Measuring Human Decision Confidence from EEG Signals in an Object Detection Task

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Abstract— **In this paper, we investigate human decision confidence during image interpretation in an object detection task using electroencephalography (EEG) signals. We develop an EEG dataset acquired from 14 subjects. Five popular EEG features, differential entropy (DE), power spectral density (PSD), differential asymmetry (DASM), rational asymmetry (RASM) and asymmetry (ASM), and two classifiers, a support vector machine (SVM) and a deep neural network with shortcut connections (DNNS), are adopted to measure decision confidence in the object detection task. The classification results indicate that the DE feature with the DNNS model achieves the best accuracy of 47.36% and F1-score of 43.5% for five decision confidence levels. For the extreme confidence levels, the recognition accuracy reaches 83.98%, with an average F1-score of 80.93%. We also found that the delta band performs better than the other four bands and that the prefrontal area and parietal area might be sensitive brain regions that represent decision confidence in object detection tasks.**

I. INTRODUCTION

With the rapid development of artificial intelligence, especially powerful deep learning techniques, many tasks can be done automatically by computers without human participation. However, there are some critical and complex tasks that still need to be performed by professionals, such as detecting objects in remote sensing images (RSIs). Recently, deep convolutional neural networks (CNNs) have made great strides in detection tasks for specific objects [1]. However, the objects in RSIs usually occupy a very small portion of the overall image and are often ignored by deep CNN models because of their large receptive field and deep structure. Moreover, object detection in optical RSIs often suffers from several increasingly difficult challenges, including, but not restricted to, large variations in the visual appearance of objects caused by differences in viewpoints, occlusion, background clutter, illumination, and shadow. Usually, the resolution of remote sensing images is very low. Therefore, interpreters are still needed in this field to identify the objects in remote sensing images.

Indeed, many researchers have employed electroencephalography (EEG) signals to assist in classification and object detection, obtaining good results [2]. The judgment made by the interpreter is very important, and any mistake may cause serious consequences. Unfortunately, full-confidence, error-free decision-making is impossible for a human being in a real-world environment. Moreover, people may lie to themselves and pretend that they are very confident in their decisions. Hence, the development of an efficient approach to objectively measuring human decision confidence during image interpretation in object detection tasks would be very meaningful and of great importance to tasks that require human participation.

The small number of existing studies on decision confidence are mainly from the fields of cognitive science and neuroscience. Studies based on functional magnetic resonance imaging (fMRI) [3], [4], [5] show that some brain regions may be sensitive to decision confidence, including the anterior cingulate cortex, prefrontal cortex, superior parietal lobule, posterior parietal cortex and ventral striatum. In addition, there are several studies interpreting neural mechanisms of human decision confidence with EEG and event-related potentials (ERPs) [6], [7]. These works demonstrate that it is possible to use EEG signals to infer human decision confidence.

In this paper, we investigate the capability of EEG signals to measure decision confidence in tasks of object detection. We design a decision confidence experimental paradigm that closely simulates real-world situations, where subjects can detect multiple targets in RSIs. We record 62-channel EEG data of subjects during their decision-making process. Moreover, two pattern classifiers, a support vector machine (SVM) and a deep neural network with shortcut connections (DNNS), are applied to classify the level of decision confidence using five popular features extracted from EEG data. The experimental results indicate that our approach is capable of measuring decision confidence in object detection tasks.

II. EXPERIMENTAL DESIGN

To collect EEG data from subjects at different decision confidence levels while performing an object detection task, we designed a decision confidence experimental paradigm for the object detection task. In the experiment, subjects first completed an object detection task wherein they must find specified target objects in optical remote sensing images. Then, the subjects were asked to report their subjective confidence levels in each decision. All of the subjects were instructed to sit comfortably and refrain from body movement to avoid muscle artifacts caused by overt movements.

