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Research Article

Sitting and Standing Intention Detection Based on Dynamical Region Connectivity and Entropy of EEG

Wenwen Chang, Wenchao Nie, Yueting Yuan, Yuchan Zhang, Renjie Lv, Lei Zheng, and Guanghui Yan

School of Electronic and Information Engineering, Lanzhou Jiaotong University, Lanzhou 730070, China

Correspondence should be addressed to Wenchao Nie; 12221912@stu.lzjtu.edu.cn

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Based on the brain signals, decoding and analyzing the gait features to make a reliable prediction of action intention are the core issues in the brain computer interface (BCI)-based hybrid rehabilitation and intelligent walking aid robot system. In order to realize the classification and recognition of the most basic gait processes such as standing, sitting, and quiet, this paper proposes a feature representation method based on the signal complexity and entropy of each brain region. Through the statistical analysis of these parameters between different conditions, these characteristics which sensitive to different actions are determined as a feature vector, and the classification and recognition of these actions are completed by combing support vector machine, linear discriminant analysis, and logistic regression. Experimental results show the proposed method can better realize the recognition of the aforementioned action intention. The recognition accuracy of standing, sitting, and quiet of 13 subjects is higher than 80.9%, and the highest one can reach 86.8%. Directed dynamic brain network analysis of the 8 brain regions shows that the occurrence of lower limb movement will weaken the dependence between brain regions, resulting in the weakening of network topological connection. The result has significant value for understanding human's brain cognitive characteristics in the process of lower limb movement and carrying out the study of BCI based strategy and system for lower limb rehabilitation.

1. Introduction

Robotic based rehabilitation training has more advantages than the traditional artificial rehabilitation, which can increase the motivation of patients and the opportunity of autonomous training, so as to improve the quality and effect of the rehabilitation process. For the gait rehabilitation, exoskeleton and intelligent walking aid robot are widely used and have achieved good results [1, 2]. With the development of brain computer interface (BCI) technology, researchers began to pay attention to the walking intelligent robot and the rehabilitation training technology combined with BCI, which can improve the rehabilitation strategy by detecting brain's motion intention more quickly and forcefully, so as to improve the rehabilitation effect. BCI-based system is a development trend of the future neurological rehabilitation system [3, 4]. It is important to investigate the relationship between brain cognitive activity and motor process in the development of BCI-based active rehabilitation technology.

At present, EEG is widely used in the detection of motor intention because of its simplicity, portability, and high time resolution [1, 5]. Studies also shown that EEG signal contains abundant gait and motion information [6, 7], while the decoding research on lower limb motion intention such as walking and gait has just started. One of the most basic movements in the gait process is to stand up (standing) and sit down (sitting). Zhong et al. investigated the event-related potentials during the attemped standing up task; they found significant midcentral-focused mu event-related desynchronization (ERD) with beta event-related synchronization (ERS) during imaginary standing up task [8]. Bulea et a1. [6] studied the corresponding EEG features of 10 subjects during the transition between sitting to standing by decoding the low-frequency band signals, and combined with Gaussian mixture model (GMM) to realize the recognition of the above two conditions. In the later work, Bulea et al. [4] still focused on the cortical slow potential before action execution and analyzed the feasibility of delta band in motor intention decoding. These signals in standing, sitting, and quiet condition were analyzed by designing two models under self-trigger and external cue trigger, and the GMM classifier was also used to completer the recognition of the three states, and obtained good results. In addition, other decoding studies on motor intention mainly focus on two types of signals, one is the event-related synchronization/desynchronization potentials and the other is the movement related brain potentials (MRPs) [1, 4]. Above discussed studies have deepened the understanding of brain cognitive mechanism corresponding to motor intention, and also realized the effective detection and recognition of the movement. However, these studies mainly focus on the slow potentials from few electrode channels in sensorimotor brain regions, which lack the feature information form spatial domain considering the interaction between different brain regions from the whole brain.

It is well known that gait is a complex cognitive and motor control process, and lower limb movements also involve the coordination and cooperation of all brain regions [4]. However, before a standing and sitting action is completed, the brain must show certain characteristic information, and the motion intention can be finally determined by decoding such information. In addition to the aforementioned representation of cortical slow potentials, it is expected to reveal new features of motor intention decoding through the analysis of dynamic change process of brain interdependence [9, 10]. Lau et al. [11] investigated the characteristics of functional brain network during standing and walking. They found that compared with standing state, the functional connection of sensorimotor areas would be weakened during walking. They think it is the reason that it needs more cognitive attention during walking. Li et al. [9] investigated the features of functional connectivity during rehabilitation with the help of exoskeleton, and indicating that the graph theory based brain network analysis has a certain role in the research of gait rehabilitation. Handiru et al. [10] have studied the balance of brain trauma patients during walking by building the functional brain networks. However, it is obviously necessary to carry out further analysis from various perspectives for action, intention, and detection.

