{X}} = (\tilde{\mathrm{x}}_1,\ \tilde{\mathrm{x}}_2, \ldots, \tilde{\mathrm{x}}_N) \in R^{N\times F\times T\times C}$ with an overlapping window size of T, in order to obtain the time sequences while keeping the sample size unchanged. For each sample, $\tilde{\mathrm{x}}_i \in R^{F\times T\times C}$.

2.2 Spectral-Spatial-Temporal Adaptive Graph Convolutional Neural Network

We build the spectral-spatial-temporal adaptive graph convolutional neural network for identifying decision confidence levels based on EEG signals inspired by the adaptive graph convolution operation for skeleton-based action recognition [14], and further take the characteristics of the brain into account. We construct a confidence brain graph represented as $\mathrm{G} = (V, E)$, here V is the set of EEG channels, serving as the vertices in this graph, $C = |V|$ and E represents the set of edges between EEG channels. The spectral EEG feature X, regarded as the information on V, contains the decision confidence knowledge in the spectral dimension. The weighted adjacency matrix $\mathrm{A} \in R^{C\times C}$ represents the set of edges E, which also means the functional brain connectivity associated with decision confidence.

Spectral-Spacial Convolution To learn dynamics and inter-channel dependencies from the data explicitly, the knowledge from the EEG features in the spectral domain and the topological structure of EEG channels in the spacial domain are merged to extract the decision confidence related features. The spectral-spatial summary of the confidence brain graph $\widetilde{B}_{ss}$ is calculated between EEG channels by the graph convolution.

The operation of the graph convolution on vertex v_i can be formulated as [14] :

$$f_{out}\left(v_i\right) = \sum_{v_j \in \mathcal{B}_i} \frac{1}{Z_{ij}} f_{in}\left(v_j\right) \cdot w\left(l_i\left(v_j\right)\right), \tag{1}$$

where f_{in} is the input feature and v denotes the vertex of the graph. The weighting function of convolution operation is represented by w, and $\mathcal{B}_i$ represents the sampling area of the convolution operation for v_i. As the sampling area $\mathcal{B}_i$ may be varied, the mapping function l_i is introduced to map each vertex with a weight vector. Z_{ij} is the cardinality of sampling area $\mathcal{B}_i$, aims to balance the contribution of each sampling area.

Considering the topological structure of the brain, we assume that the functional connections may exist between all channels, and the spatial convolution mechanism considers all channels. In consequence, the sampling area of the vertex v_i contains all of the vertices in the confidence brain graph we constructed. The graph convolution operation implemented in this paper is as follows:

$$\widetilde{\mathrm{B}}_{ss} = \mathrm{W}\mathrm{B}_{in}(\mathrm{A}_{public} + \mathrm{A}_{private}), \tag{2}$$

where W is the $S_{out} \times S_{in} \times 1 \times 1$ weight vector of 1×1 convolution operation. The input confidence brain embedding can be represent as $\mathrm{B}_{in} \in R^{S_{in} \times T \times C}$. S_{in} denotes the number of the channels in the spectral dimension. In the first layer, $\mathrm{B}_{in} = \tilde{\mathrm{x}}_i \in R^{F \times T \times C}$, where S_{in} equals F. A_{public} and $\mathrm{A}_{private}$ denote the public and private weighted adjacency matrices, respectively, representing the connection strength between vertices.

In particular, $\mathrm{A}_{private}$ is a $C \times C$ private weighted adjacency matrix representing the strength of the connections between EEG channels of each sample, which is obtained by the dot product operation to measure the similarity between two vertices in an embedding space. Since we aim to identify the most relevant channels, we project them into the same embedding space and compare with the EEG channel of interest. The input feature $\mathrm{B}_{in} \in R^{S_{in} \times T \times C}$ is transformed into the embedding space using two 1×1 convolution functions, obtaining two embed features $\mathrm{E}_{\theta} \in R^{S_e \times T \times C}$ and $\mathrm{E}_{\tau} \in R^{S_e \times T \times C}$, respectively. E_{θ} and E_{τ} in the embedding space are then reshaped and multiplied to get the private adjacency matrix with the shape of $C \times C$. Then the $softmax$ operation is conducted to normalize the matrix into $0-1$. The calculation of $\mathrm{A}_{private}$ can be formulated as:

$$\mathrm{A}_{private} = softmax\left(\mathrm{E}_{\theta}{}^{T}\mathrm{E}_{\tau}\right). \tag{3}$$