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A. Stimuli

The experimental materials were obtained from two geospatial object detection datasets, NWPU VHR-10 [8] and DOTA [9], which contain two categories of objects, i.e., aircraft and ships. To obtain the EEG data at different decision confidence levels, the images were downsampled to different degrees. The two categories of objects are separately divided into three difficulty grades: easy, medium and difficult. There are 12 images in each grade; thus, the total number of images is 72, and each image contains 1 to 15 targets.

B. Participants

Fourteen subjects (7 males and 7 females) aged between 18 and 24 years participated in the experiment. This research was approved by the Scientific and Technical Ethics Committee of the Bio-X Institute at Shanghai Jiao Tong University, and subjects provided informed consent before participation. All of the subjects were native Chinese students and had normal or corrected-to-normal vision. Before the formal experiment began, subjects were instructed to become familiar with the experimental procedure and precautions.

C. Procedure

In our experiment, the subjects needed to identify all the aircraft or ships they could see in the images with a mouse click and score the confidence of their decisions across 72 trials. The images were presented randomly, one image per trial.

Each trial in our proposed decision confidence experiment consisted of the following three steps: 1) First, an image containing one kind of target object is presented on the screen, and then the subjects determine all the objects in the images with a mouse click on the object. Each click on a target causes a red circle to appear on the target and is considered one decision, so each trial can contain several decisions. As shown in Fig. 1, the red circles represent the objects identified by the subject with a mouse click, indicating that the subject made 4 decisions in this trial. 2) After all of the objects in an image that the subjects can see are selected according to their subjective judgments, the subjects need to click the end button at the bottom of the screen to move to the next stage. 3) All of the clicks made by the subject were replayed, and a 5-point confidence scale is displayed on the screen. The 5-point decision confidence scale includes certainly wrong: 1; probably wrong: 2; not sure: 3; probably correct: 4; and certainly correct: 5. All of the subjects needed to recall the confidence they had when they made their previous decisions and score their confidence in each decision one by one.

The protocol of the decision confidence experiment proposed in this paper is illustrated in Fig. 1. During the experiment, participants were asked to wear a 62-channel electrode cap. The EEG data were recorded using an ESI NeuroScan system at a sampling rate of 1000 Hz according to the international 10-20 system. The impedance of each electrode was limited to less than 5 kΩ. All of the subjects were asked to perform the experiment seriously.

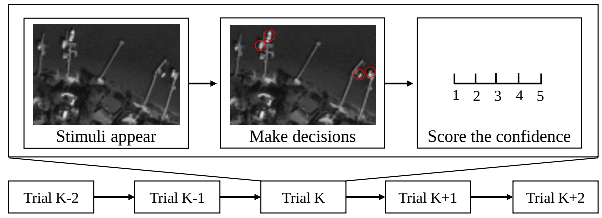

Fig. 1. The protocol of the object detection decision confidence experiment.

III. METHODOLOGY

A. Data Preprocessing

To explore the relationship between the subjects' EEG data and their confidence in the decision-making process in the object detection task, only a portion of the EEG data, the EEG segment acquired from the start to the end of a decision-making process, namely, the decision segment, was chosen for analysis in this study. As illustrated in Fig. 2, each trial contains several decision segments for data analysis, and each segment corresponds to one confidence level.

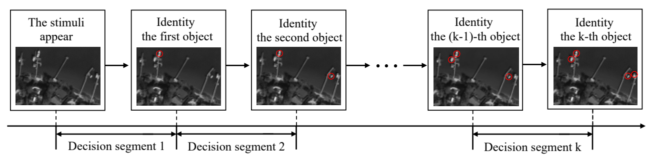

Fig. 2. The decision segment chosen for analysis in one trial. Each decision segment corresponds to one mouse click and is considered one decision.

We applied a bandpass filter between 0.3 and 50 Hz to each channel to filter the noise in the recording. After preprocessing, we extracted the EEG segments in the decision-making process, as shown in Fig. 2. We divided the EEG data into equal-sized epochs measuring 1 second in length. Then, the features were extracted from each epoch of EEG data.

