Discrimination of Decision Confidence Levels from EEG Signals

Rui Li, Le-Dian Liu and Bao-Liang Lu* *Fellow, IEEE*

***Abstract*— To explore the capability of utilizing electroencephalograms (EEGs) for the measurement of human decision confidence levels, this paper develops a new visual perceptual decision confidence experiment. In this experiment, a visual perceptual decision-making task is performed by 14 participants, and their EEG data are recorded. The problem of measuring decision confidence levels is considered to be a pattern classification task, and two pattern classifiers are trained with differential entropy (DE), power spectral density (PSD), differential asymmetry (DASM), rational asymmetry (RASM), and asymmetry (ASM) features extracted from multichannel EEG data. We compare the performance of these features and find that the DE feature performs better than the others for measuring levels of decision confidence. The experimental results indicate that EEG signals offer good capability for measuring human decision confidence levels. The best performance of our proposed method in measuring five levels of decision confidence reaches an accuracy of 49.14% and F1-score of 45.07%, and for the extreme levels of decision confidence, the recognition accuracy reaches 91.28%, with an average F1-score of 88.92%. Topographic maps are also used to depict the neural patterns of EEG signals, suggesting that the posterior parietal cortex and occipital cortex might be sensitive brain areas for indicating decision confidence.**

I. INTRODUCTION

Decision confidence is the feeling of correctness or optimization of an individual when making a decision and can reflect the probability of being correct [1]. In addition, decision confidence is a very common psychological phenomenon and may be the most basic component in the decision-making process [2]. Existing research indicates that decision confidence is closely related to perceptual decision-making and may influence the accuracy of perceptional choices. Therefore, the investigation of human decision confidence is not only of very high scientific value but also of great practical significance.

Moreover, people do not act honestly all the time, and they may sometimes pretend to be right and assume that their judgments are definitely reliable. Considering that people's decisions are not completely reliable and that some mistakes may be inevitable, it is necessary to find an objective way to measure the reliability of decisions.

In recent years, researchers have carried out a series of studies on decision confidence from low rodents to higher primates and human subjects by using a variety of techniques such as single-cell recording and functional magnetic resonance imaging (fMRI). The research pertaining to human subjects based on fMRI methods [3], [4], [5] reveals that the anterior cingulate cortex, prefrontal cortex, superior parietal lobule, posterior parietal cortex and ventral striatum may be the most sensitive brain regions with respect to human decision confidence and that different decision-making tasks with different difficulty levels may have different neural bases.

There are several studies that employ event-related potential (ERP) to investigate the neural mechanisms of human decision confidence [6], [7]. These research endeavors have demonstrated that electroencephalography (EEG) signals have the capability to enable distinguishing between different levels of decision confidence when making a decision. Nevertheless, the ERP experiment needs to be repeated many times to average the results so that random brain activity may be averaged and to ensure that the relevant waveform is retained. In addition, the ERP experimentation usually requires rapid presentation of the stimulus in an ideal laboratory environment. These restrictions on ERP experimentation are not appropriate for the single trial scenario in real-world applications.

In this study, our aim is to develop a novel objective approach to assess the reliability of people's judgments and to develop an efficient method for measuring different levels of decision confidence from EEG signals in the visual perception task, as it is easy to understand and operate and readily inspires different decision confidence levels.

In this paper, we focus on investigating the neural patterns and the capability of EEG signals for measuring five levels of decision confidence in a visual perceptual task. We design a decision confidence experimental paradigm in which subjects perform a visual perception task. During the experiment, multichannel EEG data are acquired from subjects with different decision confidence levels. Furthermore, we adopt two pattern classifiers to recognize the level of decision confidence from EEG data. The experimental results demonstrate that EEGs are able to distinguish different levels of decision confidence and that neural patterns of EEG signals for decision confidence in the visual perception task do exist.

II. CONFIDENCE EXPERIMENT DESIGN

It is important to design a reliable and effective decision confidence experiment to help people make decisions more credibly. We design a new visual perceptual decision experiment to investigate discrimination capability of different levels of decision confidence.