To this end, this paper designed a motion experiment from sitting to standing and then from standing to sitting, during which 32 channel EEG signals were collected synchronously and the brain were divided into eight sub regions. By constructing a multi-layer network for the eight regions, we first discussed the dynamic process of the brain before and after the onset of the action and then the complexity and entropy parameters of the EEG signals during the whole action were fully analyzed. These features which are sensitive to different actions are screened by statistical analysis, and the feature vector is formed using these parameters. Finally, the recognition of standing, sitting, and quiet condition is realized by combing the feature vector with several machine learning classifiers. Figure 1 is the block diagram of this study.

2. The Experimental Process

2.1. Experiment Materials and Methods Experimental Protocol. Thirteen right-handed health subjects aged between 19 and 24 years participated in the study. All subjects had normal or corrected vision and did not have any history of neurological disease. This project was approved by the university's ethics committee. Before the experiment, subjects were required to sign an informed consent and all were paid 100 Yuan after the experiment. During the experiment, subject sit in front of the monitor, which display the time to the subject. Subject was required to sit still for 1 minute and then stand up, which change from sitting to standing and keep standing for 1 minute. After that, the subject sat down again. These actions were completed repeatedly and alternatively, as shown in Figure 2. EEG signals were recorded during the whole process, and one session took about 10 minutes, during which 1 minute is rest. Each subject finished 6 sessions. Subjects are required to keep quiet as much as possible during the whole experiment, especially when they are sitting down and standing up, so as to ensure as few other movements as possible.

2.2. Data Recording and Preprocessing. EEG was recoded with a 32-electrode cap arranged with the international 10–20 system using the NeuSen W system (Neuracle, China) and SAGA 32+ system (TMSi, Netherlands), with an averaged reference during the EEG recording. Four electrodes were placed laterally to right and left eyes to record the horizontal and vertical electrooculograms (EOG), and the electrodes below and above the left eyes were used to monitor the eye movements and blinks. The impedance of the electrode was set below 10 kΩ, EEG signal was recorded at the laptop with 1024 Hz sampling rate, and the online sampling frequency band is 0–200 Hz.

Besides the 30 channel EEG signal, 4 extra channel which record the IMU data are fixed on the left upper leg and four pressure sensors (FSR sensors) are fixed under the left foot to record the foot pressure synchronously, which is shown in Figure 3. The preprocessing of all subjects was completed one by one in EEGLAB. First, all session data of each subject were merged together, then the data were down sampled to 250 Hz, and the band-pass filtering from 0.1 Hz to 48 Hz was completed. The linear filtering of signals was completed using the cleanline tool, the electrode positioning of all the channels was completed according to the electrode position of EEG system, and all the bad electrode and irrelevant channels were removed.

After the basic preprocessing, IMU data are filtered with a low-passed filter (cut-off frequency is 10 Hz) and combing with the foot pressure signals from the heels, the onset of each standing and sitting action is determined. Then, all the data were segmented into the epochs lasting about 7 s under three conditions, in which 4.5 s prior and 2.5 s after the onset of the motion action, and baseline correction were

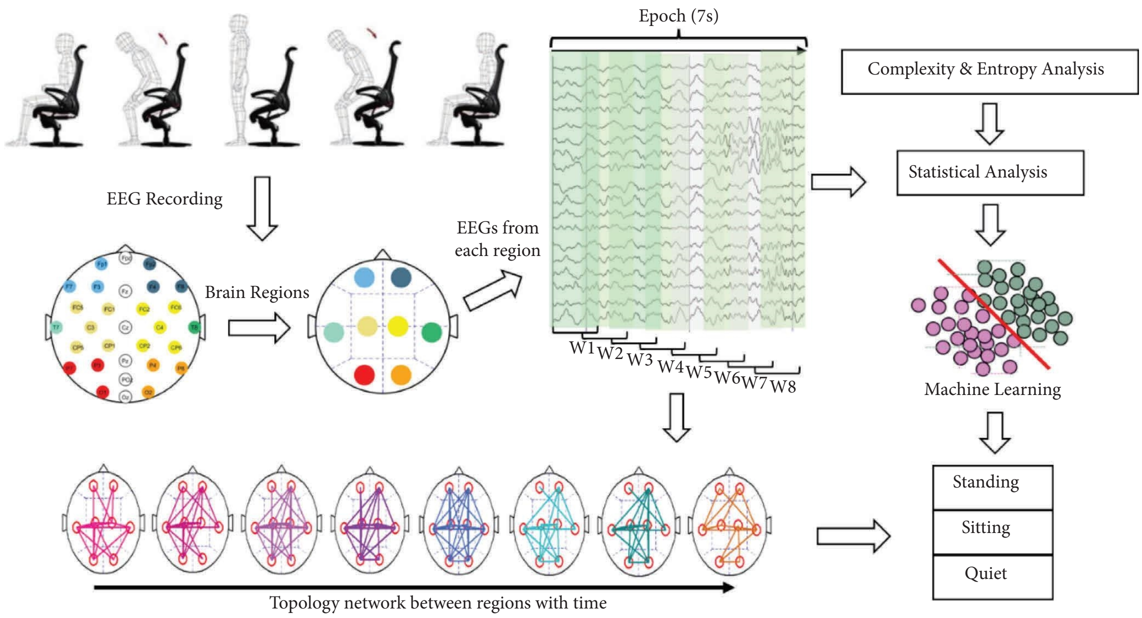

Figure 1: The block diagram of this study.