In addition, A_{public} is a $C \times C$ public weighted adjacency matrix shared by all the samples to capture the general functional brain connectivity patterns for decision confidence recognition, which is a data-driven parameter and is set to be trainable. From the element of A_{public}, the neural patterns of decision confidence can be clearly illustrated.

Spectral-Temporal Convolution Consider the temporal characteristics of EEG signals, the convolution operation in the spectral-temporal dimension is introduced in the model. Time-series of EEG signals are represented as contiguous sequences of every single channel. Therefore, we calculate a spectral-temporal summary $\widetilde{\mathrm{B}}_{st}$ for each channel from the input spectral feature $\mathrm{B}_{in} \in R^{S_{in} \times T \times C}$. The temporal aspect of the graph is constructed by connecting the same EEG channels across consecutive sequences to model the temporal dynamics within EEG sequence. Then extending the concept of neighbor-hood to temporally connected EEG channels, the graph convolution operation can be extend to the temporal dimension. The spectral-temporal embedding $\widetilde{\mathrm{B}}_{st}$ is updated by the adjacent frames of the same channel and is formulated as:

$$\widetilde{\mathrm{B}}_{st} = \mathrm{Conv}_t(\mathrm{B}_{in}), \tag{4}$$

where $\widetilde{\mathrm{B}}_{st} \in R^{S_{out} \times T \times C}$ and S_{out} denotes the number of the output channel in the spectral dimension. The convolution operation Conv_t is performed on the temporal dimension T of the input spectral features in each EEG channel with the kernel size of $K_t \times 1$. The parameter K_t controls the temporal range to be included in the neighbor graph and can thus be called the temporal kernel size.

Aggregation For each SST-AGCN block, the spectral-spatial and spectral-temporal convolutions run in parallel to calculate embedding summaries $\widetilde{B}$. Moreover, the batch normalization (BN) and the residual connection [5] are introduced to ensure the stability of the network and retain the original information, which is achieved by 1×1 convolution operation. The aggregation process can be formulated as:

$$\widetilde{B} = \sigma(\mathrm{BN}(\widetilde{B}_{ss}) + \mathrm{BN}(\widetilde{\mathrm{B}}_{st}) + \mathrm{residual}(\mathrm{B}_{in})), \tag{5}$$

where σ denotes the Relu activation function. We stack L such basic SST-AGCN blocks to successively update the embeddings, followed by a global average pooling layer and a linear classifier layer to predict the decision confidence levels.

3 Experiment

3.1 Dataset

We design a novel decision confidence experiment to collect EEG data during the decision-making process in a text exam task. Twenty-four healthy subjects (11 men and 13 women) aged from 19 to 24 (mean: 22.5, std: 1.69) took part in the experiment. In the experiment, participants were supposed to answer questions in the form of single choice based on the text in Chinese, and score the confidence levels of each choice. The EEG signals were recorded during the decision confidence experiment.

Stimuli The stimulus material were composed of 80 text-based exam questions in Chinese in the form of single choice and each question offered 4 options containing several words. The exam questions were some incomplete sentences lacking some words, and the options were alternative words to fill in the sentences. The participants were supposed to decide which of the words in the option were the most appropriate. These questions came from the exam question bank in Chinese high school exam, making the experiment very close to the real scene.