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A. Stimuli

The stimuli materials that we used in this confidence experiment were selected from the Caltech 101 dataset [8], which was collected by Fei-Fei Li and colleagues. We selected three groups of images, each containing three types of similar animals (duck, goose, swan; cougar, leopard, wild cat; goat, gerenuk, elk), and every type includes five images. There are a total of 135 images, and every image represents one trial as well as one decision. Different degrees of downsampling are performed to distinguish the task difficulty and each type of animal is divided into three difficulty grades according to the downsampling rate: easy, medium and difficult. As a result, we can obtain the EEG data of different decision confidence levels. The subjects are required to identify the types of the animals in the images and to report their confidence levels for each decision.

B. Subjects

Fourteen healthy subjects (7 males and 7 females, aged from 18 to 24) participated in the experiment, and each subject self-reported normal or corrected-to-normal vision. All subjects were informed about the experimental procedures and were required to refrain from body movement to obtain EEG data of high quality. To encourage the subjects to participate more actively in the experiment, the payment for the participation was calculated according to the decision accuracy of each participant and was reported in advance.

C. Protocol

The experiment consists of 135 trials, where each trial contains one image, which corresponds to one decision. In each trial, the subject is supposed to identify the animal in the image and is required to complete three sections: 1) First, an image appears randomly on the screen, along with three different options including the correct answers for the other two animals in the same group, and the subject is required to make a decision about which option to choose; 2) Second, once the subject has made the decision, the option should be clicked with a mouse; and 3) Finally, the subjects should report their subjective decision confidence levels about this decision by scoring based on a 5-point confidence scale appearing on the screen. The 5-point confidence scale includes the following: certainly wrong: 1; probably wrong: 2; not sure: 3; probably correct: 4; and certainly correct: 5. The protocol of the experiment in this paper is illustrated in Fig. 1.

The experiment was conducted in a separate and quiet room, and EEG data were recorded during the entire experiment using a 62-channel active AgCl electrode cap with the ESI NeuroScan System at a sampling rate of 1000 Hz according to the international 10-20 system. This study was reviewed by the Scientific and Technical Ethics Committee of the Bio-X Institute at Shanghai Jiao Tong University, and all subjects proactively signed an informed agreement describing the details and the matters requiring attention in this experiment.

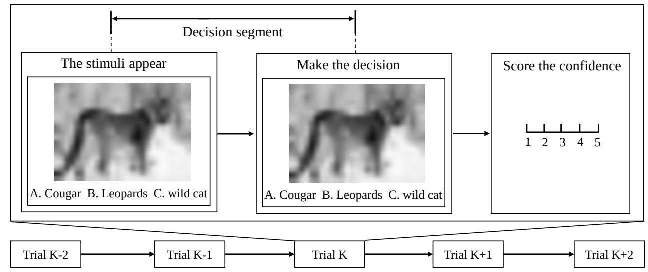

Fig. 1. The protocol of the visual perception decision confidence experiment proposed in this paper.

III. METHODOLOGY

A. Data Preprocessing

We first checked the EEG signals visually, and then, a bandpass filter between 0.3 and 50 Hz was applied to each channel to filter the noise and remove artifacts. After data preprocessing, we extracted only the EEG segments that were acquired during the decision-making process and that were related to decision confidence. The decision segments utilized in our analysis are illustrated in Fig. 1, which is from the presentation of a stimulus in response to the press of a button to cause a decision. We then divide the segments into epochs of the same length of 1 s without overlapping.

B. Feature Extraction

Feature extraction is performed for each epoch of the preprocessed EEG data through the short-term Fourier transform (STFT) of a Hanning window of 1 s. Five different 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) are extracted in our experiments: power spectral density (PSD), differential entropy (DE), differential asymmetry (DASM), rational asymmetry (RASM) and asymmetry (ASM) features [9], [10]. The DE feature is proven to be equivalent to the logarithmic PSD for EEG sequences of a fixed length [10]. The DASM and RASM features are computed as the differences and ratios, respectively, between the DE features of 27 pairs of hemispheric asymmetry electrodes. The ASM features represent the direct concatenation of DASM and RASM features.

The dimensions of the PSD, DE, DASM, RASM, and ASM features are 310 (62 electrodes$\times$5 bands), 310 (62 electrodes$\times$5 bands), 135 (27 electrode pairs$\times$5 bands), 135 (27 electrode pairs$\times$5 bands) and 270 (54 electrode pairs$\times$5 bands), respectively. The linear dynamic system (LDS) algorithm was also applied to filter out irrelevant components [11].