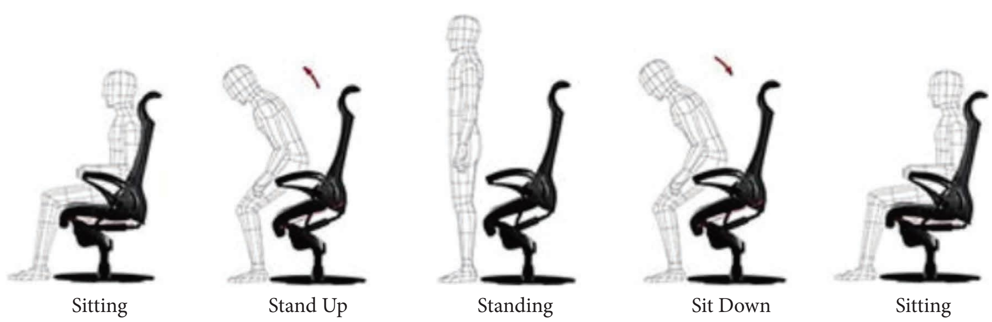

Figure 2: Schematic diagram of the standing-sitting experiment (the figure refers to reference [3]).

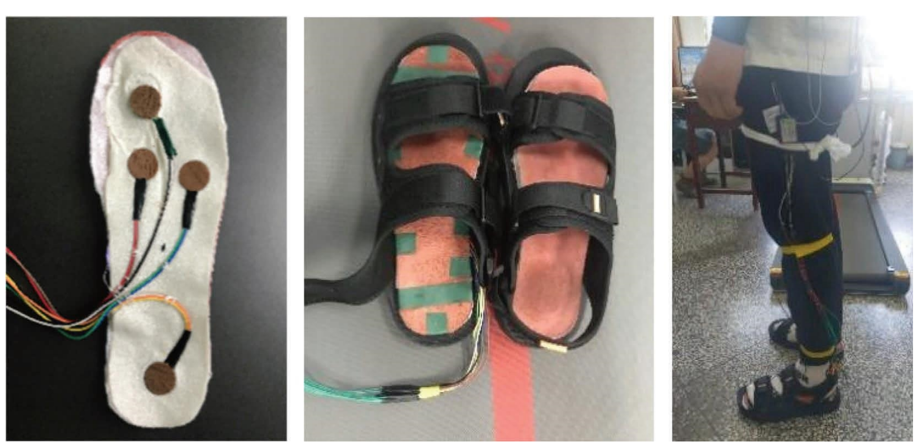

Figure 3: EEG recoding and additional sensing system.

completed. Then, the epochs which is greatly affected by artifact is removed through visual detection, and the ICA decomposition of all signals is completed using Runica. Artifact components such aseye movement, eye blink, muscle artifact, and other artifacts mainly caused by the movement are removed with the help of SASICA toolbox. After the artifact is removed, if necessary, the bad electrode is interpolated and the data is re-referenced. Finally, we got 150 epochs for each subject and thus there are 1950 samples in total processed in the following sections and machine learning classifiers.

2.3. Slow Wave Extraction and Brain Region Division. Previous studies about motor intention have found that the EEG potentials such as ERD/ERS and MRPs are slow waves [12]. Therefore, this study mainly focuses on the delta band (0.1 Hz–4 Hz) signals, which is obtained through a zero-phase 4 order Butterworth filter. In order to focus on the complexity and entropy of EEGs in different brain regions and the interdependence of different brain regions, as shown in Figure 4, the 30 channels from the whole brain are divided into 8 regions, which is left frontal (LF: FP1, F3, F3), right frontal (RF: FP2, F4, F8), left central (LC: FC1, FC5, C3, CP1, CP5), right central (RC: FC2, FC6, C4, CP2, CP6), left temporal (LT: T7), right temporal (RT: T8), left occipital (LO: P3, P7, O1), and right occipital (RO: P4, P8, O2).

2.4. Functional Brain Network Construction. Functional brain network is an intuitive expression of dynamic neural interaction between different neurons, neuronal clusters, or cerebral cortex regions, which can represent the topological structure and dynamic characteristics of brain network. Based on the same EEG data set, different brain network types and characteristics can be obtained according to different construction methods, which have an important role in the detection and recognition of different brain states. In order to quantify the independence of different brain regions, phase transfer entropy (PTE) is applied to discuss the causal dependence of brain regions. PTE is a useful measure for directed functional connectivity in a large-scale investigation of human functional connectivities [13, 14]. Compare to other measures, it is more robustness to noise and more efficient. When constructing the functional network, all channel signals in each brain region were averaged as the final signals of EEG in this brain region. Through the above analysis, we had a total of eight brain regions and then got a value as an edge of our functional network connection by calculating the PTE between two signals of each pair of brain regions, as shown in Figure 5. In the end, we can obtain an $8 * 8$ PTE weight matrix. The matrix is the representation of the interdependence between brain regions and can be used to describe the topological connections between brain regions.