B. Feature Extraction

Five kinds of EEG features were adopted in this paper, power spectral density (PSD), differential entropy (DE), differential asymmetry (DASM), rational asymmetry (RASM) and asymmetry (ASM), which have been shown to be highly effective in the field of affective brain-computer interfaces [10], [11]. Short-term Fourier transform (STFT) with a Hanning window of 1 s was used to compute the EEG features in five frequency bands: delta (1-4 Hz), theta (4-8 Hz), alpha (8-14 Hz), beta (14-31 Hz) and gamma (31-50 Hz). Furthermore, to filter rapid fluctuations, we utilized the linear dynamic system (LDS) method for feature smoothing [12]. The total numbers of dimensions for the PSD, DE, DASM, RASM, and ASM features are 310, 310, 135, 135, and 270, respectively.

C. Classification

In this paper, we compared the performance of two pattern classifiers: a support vector machine (SVM) and a deep neural network with shortcut connections (DNNS) [13] for measuring decision confidence levels based on EEG data. The classifiers were trained for each subject with stratified five-fold cross-validation, and the levels of confidence (1-5) were used as classification labels, which means that for each subject, four-fifths of the features of each class were used as the training set and one-fifth as the test set.

For the SVM classifier, we employed the RBF kernel, and the parameter C was searched within the range of $2^{[-5:10]}$ to determine the optimal value. We also constructed a deep neural network with shortcut connections. We utilized the shortcut connections to retain the information from the previous layers and avoid losing the information from the original EEG features. The network consists of two residual blocks and one output layer. Each residual block contains two linear layers, two batch normalization layers, two ReLU functions and one shortcut connection. The size of the layers ranges from 50 to 700, and the learning rate is set to 0.0001. Before inputting the EEG features into the classifiers, the values of the features were normalized between 0 and 1.

IV. EXPERIMENTAL RESULTS

In this section, we evaluate the performance of the classifiers in recognizing five levels of decision confidence in the object detection task. We trained the classifiers using the five features. The mean accuracies and F1-scores of the SVM and DNNS with different features in the five frequency bands are represented in Table I.

We can see that the DNNS performs better than the SVM in most cases, and the model trained with the DE feature performs best, as it achieves the best classification accuracy of 47.36% and F1-score of 43.5% with DNNS for the total frequency range. For different single frequency bands, the results demonstrate that the performance of the delta band is better than that of the other four bands. The accuracy of the delta band with the DNNS is 42.77%, with an F1-score of 38.09%. Fig. 3 shows the confusion matrices of the two

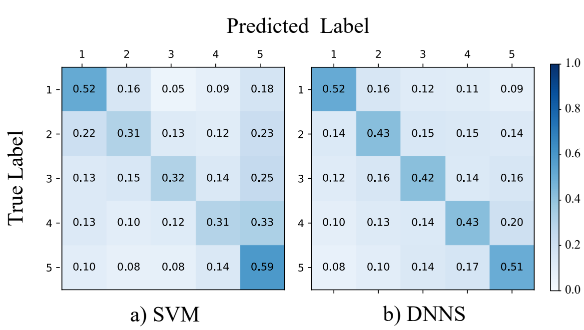

Fig. 3. Confusion matrix of the two classifiers for the five decision confidence levels with the DE feature. The rows represent the target class, and the columns represent the predicted class.

classifiers. From the figure, we can see that DNNS performs better than the SVM, and a moderate level of decision confidence (2,3,4) can be measured with high recognition accuracy, while the extreme levels of decision confidence (1 and 5) are easier to detect. The moderate decision confidence levels 2, 3 and 4 are easily confused with both of these classifiers. They are unable to classify moderate levels of decision confidence very well in this object detection task.