C. Classification

The extracted EEG features are normalized between 0 and 1 separately and fed to two classifiers: support vector machine (SVM) and deep neural network with shortcut connections (DNNS) [12]. The confidence levels (1-5) are used as labels to investigate the capability of EEG signals for measuring human decision confidence. The classifiers are trained for each subject with stratified five-fold cross-validation. For each subject, the features belonging to each class are divided into five parts of the same size according to the confidence level: four for the training set and one for the test set.

We use the SVM classifier with the RBF kernel and search the parameter space from $2^{[-5:10]}$ for C. The deep neural network with shortcut connections is also employed to measure the decision confidence levels. We construct a neural network with four hidden layers and one output layer and introduce two short connections to ensure that the original information is not lost. The ReLU function is employed as the activation function, and batch normalization layers are also employed. The size of the hidden layers is searched, the range is from 50 to 700, and the learning rate is set to 0.0001.

IV. EXPERIMENTAL RESULTS

The mean accuracy rates and F1-scores of SVM and DNNS for different features obtained from different frequency bands and total frequency bands that represent the direct concatenation of all five frequency bands are described in Table I. First, the results in Table I demonstrate that

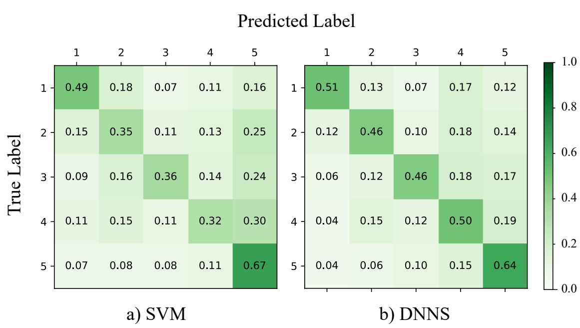

Fig. 2. The confusion matrix of two classifiers with the DE feature. The rows of the confusion matrix represent the target class and the columns represent the predicted class that the classifier outputs. The numbers inside the figures denote the classification accuracy.

DNNS performs better than SVM, with the best classification accuracy of 49.14% and F1-score of 45.07% for the DE feature. Furthermore, the performance with respect to different features is compared. It can be determined that the DE feature achieves higher classification accuracy than the other features, indicating the superior performance of DE features over the other features in this task.

The results also illustrate that the delta band performs better than the other four bands, with an accuracy of 45.12% and F1-score of 39.08%. The confusion matrices of these two classifiers with the DE feature in the total band are shown in Fig. 2. From the confusion matrices, we can find that extreme confidence levels 1 and 5 are easy to recognize and that the intermediate confidence levels (2, 3 and 4) are difficult to be distinguished. Additionally, DNNS is better than SVM in identifying intermediate confidence levels.

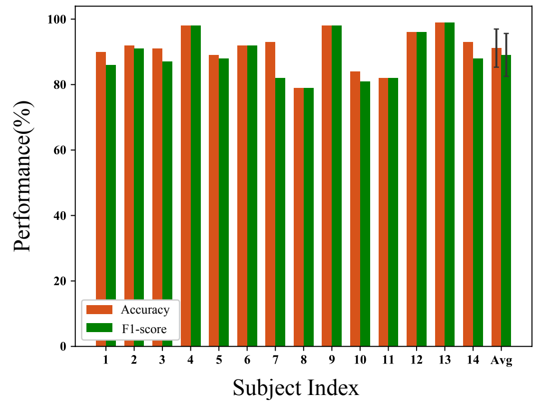

Fig. 3. The accuracy and F1-score (%) of DNNS of 14 subjects for the DE feature in identifying extreme confidence levels.

A. Extreme Levels of Decision Confidence

We then further distinguish the lowest decision confidence level of 1 from the highest decision confidence level of 5. The performance of this binary classification achieves an average accuracy and standard deviation of 91.28%/5.83% and an average F1-score and standard deviation of 88.92%/6.55%. The classification results of 14 subjects are shown in Fig. 3, which describes the classification performance of DNNS with respect to the DE feature for the extreme levels of decision confidence: 1 and 5.