2.5. Signal Complexity Analysis. Complexity analysis of a signal is an important tool to reveal the characteristics of a nonlinear system. In recent years, more and more researchers began to evaluate the activity state of the brain through the nonlinear dynamic analysis [15]. Among them, entropy is one of the most widely used analysis methods. At present, various entropy analyses [15, 16] have been used for the neural signal analysis. In order to more comprehensively discuss the representation of various entropy on EEGs during motion, this paper calculate various time-domain entropies, such as Shannon entropy (ShEn), approximate entropy (ApEn), sample entropy (SaEn), permutation entropy (PeEn), conditional entropy (CoEn), and fuzzy entropy (FuEn). Besides, spectral entropy (SpEn) and wavelet entropy (WaEn), which represents time-frequency characteristics, were also discussed. In addition, we also discussed the Hurst index (here we refer to Hurst Exponent, HE), Kurtosis index (Kurtosis). Specifically, Hurst index reflects the autocorrelation of time series, especially the long-term trend hidden in the series. These parameters are normal slope descriptors (NSDs) used in EEG. These measures were calculated for the averaged signals in each region. Finally, through the statistical analysis, we selected the brain regions and the complexity measures which have significant differences for the three conditions to form the feature vector.

3. Results

3.1. Complexity for Each Region. In order to conduct quantitative analysis of the complexity measure in each brain region under the three conditions, as shown in Tables 1–3, ten complexity measures are calculated for averaged EEGs of each brain region, respectively. It can be seen that the values of various parameters in the 8 brain regions are very close and these parameters in LO and RO region are the largest, followed by the LC and RC region. In order to determine the difference among the three conditions, statistical analysis of various parameters found that PeEn, ShEn, SpEn, and Kurtosis in RT region were significantly different from that of standing and sitting comdition. The ShEn and Kutosis in LF region; Kutosis in RF region; CoEn, ShEn, and Kurtosis in RT region; and Kurtosis in LC, RC, LO, and RO region show significant difference in standing and quiet condition. While the CoEn, SaEn, ShEn and Kurtosis in LF region; Kurtosis in RF region; ShEn in RT region; Kurtosis in LC region; ShEn and Kurtosis in RC region; and Kurtosis in LO and RO region show significant difference in sitting and quiet condition.

3.2. Topology Network between Brain Regions. In addition to the aforementioned complexity analysis of the EEGs from the eight regions, this study also discussed the causal dependence of these regions using PTE measures. As shown in Figure 6 is the adjacency matrix of PTE interdependence among the eight regions in the three conditions. Since PTE can represent the causal dependence between two signals, the corresponding adjacency matrix is an asymmetric matrix. It can be seen from the figure that both of the weight of the network in the three conditions is large and mainly between 0.4 and 0.6. Besides, the standing and sitting condition present obvious dependency characteristics different from other windows in w5, which we believe is mainly due to the fact that standing and sitting actions mainly appeared in this time window. While in quiet condition, the connection between the brain regions of each window is basically stable. It can also be seen from the figure that there is no obvious difference between standing and sitting condition.

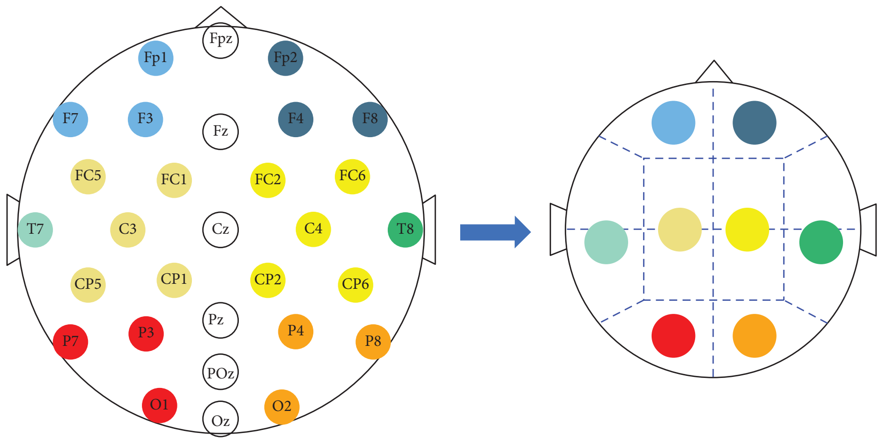

Figure 4: The eight brain regions.

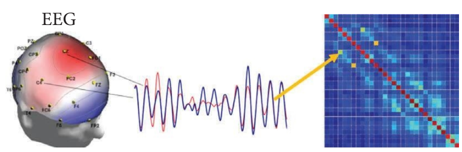

Figure 5: Functional brain network construction.

Table 1: Complexity parameters for each brain region (standing condition).