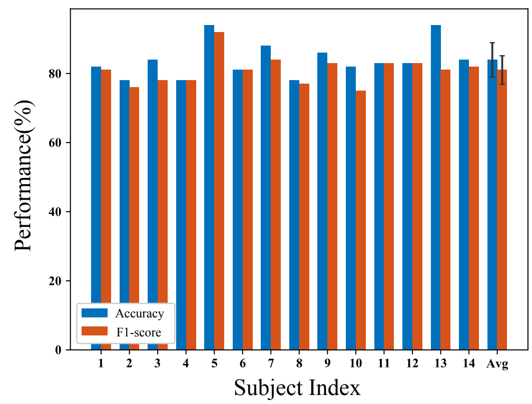

Fig. 4. The performance (%) of 14 subjects for the DE feature with the DNNS model in recognizing extreme levels of confidence.

We further analyzed the differences between extreme confidence levels 1 and 5. Fig. 4 illustrates the accuracies and F1-scores of the DNNS for the two confidence levels with the DE feature, which is a binary classification problem. The performance of the DNNS in this binary classification problem achieves an average accuracy/standard deviation of 83.98%/4.97% with an F1-score/standard deviation of 80.93%/4.12%.

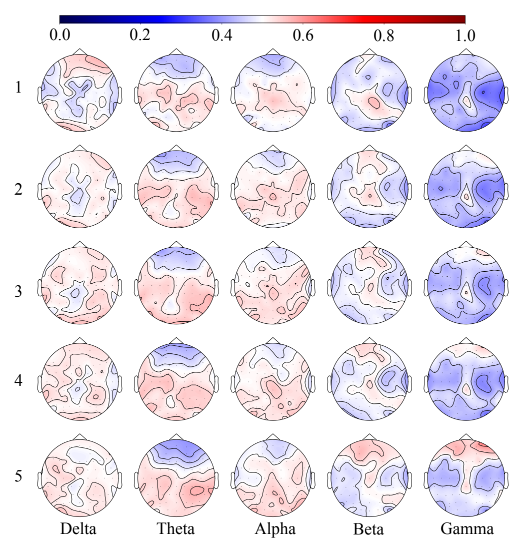

Fig. 5. The average neural patterns of all subjects for different decision confidence levels. The columns denote the five frequency bands, and the rows denote the five decision confidence levels.

To investigate the neural patterns underlying decision confidence in the object detection task, we depict the topographic maps for the five levels of decision confidence across the five frequency bands in Fig. 5, which is obtained by averaging the DE features from all subjects in each channel. As shown in Fig. 5, the energy in the prefrontal area in the delta and theta

TABLE I

THE MEAN ACCURACIES AND F1-SCORES (%) OF THE SVM AND DNNS CLASSIFIERS IN DIFFERENT FREQUENCY BANDS WITH FIVE FEATURES.

Feature	Classifier	Delta		Theta		Alpha		Beta		Gamma		Total	
		acc	F1	acc	F1	acc	F1	acc	F1	acc	F1	acc	F1
PSD	SVM	30.82	26.73	30.31	25.71	30.78	25.37	31.82	26.49	32.01	25.19	34.75	29.75
	DNNS	40.48	35.7	38.42	33.33	38.9	34.5	39.66	34.24	40.29	32.76	43.88	38.82
DE	SVM	36.18	30.87	32.73	27.99	32.25	27.42	36.45	31.71	34.87	29.35	**40.86**	**35.64**
	DNNS	**42.77**	**38.09**	40.77	35.12	40.46	35.81	41.62	37.51	41.1	36.7	**47.36**	**43.5**
RASM	SVM	31.24	25.19	29.84	24.5	30.35	24.77	33.26	28.6	30.8	26.04	36.94	32.65
	DNNS	38.84	32.63	36.91	30.71	38.51	32.79	40.82	35.45	40.44	35.95	45.16	41.02
DASM	SVM	29.83	24.39	29.62	24.27	30.13	25.17	32.68	28.18	31.68	27.61	37.76	33.85
	DNNS	37.99	32.66	38.01	31.51	39.16	32.8	41.09	35.95	41.79	37.34	46.07	41.55
ASM	SVM	31.09	25.41	29.83	24.67	30.4	24.85	32.94	28.46	31.57	27.34	37.4	33.3
	DNNS	39.3	33.55	37.01	31.65	38.78	33.31	41.96	36.8	40.88	36.49	46.14	41.27

bands increases as the decision confidence level decreases, while in the delta band, we can also see that as the decision confidence level increases, the energy in the parietal cortex also increases. For the gamma band, the neural patterns show more activation in the prefrontal and parietal areas at higher levels of decision confidence.