Procedure In our experiment, the participants need to choose the appropriate words in Chinese in the options to fill in incomplete sentences from the questions and score their confidence levels. The experiment consists of 80 trials and each trial contains one exam question, corresponding to one decision. In each trial, the subjects are asked to choose which option they think was correct. Just as there is a time limit in the real exam, we have a fixed time limit for each question so that the participants must decide within a certain time limit. The subjects are told to click the choice button by a mouse to choose the appropriate answer they thought, and then the subjects should report their subjective confidence about this decision by scoring on the confidence scale on the screen. The 5-point confidence scale includes: certainly wrong: 1; probably wrong: 2; not sure: 3; probably correct: 4; and certainly correct: 5.

During the experiment, subjects wore 62 channel electrode caps. The EEG data are collected by an ESI neuroscan system, and the sampling frequency was 1000 Hz according to the international 10-20 system. The impedance of each electrode was controlled below 5 $k\Omega$. Only the EEG data collected during the decision-making process were used to recognize the decision confidence levels.

3.2 Implementation Details

The five levels of decision confidence (1-5) reported by the subjects are used as classification labels to investigate the capability of EEG signals for measuring human decision confidence levels in the text-based exam task. All the classifiers are trained for each subject with stratified five-fold cross validation, which means that the EEG features of each confidence level are divided into the training set and the test set in a ratio of 4:1, in order to make the proportion of each confidence level in the training set and the test set same. To evaluate the performance of SST-AGCN for classifying human decision confidence levels in the text-based exam task, we compare with other four classifiers, support vector machine (SVM) [3], long short-term memory neural networks (LSTM) [6], regularized graph neural networks (RGNN) [16], and spectral-spatial adaptive graph convolutional neural network (SS-AGCN). RGNN is proved to be a powerful model in EEG-based recognition tasks [16], and SS-AGCN is constructed by the SST-AGCN removing the spectral-temporal aspect to evaluate the contributions of the temporal components.

For the SST-AGCN and SS-AGCN classifiers, the EEG features $\mathrm{X} \in R^{N\times F\times C}$ are transformed into $\tilde{\mathrm{X}} \in R^{N\times F\times T\times C}$ by an overlapping window with the size of T. In our experiments, T is set to 5 seconds and C equals to 62. The number of the SST-AGCN blocks L is set to 6, and the channel size of the graph convolutional layer of each SST-AGCN block is ranged from 30 to 120. RGNN adopted in this paper is implemented using the public code [16]. The adopted LSTM classifiers have two layers, with the layer size ranged from 300 to 600, and the overlap operation is also conducted in LSTM by the window size of T, which equals to 5. The SST-AGCN, SS-AGCN, RGNN and LSTM are all implemented by PyTorch [12] deep learning framework, and employ the cross-entropy as the loss function. The SVM classifiers applied in this paper are with the RBF kernel and the range of parameter C is $2^{[-10:10]}$.

3.3 Results Analysis

In this section, we compared the performance of SST-AGCN with other four pattern classifiers, SVM [3], LSTM [6], RGNN [16], and SS-AGCN to recognize five confidence levels and two extreme confidence levels. The neural patterns of decision confidence in the text-based exam task are also investigated.

Table 1. The mean accuracies and F1-scores (%) of SST-AGCN and baseline models for classifying five decision confidence levels with DE features in five frequency bands and the total frequency band.

Classifier	Delta		Theta		Alpha		Beta		Gamma		Total	
	acc	F1	acc	F1	acc	F1	acc	F1	acc	F1	acc	F1
SVM	42.82	39.68	43.35	40.78	42.67	39.98	40.67	38.40	39.87	36.75	**46.73**	**45.22**
LSTM	47.76	46.88	48.41	45.73	45.98	42.38	43.09	38.87	45.26	41.84	**51.30**	**49.97**
RGNN	50.52	48.20	50.80	46.54	49.74	46.91	48.62	44.95	49.38	44.83	**53.58**	**52.83**
SS-AGCN	53.23	52.81	53.79	52.83	52.57	53.17	52.05	51.42	51.16	51.27	**55.14**	**54.88**
SST-AGCN	**54.49**	**53.75**	**54.61**	**54.18**	**54.40**	**54.22**	53.05	52.82	53.61	53.25	**58.16**	**57.92**