Parameters	LF	RF	LT	RT	LC	RC	LO	RO
ApEn	0.0817	0.0834	0.0762	0.0784	0.0940	0.0935	0.1015	0.1021
WaEn	0.0041	0.0044	0.0036	0.0041	0.0041	0.0044	0.0054	0.0055
CoEn	0.1272	0.1304	0.1220	☆0.1239	0.1489	0.1474	0.1552	0.1540
FuEn	0.0113	0.0115	0.0095	0.0111	0.0114	0.0116	0.0138	0.0133
PeEn	1.0651	1.0707	1.0600	★1.0684	1.2769	1.2784	1.2887	1.2879
SaEn	0.0672	0.0687	0.0623	0.0625	0.0757	0.0765	0.0829	0.0832
ShEn	☆2.0260	2.0587	2.0389	☆★1.9843	2.4558	2.4478	2.4423	2.4338
SpEn	0.4964	0.5011	0.5162	★0.5077	0.5983	0.6013	0.5902	0.5967
Kurtosis	☆3.2039	☆2.9912	2.8832	☆★3.3799	☆3.4615	☆3.5853	☆3.9149	☆3.8530
HE	0.9841	0.9841	0.9835	0.9837	1.1820	1.1815	1.1809	1.1807

Notice: "★" standing vs. sitting, $p < 0.05$; "☆" standing vs. quiet, $p < 0.05$; "#" sitting vs. quiet, $p < 0.05$.

Table 2: Complexity parameters for each brain region (sitting condition).

Parameters	LF	RF	LT	RT	LC	RC	LO	RO
ApEn	0.0731	0.0770	0.0779	0.0834	0.0897	0.0933	0.0961	0.0962
WaEn	0.0032	0.0035	0.0034	00039	0.0044	0.0051	0.0049	0.0047
CoEn	#0.1166	0.1209	0.1227	0.1304	0.1453	0.1497	0.1512	0.1508
FuEn	0.0091	0.0096	0.0092	0.0103	0.0114	0.0123	0.0124	0.0125
PeEn	1.0661	1.0705	1.0805	★1.0903	1.2859	1.2916	1.2974	1.2948
SaEn	#0.0569	0.0606	0.0626	0.0667	0.0719	0.0768	0.0776	0.0774
ShEn	#1.9936	2.0240	2.0374	#★2.0889	2.4077	2.4137	2.4478	2.4407
SpEn	0.5064	0.5031	0.4997	★0.4699	0.6039	0.6088	0.5886	0.5910
Kurtosis	#2.9882	#2.9582	2.8268	★2.6581	#3.6595	#3.7483	#3.5659	#3.5773
HE	0.9844	0.9844	0.9840	0.9834	1.1803	1.1801	1.1800	1.1804

Notice: "★" standing vs. sitting, $p < 0.05$; "☆" standing vs. quiet, $p < 0.05$; "#" sitting vs. quiet, $p < 0.05$.

Actually, there are a large number of weak connections in the adjacency matrix, which may be caused by the interaction between noise or other noncharacteristic signals. Therefore, it is necessary to set an appropriate threshold to screen the weights of the connected edges in the above adjacency matrices and to retain the important edges with a certain degree of discrimination between different conditions. To this end, first, the weight of the PTE adjacency

Table 3: Complexity parameters for each brain region (quiet condition).

Parameters	LF	RF	LT	RT	LC	RC	LO	RO
ApEn	0.0817	0.0800	0.0735	0.0878	0.0953	0.0923	0.0947	0.0947
WaEn	0.0040	0.0038	0.0035	0.0042	0.0046	0.0045	0.0044	0.0047
CoEn	#0.1294	0.1288	0.1192	☆0.1433	0.1531	0.1489	0.1521	0.1564
FuEn	0.0098	0.0093	0.0077	0.0111	0.0107	0.0101	0.0106	0.0113
PeEn	1.0772	1.0735	1.0611	1.0795	1.2851	1.2808	1.2818	1.2851
SaEn	#0.0695	0.0677	0.0626	0.0744	0.0810	0.0788	0.0807	0.0832
ShEn	#☆2.1169	2.1212	2.0764	#☆2.1990	2.5560	#2.5301	2.5437	2.5680
SpEn	0.5027	0.5035	0.5093	0.4784	0.5970	0.6011	0.5987	0.5909
Kurtosis	#☆2.5608	#☆2.4897	2.4315	☆2.4392	#☆2.8588	#☆2.8480	#☆2.8988	#☆2.8499
HE	0.9845	0.9847	0.9841	0.9834	1.1813	1.1810	1.1808	1.1809

Notice: "★" standing vs. sitting, $p < 0.05$; "☆" standing vs. quiet, $p < 0.05$; "#" sitting vs. quiet, $p < 0.05$.