V. CONCLUSIONS

We applied two classifiers, the DNNS and the SVM, to evaluate the performance of different popular EEG features, frequency bands and pattern classification methods in measuring the levels of decision confidence in an object detection task. From the experimental results, we found that the DNNS with the DE feature outperformed all other approaches. For the five different decision confidence levels, the best average recognition accuracy reached 47.36%, and the F1-score was 43.5%. Furthermore, we investigated the distinctions between the extreme decision confidence levels, and an average of 83.98% was achieved, with an average F1-score of 80.93%. The delta band had the best performance among all five frequency bands, and the topographic maps suggested that the prefrontal area and parietal cortex may be the sensitive brain areas of decision confidence in this object detection task.

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REFERENCES

[1] J. Han, D. Zhang, G. Cheng, N. Liu, and D. Xu, "Advanced deep-learning techniques for salient and category-specific object detection: a survey," *IEEE Signal Processing Magazine*, vol. 35, no. 1, pp. 84–100, 2018.

[2] C. Spampinato, S. Palazzo, I. Kavasidis, D. Giordano, N. Souly, and M. Shah, "Deep learning human mind for automated visual classification," in *CVPR'17*, 2017, pp. 6809–6817.

[3] M. N. Hebart, Y. Schriever, T. H. Donner, and J.-D. Haynes, "The relationship between perceptual decision variables and confidence in the human brain," *Cerebral Cortex*, vol. 26, no. 1, pp. 118–130, 2014.

[4] P. Molenberghs, F.-M. Trautwein, A. Böckler, T. Singer, and P. Kanske, "Neural correlates of metacognitive ability and of feeling confident: a large-scale fMRI study," *Social Cognitive and Affective Neuroscience*, vol. 11, no. 12, pp. 1942–1951, 2016.

[5] D. Bang and S. M. Fleming, "Distinct encoding of decision confidence in human medial prefrontal cortex," *Proceedings of the National Academy of Sciences*, vol. 115, no. 23, pp. 6082–6087, 2018.

[6] S. Gherman and M. G. Philiastides, "Neural representations of confidence emerge from the process of decision formation during perceptual choices," *Neuroimage*, vol. 106, pp. 134–143, 2015.

[7] A. Boldt, A.-M. Schiffer, F. Waszak, and N. Yeung, "Confidence predictions affect performance confidence and neural preparation in perceptual decision making," *Scientific Reports*, vol. 9, no. 1, p. 4031, 2019.

[8] G. Cheng, J. Han, P. Zhou, and L. Guo, "Multi-class geospatial object detection and geographic image classification based on collection of part detectors," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 98, pp. 119–132, 2014.

[9] G.-S. Xia, X. Bai, J. Ding, Z. Zhu, S. Belongie, J. Luo, M. Datcu, M. Pelillo, and L. Zhang, "Dota: A large-scale dataset for object detection in aerial images," in *CVPR'18*, 2018, pp. 3974–3983.

[10] W. Zheng, J. Zhu, and B. Lu, "Identifying stable patterns over time for emotion recognition from EEG," *IEEE Transactions on Affective Computing*, vol. 10, no. 3, pp. 417–429, July 2019.

[11] R.-N. Duan, J.-Y. Zhu, and B.-L. Lu, "Differential entropy feature for EEG-based emotion classification," in *2013 6th International IEEE/EMBS Conference on Neural Engineering*. IEEE, 2013, pp. 81–84.

[12] L.-C. Shi and B.-L. Lu, "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*. IEEE, 2010, pp. 6587–6590.

[13] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *CVPR'16*, 2016, pp. 770–778.