The experimental results mentioned above demonstrate that EEG signals have the capability to distinguish different decision confidence levels.

B. Neural Patterns

We further explored the neural patterns corresponding to different levels of decision confidence. Fig. 4 demonstrates the neural patterns for decision confidence by averaging the DE features from all participants in each channel. We can find that the neural patterns that correspond to the decision confidence levels do exist, which are reflected in the degree of activation of brain regions and frequency bands with different decision confidence levels. In particular, we can find that a higher decision confidence level corresponds with higher energies of the posterior parietal cortex and occipital cortex in the delta, theta and alpha bands, indicating that the sensitive areas with respect to the decision confidence in this task might be the posterior parietal cortex and occipital cortex.

V. CONCLUSIONS

In this paper, we have investigated the capability of EEG signals for measuring different levels of human decision confidence in a visual perceptual decision task. We have adopted SVM and DNNS to build EEG-based decision confidence detection models for measuring five levels of decision confidence. The experimental results indicate that EEG signals have the capability of measuring decision confidence and that the DE feature is more effective than

TABLE I

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

Feature	Classifier	Delta		Theta		Alpha		Beta		Gamma		Total	
		acc	F1	acc	F1	acc	F1	acc	F1	acc	F1	acc	F1
PSD	SVM	35.04	29.64	34.57	29.67	32.9	28.92	34.4	29.74	31.85	26.02	38.34	34.62
	DNNS	44.81	38.36	44.48	38.86	44.98	37.55	44.91	37.25	41.74	34.17	46.76	41.08
DE	SVM	34.71	31.43	33.88	29.06	31.26	27.46	33.39	29.12	34.14	29.38	**40.93**	**37.43**
	DNNS	**45.12**	**39.08**	43.06	35.19	42.01	34.94	43.58	38.06	42.83	37.86	**49.14**	**45.07**
RASM	SVM	33.92	27.8	29.44	25.63	31.19	26.64	30.77	25.85	32.92	27.45	34.72	31.86
	DNNS	40.65	33.79	42.39	33.59	42.94	35.41	42.09	35.01	41.05	34.65	45.31	39.7
DASM	SVM	31.91	26.32	30.94	26.56	29.8	26.31	31.18	26.21	32.55	28.07	34.89	32.22
	DNNS	39.14	32.89	41.04	32.88	42.25	35.52	41.24	34.06	43.58	35.89	45.53	39.32
ASM	SVM	31.17	26.25	29.34	25.6	31.67	26.47	30.72	26.06	32.22	28.04	34.8	32.21
	DNNS	41.43	35.12	41.98	34.4	42.71	35.69	41.61	34.55	43.03	36.21	47.13	40.49

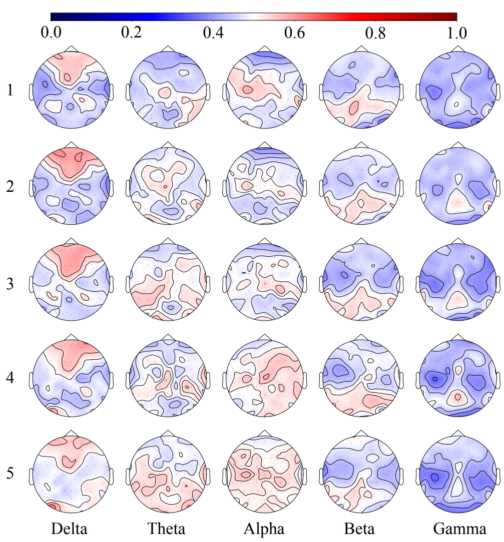

Fig. 4. The average neural patterns of 14 subjects for five confidence levels. Rows represent the different frequency bands, and columns represent the confidence levels.

other features in this decision confidence detection task. The best detection performance reaches an accuracy of 49.14% and F1-score of 45.07%, and for extreme levels of decision confidence, the recognition accuracy reaches 91.28%, with an average F1-score of 88.92%, suggesting that specific decision confidence levels can be identified based on brain activities. The existence of neural patterns has also been identified in the context of decision confidence for the visual perception task, as the posterior parietal cortex and occipital cortex might be sensitive regions in measuring the levels of decision confidence.

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