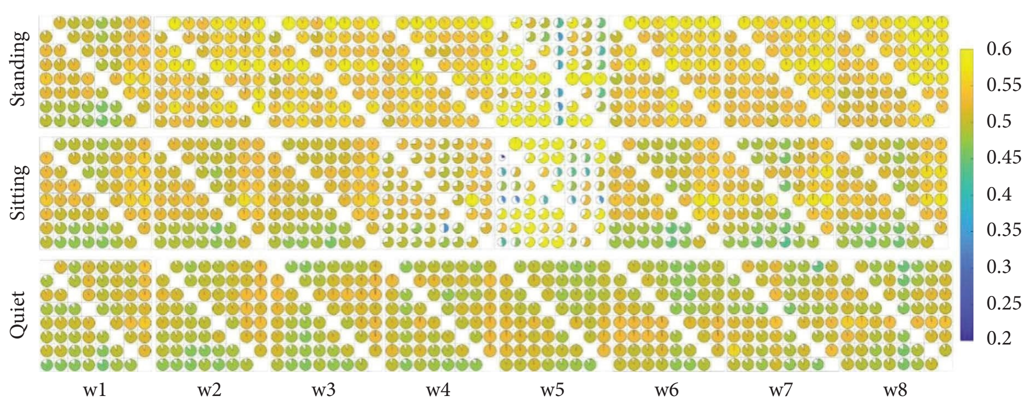

Figure 6: Adjacency matrix of eight windows under the three conditions.

matrix corresponding to the three conditions in each window is flattened and combined to form a one-dimensional vector and then the median in the distribution of the vector is taken as the threshold for all these connection matrices. Figure 7 shows the frequency histogram distribution of the vector and the determined threshold ($T = 0.51$), which is used to binarize the aforementioned connection matrices. Figure 8 shows the corresponding topological network after the threshold filtering.

Intuitively, the difference between standing and sitting is not clear, but there are obvious differences between quiet, standing, and sitting. Generally speaking, during the whole movement process, for the quiet condition, the connections between the brain regions are mainly concentrated in the frontal-parietal-temporal area, lacking the interaction with the occipital region, and the interaction of different brain regions has not changed much from w1 to w8. However, for standing and sitting condition, there are extensive interactions among the eight brain regions. It can be seen that w5 has the strongest connection in the brain regions, the connections before w5 is weaker and, on the whole, the interactions become weaker after w5.

3.3. Classification. Based on the above discussed signal complexity of the EEGs in each region and the interdependence between brain regions, combined with the statistical analysis results, the feature vector was constructed with these parameters which has significant difference among the three conditions. When constructing feature vectors, we used the network parameters with significant differences in Tables 1–3 to complete the construction. In contrast with different states, the characteristic composition of this vector is different. According to the statistical analysis results in the table, four parameters of RT brain region PeEn, ShEn, SpEn, and Kurtosis were used for sitting and standing states. For standing and quiet states, ShEn in LF brain region, ShEn and CoEn in RT brain region, and Kurtosis from all brain regions except the LT brain region were used. For sitting and quiet states, CoEn, SaEn, and ShEn in LF brain region; ShEn in RT brain region; ShEn in RC brain region and Kurtosis on other brain regions except LT and RT brain regions were used. Tables 1–3 show the statistical significance of each parameter.

The specific feature vector for sitting and standing condition is defined as follows:

$$V_{\text{para}} = (\text{PeEn}, \text{ShEn}, \text{SpEn}, \text{Kurtosis})_{\text{RF}}. \tag{1}$$

Three machine learning algorithms including support vector machine (SVM), logistic regression (LR), and linear discriminant analysis (LDA) are used to test the feature vector to complete the recognition of the two types of motion condition. Figure 9 shows the averaged classification accuracy obtained after five-fold cross-validation. It can be seen that all the classification accuracies are over 80.9% and the SVM has the best effect, which proves the effectiveness of this method.

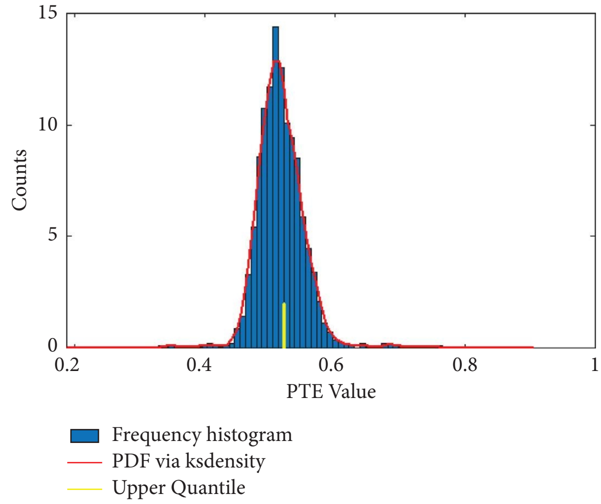

FIGURE 7: Statistical distribution of PTE value and the probability density function (PDF) for all the conditions. Yellow line is the median of the distribution which is set as the threshold.

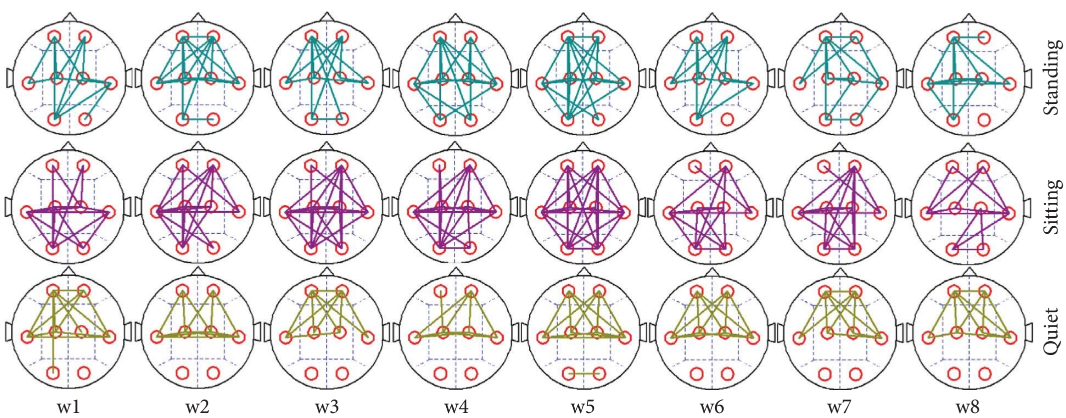

FIGURE 8: Topology network for each condition.