Measuring Five Decision Confidence Levels The mean accuracies and F1-sores of SVM, LSTM, RGNN, SS-AGCN, and SST-AGCN for the EEG features obtained from five frequency bands are listed in Table 1, as well as the total frequency band that contains all of the five frequency bands. From Table 1, the experimental results demonstrate that SST-AGCN performs best among these five pattern classifiers, achieving the best performance with the classification accuracy of 58.16% and F1-score of 57.92% using the DE features in the total frequency band. Furthermore, the delta, theta and alpha bands seem to be important in investigating decision confidence levels in the text exam task, as they achieve the best accuracies/F1-cores of 54.49%/53.75%, 54.61%/54.18% and 54.40%/54.22%, respectively, with the SST-AGCN classifier. The reason why SST-AGCN performs better than other models is that others do not take the all of the spectral, spatial and temporal information of EEG into account. The fact that SST-AGCN always surpasses SS-AGCN also indicates the importance of the spectral-temporal convolutional layer.

To further study each levels of decision confidence, the confusion matrices of five classifiers with the EEG feature in the total frequency band are presented in Fig. 2. One of the interesting things we find from these confusion matrices is that extreme confidence levels (1 and 5) are much easier to be distinguished than the intermediate confidence levels (2,3,4) by all models. In addition, the neighboring confidence levels are more easily confused in most cases which is consistent with

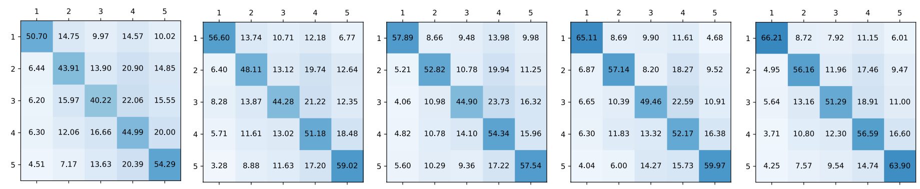

Fig. 2. The confusion matrices of five classifiers for identifying five decision confidence levels in the total frequency band.

our common sense. Moreover, the SST-AGCN is better for discriminating most of the five confidence levels than other classifiers.

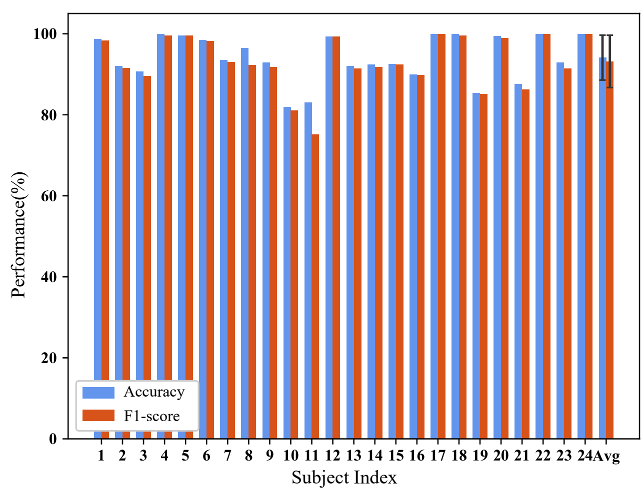

Fig. 3. The accuracies and F1-scores (%) of 24 subjects and their average with SST-AGCN for discriminating extreme confidence levels based on the EEG feature in the total frequency band.

Measuring Extreme Confidence Levels We further distinguish the lowest decision confidence level of 1 with the highest decision confidence level of 5. Fig. 3 demonstrates the discriminating performance of two extreme confidence levels (1 and 5) of 24 subjects with SST-AGCN using EEG features in the total band, which can be regarded as a binary classification problem. The experimental results show that the extreme confidence levels can be well distinguished with the average accuracy of 94.11% and the average F1-score of 93.17%.

Visualization of the Brain Topographic Maps The neural patterns corresponding to different levels of decision confidence are illustrated in Fig. 4, which are obtained by averaging the DE features from all 24 participants in each EEG channel. From Fig. 4, we can see that the energy of bilateral frontal cortex and temporal cortex in the low confidence levels were stronger in the delta and theta bands than in high confidence levels. Moreover, as confidence levels increasing, the energy increases in the central frontal cortex, parietal cortex, and occipital cortex in the Delta band, as well as in parts of the occipital cortex in the Alpha and Beta bands. These phenomena illustrate that the neural patterns that correspond to the confidence levels might exist.

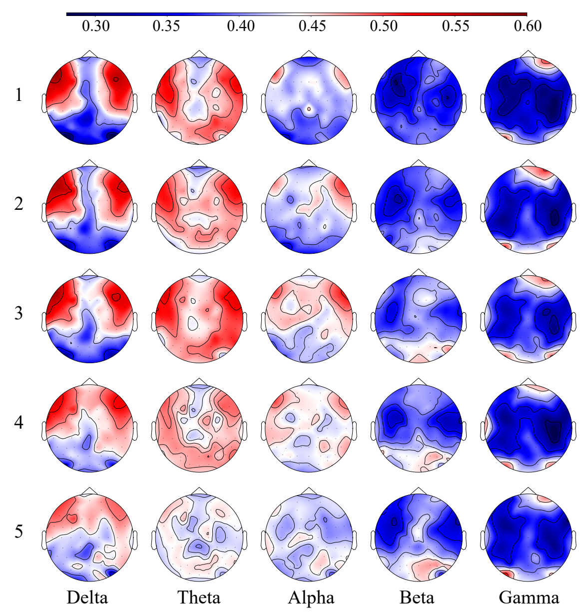

Fig. 4. The average topographic maps of 24 subjects for five decision confidence levels with five frequency bands. The column denotes the different confidence levels and the row denotes the different frequency bands.

Visualization of the Learned Functional Connectivities We visualized the functional brain connectivities learned in each SST-AGCN block while classifying five confidence levels in Fig. 5, from which we can see that the learned functional connections mainly aggregate on the frontal and parietal regions at the first block, and the complicated connections appear in the deep blocks. This phenomenon is consistent with the brain topographic mapping discussed above, indicating that the frontal and parietal brain areas may be important for measuring decision confidence levels based on EEG signals in the text exam task.

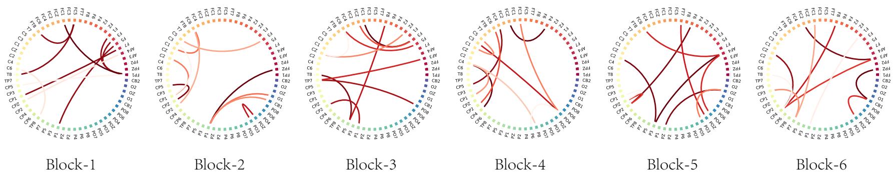

Fig. 5. The functional brain connectivities learned by SST-AGCN represented as the edge weight of the adjacency matrix are visualized by top 10 connections between EEG channels. The rows present the six basic SST-ACGN blocks. Darker color of the line denotes the stronger connection between EEG channels.

Furthermore, the SST-AGCN model can process complicated global connectivities with the deep layers.

4 Conclusion

In this paper, we propose a spectral-spatial-temporal adaptive graph convolutional neural network (SST-AGCN) to fully exploit the knowledge of EEG data in different domains, and address the problem of measuring decision confidence levels in a text-based decision confidence task. A novel decision confidence experiment was designed based on the text exam task in Chinese to investigate the discrimination ability of EEG signals for identifying human decision confidence levels in a realistic scenario. We compared the performance of SST-AGCN with four baseline pattern classifiers for recognizing the different levels of decision confidence. The experimental results demonstrate that the SST-AGCN model performs best in five levels classification problems. And the extreme confidence levels can be distinguished best through the SST-AGCN model. The experimental results also indicate that the delta, theta and alpha bands are critical in the text-based exam task with the highest accuracy and F1-score. In addition, according to the analysis of the brain topographic maps and the learned functional connectivities by SST-AGCN, the frontal and parietal area may play important roles in measuring decision confidence levels.