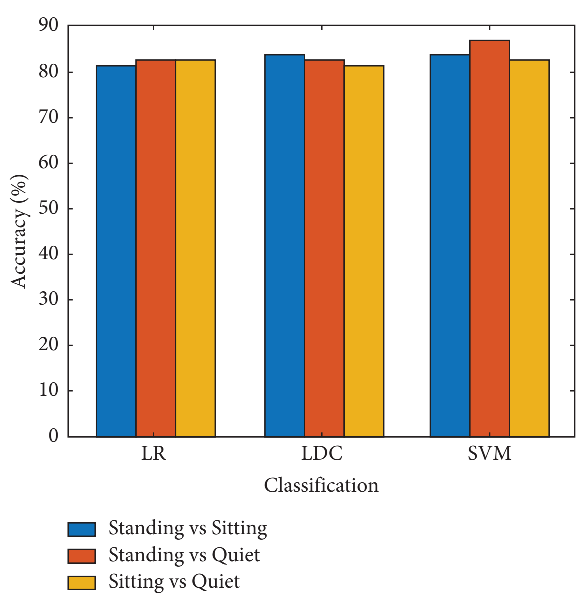

FIGURE 9: Classification accuracy of different classifiers in the three conditions.

4. Discussion and Conclusion

Through the above analysis, we get a good result, because the complexity parameters selected in this paper, respectively, represent different feature information in each brain region. Indeed, the production of movement is mainly controlled by the sensorimotor brain region, but it also requires coordination and collaboration between brain regions. The changes of the topological relationships connected by functional networks can reflect the interaction between brain regions during the whole movement process, and the complexity and entropy of different brain regions can better represent the characteristic information of each brain region in the corresponding action process. The characteristic quantity sensitive to different actions can be found by statistical analysis, so different states can be effectively identified based on these parameters.

The control of this movement is mainly in the sensory and motor brain regions. We discussed eight brain regions in the whole brain in this paper and calculated the average of each channel in each brain region, which may eliminate some characteristic information of electrode channels in specific regions. For example, the features of C3 and C4 electrodes in the motor brain region may be weakened, that is why some of our classifiers do not work very well. So we will consider discussing the complexity parameters of each electrode in the sensory-motor brain region in the future work. The sensitive channels and characteristic quantities of standing and sitting movements were determined by statistical analysis; it should be helpful to improve the efficiency of recognition. And this is also an aspect of our future work.

In our preprinted paper [17], we proposed a feature representation method based on the complexity and entropy of each brain region signal. The sensitivity features of actions are determined by statistical analysis and classified by machine learning algorithm. However, we neglected the directed dynamic brain network analysis of brain regions so that we did not find the effect of action on brain region dependence. This paper is an improvement on the previous preprint and is discussed in detail to make its results more complete.

In this paper, first, the complexity parameters of each brain region are described in detail through several tables for the reader to understand. Second, we also discussed the causal dependence of these brain regions using PTE measures, which is a strong robustness and high efficient method. Finally, we constructed the corresponding topological network after threshold filtering and found actions that weakened the dependency between brain regions leading to weakened network topology connections.

This paper completes the phase transfer entropy analysis of EEGs in different brain regions of the subjects in standing, sitting, and quiet conditions by designing a motion experiment from sitting to standing. By constructing the functional brain network on eight-time windows before and after the onset of the action, the directional dependence of different brain regions during the whole action is displayed and analyzed in the form of network topology. In addition, this paper discusses a series of entropy features and complexity parameters, respectively, for the grand averaged EEGs from each brain region. Through the statistical analysis, relevant features with significant differences among the three states are screened out and combined with SVM, LDA and LR to realize the classification of standing, sitting, and quiet. The classification accuracy is up to 86.8%, which proves the feasibility of detecting and recognizing the lower limb motion intention based on the complexity parameters of EEGs. Functional connectivity analysis shows that the occurrence of standing and sitting actions will weaken the interdependence of brain regions, resulting in the simplification of network topology. This study also provides a new insight into EEG-based motion intention detection and have certain reference value for the development of BCI-based lower limb walking aid and rehabilitation robot.

Data Availability

The data supporting the findings of this study are available from author W. Chang upon reasonable request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this study.