Acknowledgments

This work was supported in part by grants from the National Natural Science Foundation of China (No. 61976135), MOST 2030 Brain Project (No. 2022ZD0208500), Shanghai Municipal Science and Technology Major Project (No. 2021SHZDZX), SJTU Global Strategic Partnership Fund (2021 SJTU-HKUST), Shanghai Marine Equipment Foresight Technology Research Institute 2022 Fund (No. GC3270001/012), and GuangCi Professorship Program of RuiJin Hospital Shanghai Jiao Tong University School of Medicine.

References

1. Bang, D., Fleming, S.M.: Distinct encoding of decision confidence in human medial prefrontal cortex. Proceedings of the National Academy of Sciences **115**(23), 6082–6087 (2018)
2. Boldt, A., Schiffer, A.M., Waszak, F., Yeung, N.: Confidence predictions affect performance confidence and neural preparation in perceptual decision making. Scientific Reports **9**(1), 4031 (2019)
3. Cortes, C., Vapnik, V.: Support-vector networks. Machine Learning **20**(3), 273–297 (1995)
4. Duan, R.N., Zhu, J.Y., Lu, B.L.: Differential entropy feature for EEG-based emotion classification. In: 2013 6th International IEEE/EMBS Conference on Neural Engineering (NER). pp. 81–84. IEEE (2013)
5. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. pp. 770–778 (2016)
6. Hochreiter, S., Schmidhuber, J.: Long short-term memory. Neural Computation **9**(8), 1735–1780 (1997)
7. Krumpe, T., Gerjets, P., Rosenstiel, W., Spüler, M.: Decision confidence: EEG correlates of confidence in different phases of an old/new recognition task. Brain-Computer Interfaces **6**(4), 162–177 (2019)
8. Li, R., Liu, L.D., Lu, B.L.: Measuring human decision confidence from EEG signals in an object detection task. In: 2021 10th International IEEE/EMBS Conference on Neural Engineering (NER). pp. 942–945. IEEE (2021)
9. Li, R., Liu, L.D., Lu, B.L.: Discrimination of decision confidence levels from EEG signals. In: 2021 10th International IEEE/EMBS Conference on Neural Engineering (NER). pp. 946–949. IEEE (2021)
10. Liu, L.D., Li, R., Liu, Y.Z., Li, H.L., Lu, B.L.: EEG-based human decision confidence measurement using graph neural networks. In: International Conference on Neural Information Processing. pp. 291–298. Springer (2021)
11. Molenberghs, P., Trautwein, F.M., Böckler, A., Singer, T., Kanske, P.: Neural correlates of metacognitive ability and of feeling confident: a large-scale fMRI study. Social Cognitive and Affective Neuroscience **11**(12), 1942–1951 (2016)
12. Paszke, A., Gross, S., Chintala, S., Chanan, G., Yang, E., DeVito, Z., Lin, Z., Desmaison, A., Antiga, L., Lerer, A.: Automatic differentiation in pytorch (2017)
13. Pouget, A., Drugowitsch, J., Kepecs, A.: Confidence and certainty: distinct probabilistic quantities for different goals. Nature Neuroscience **19**(3), 366 (2016)
14. Shi, L., Zhang, Y., Cheng, J., Lu, H.: Two-stream adaptive graph convolutional networks for skeleton-based action recognition. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 12026–12035 (2019)
15. Shi, L.C., Lu, B.L.: Off-line and on-line vigilance estimation based on linear dynamical system and manifold learning. In: 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology. pp. 6587–6590. IEEE (2010)
16. Zhong, P., Wang, D., Miao, C.: EEG-based emotion recognition using regularized graph neural networks. IEEE Transactions on Affective Computing (2020)
17. Zizlsperger, L., Sauvigny, T., Händel, B., Haarmeier, T.: Cortical representations of confidence in a visual perceptual decision. Nature Communications **5**, 3940 (2014)