Authors' Contributions

Wenwen Chang performed methodology, visualization, and investigation and wrote, reviewed and edited the manuscript. Wenchao Nie performed methodology and visualization and wrote the original draft. Yueting Yuan perfoemed investigation and conceptualization. Yuchan Zhang developed software and performed visualization. Renjie Lv performed data curation and formal analysis and developed software. Lei Zheng performed investigation and data curation. Guanghui Yan performed supervision, collected resources and wrote, reviewed, and edited the manuscript.

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References

[1] D. Hamacher, F. Herold, P. Wiegel, D. Hamacher, and L. Schega, "Brain activity during walking: a systematic review," *Neuroscience and Biobehavioral Reviews*, vol. 57, pp. 310–327, 2015.

[2] O. Lennon, M. Tonellato, A. Del Felice et al., "A systematic review establishing the current state-of-the-art, the

limitations, and the DESIRED checklist in studies of direct neural interfacing with robotic gait devices in stroke rehabilitation," *Frontiers in Neuroscience*, vol. 14, p. 578, 2020.

[3] A. C. Villa-Parra, D. Delisle-Rodriguez, A. Lopez-Delis, T. Bastos-Filho, R. Sagaro, and A. Frizera-Neto, "Towards a robotic knee exoskeleton control based on human motion intention through EEG and sEMGsignals," *Procedia Manufacturing*, vol. 3, pp. 1379–1386, 2015.

[4] T. C. Bulea, S. Prasad, A. Kilicarslan, and J. L. Contreras-Vidal, "Sitting and Standing intention can be decoded from scalp EEG recorded prior to movement execution," *Frontiers in Neuroscience*, vol. 8, p. 376, 2014.

[5] J. T. Gwin, K. Gramann, S. Makeig, and D. P. Ferris, "Electrocortical activity is coupled to gait cycle phase during treadmill walking," *NeuroImage*, vol. 54, no. 2, pp. 1289–1296, 2011.

[6] T. C. Bulea, S. Prasad, A. Kilicarslan, and J. L. Contreras-Vidal, "Classification of stand-to-Sit and sit-to-stand movement from low frequency EEG with locality preserving dimensionality reduction," in *Proceedings of the 35th Annual International Conference of the IEEE EMBS*, pp. 3–7, Osaka, Japan, July 2014.

[7] Y. He, T. P. Luu, K. Nathan, S. Nakagome, and J. L. Contreras-Vidal, "Data descriptor: a mobile brain body imaging dataset recorded during treadmill walking with a brain-computer interface," *Scientific Data*, vol. 5, no. 1, Article ID 180074, 2018.

[8] Z. Zhong, M. Dong, W. Bai-kun, and C. Long-long, "Event-related EEGchanges during attempted standing up task," in *Proceedings of the Joint Meeting 6th International Symposium Noninvasive Functional Source Imaging of the Brain and Heart and International Conference Functional Biomedical Imaging (NFSI-ICFBI)*, pp. 66–69, Hangzhou, China, October 2007.

[9] J. Li, N. Thakor, and A. Bezerianos, "Brain functional connectivity in unconstrained walking with and without an exoskeleton," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 3, pp. 730–739, 2020.

[10] V. S. Handiru, A. Alicar, A. Hoxha et al., "Graph-theoretical analysis of EEG functional connectivity during balance perturbation in traumatic brain injury: a pilot study," *Human Brain Mapping*, vol. 42, pp. 1–21, 2021.

[11] T. M. Lau, J. T. Gwin, and D. P. Ferris, "Walking reduces sensorimotor network connectivity compared to standing," *Journal of NeuroEngineering and Rehabilitation*, vol. 11, no. 1, p. 14, 2014.

[12] A. Ikeda, H. O. Lüders, R. C. Burgess, and H. Shibasaki, "Movementrelated potentials recorded from supplementary motor area and primary motor area," *Brain*, vol. 115, no. 4, pp. 1017–1043, 1992.

[13] M. Lobier, F. Siebenhuhner, S. Palva, and J. M. Palva, "Phase transfer entropy: a novel phase-based measure for directed connectivity in networks coupled by oscillatory interactions," *NeuroImage*, vol. 85, pp. 853–872, 2014.

[14] W. Chang, H. Wang, G. Yan, and C. Liu, "An EEG based familiar and unfamiliar person identification and classification system using feature extraction and directed functional brain network," *Expert Systems with Applications*, vol. 158, Article ID 113448, 2020.

[15] J. L. Rodríguez-Sotelo, A. Osorio-Forero, A. Jiménez Rodríguez, D. Cuesta-Frau, E. Cirugeda-Roldán, and D. Peluffo, "Automatic sleep stages classification using EEG entropy features and unsupervised pattern analysis techniques," *Entropy*, vol. 16, no. 12, pp. 6573–6589, 2014.

[16] X. Xi, J. Zuo, and Z. Luo, "Weighted kernel FDA fall recognition of EMG fuzzy entropy," *Acta Electronica Sinica*, vol. 44, no. 06, pp. 1376–1382, 2016.

[17] W. Chang, W. Nie, Y. Yuan, Y. Zhang, and G. Yan, "Sitting and standing intention detection based on the complexity of EEG signal," *Authorea Preprints*, no. 8, pp. 1–9, 2022.