Sitting and Standing Intention Detection based on the Complexity of EEG Signal

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Abstract

Based on the brain signals, decoding the gait features to make a reliable prediction of action intention is the core issue 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 signal in each brain region. Through the statistical analysis of the 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 result shows that the proposed method can better realize the recognition of the above-mentioned action intention. The recognition accuracy of standing, sitting and quiet of 13 subjects is higher than 81%, and the highest one can reach 87%. The result has significant value for understanding human's cognitive characteristics in the process of lower limb movement and carrying out the study of BCI based strategy and system for lower limb rehabilitation.

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Based on the brain signals, decoding the gait features to make a reliable prediction of action intention is the core issue 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 signal in each brain region. Through the statistical analysis of the 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 result shows that the proposed method can better realize the recognition of the above-mentioned action intention. The recognition accuracy of standing, sitting and quiet of 13 subjects is higher than 81%, and the highest one can reach 87%. The result has significant value for understanding human's cognitive characteristics in the process of lower limb movement and carrying out the study of BCI based strategy and system for lower limb rehabilitation.

Introduction: It has lots of advantages using robot than traditional artificial method in the rehabilitation training, which can increase the motivation of patients and the opportunity of autonomous training, so as to improve the quality and effect of the rehabilitation. Exoskeleton and intelligent walking aid robot are widely used in the gait rehabilitation and have achieved good results [1,2]. With the development of brain computer interface (BCI) technology, researchers began to pay attention to the BCI based intelligent walking robot and rehabilitation training technology. It can improve the rehabilitation strategy by detecting brain's motion intention more quickly, which is the development trend of future neurological rehabilitation [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.

Electroencephalograph (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], 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 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 ERD with beta ERS during imaginary standing up task [7]. Bulea et al. [6] studied the corresponding EEG features of 10 subjects during the transition between sitting and standing by decoding the low-frequency band signals, and combined with Gaussian mixture model (GMM) to realize the recognition of the two conditions. In the subsequent work, Bulea and Contreras-Vidal et al. [4] analyzed the feasibility of delta frequency 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 obtain a good result. In addition, other decoding studies on motor intention mainly focus on two types of signals, one is the event-related synchronization/desynchronization (ERS\ERD) 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 realized the effective detection and recognition of the movement. However, these studies mainly focus on the slow potentials from few electrode channels in sensorimotor regions, which lack the characteristic information from spatial domain which 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 above-mentioned 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 [8,9]. Lau et al [10] investigated the characteristics of functional brain network during standing and walking, and they found that compared with standing condition, the functional connection of sensorimotor areas would be weakened during walking. They think it is because it needs more cognitive attention during walking. Li et al [8] 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 [9] studied the balance of brain trauma patients during walking by building the functional brain networks and they found the significant network features for patient walking. However, it is obviously necessary to carry out further analysis from various perspective for action intention detection. To this end, this study designed a motion experiment for sitting and standing actions. EEG signals were collected synchronously and the brain were divided into eight regions. The complexity and entropy characteristics of the EEG signals for eight regions during the whole action onset were fully analyzed. These features which sensitive to different actions are screened by a statistical analysis. Finally, the recognition of standing, sitting and quiet condition is realized by combing several machine learning classifiers, as shown in Fig.1 is the block diagram of this study.

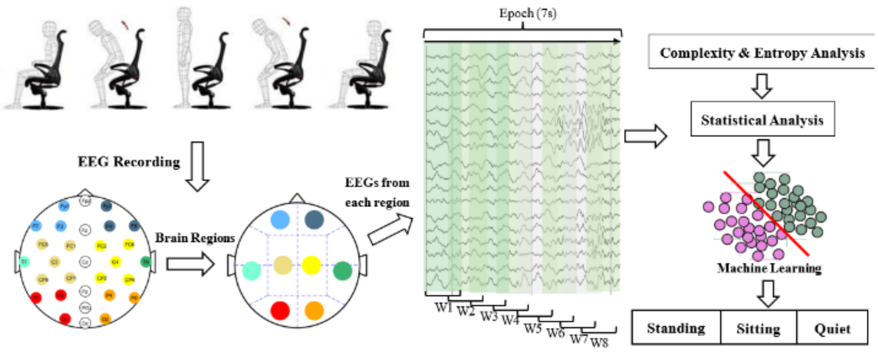

Fig.1 the block diagram of this study

Experiment Materials and Methods : 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 was required to sit still for 1 minute and then stand up and keep standing for 1 minute and then sitting down again, and these actions are completed repeatedly and alternately, as shown in Fig.2. EEG signals were recorded during the whole process and each subject finished 6 sessions which takes about 10 min and 1 min break after. Subjects were required to keep quiet during the experiment, especially when they sitting down and stand up, to minimize other movement artifact.

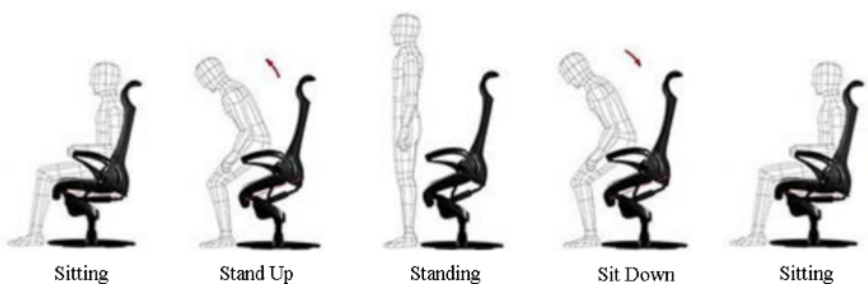

Fig.2 Schematic diagram of the standing - sitting experiment

EEGs was recoded with a 32-electrode cap arranged with the international 10-20 system using the SAGA 32+ device (TMSi, Netherlands), with an averaged reference during data recording. Four electrodes were placed laterally to right and left eyes to record the horizontal and vertical electrooculograms (EOG). The impedance of the electrode was set below 10KΩ and EEGs was recorded at the laptop with 1024Hz sampling rate and the online sampling frequency band is 0-200Hz.

Besides the 32 channel EEG signal, 4 extra channel which record the IMU data were fixed on the left upper leg and four pressure sensors (FSR sensors) were fixed under the left foot to record the foot pressure synchronously, which is shown in Fig.3. The preprocessing of all subjects was completed one by one in EEGLAB. Firstly, all sessions' data of each subject were merged together, then the data were down sampled to 250Hz and the band-pass filtering from 0.1Hz to 48Hz was completed. Cleanline tool was used to do the linear filtering to the signals and the electrode positioning of all the channels was completed according to the electrode position of SAGA system, and finally all the bad electrodes and irrelevant channels were removed.

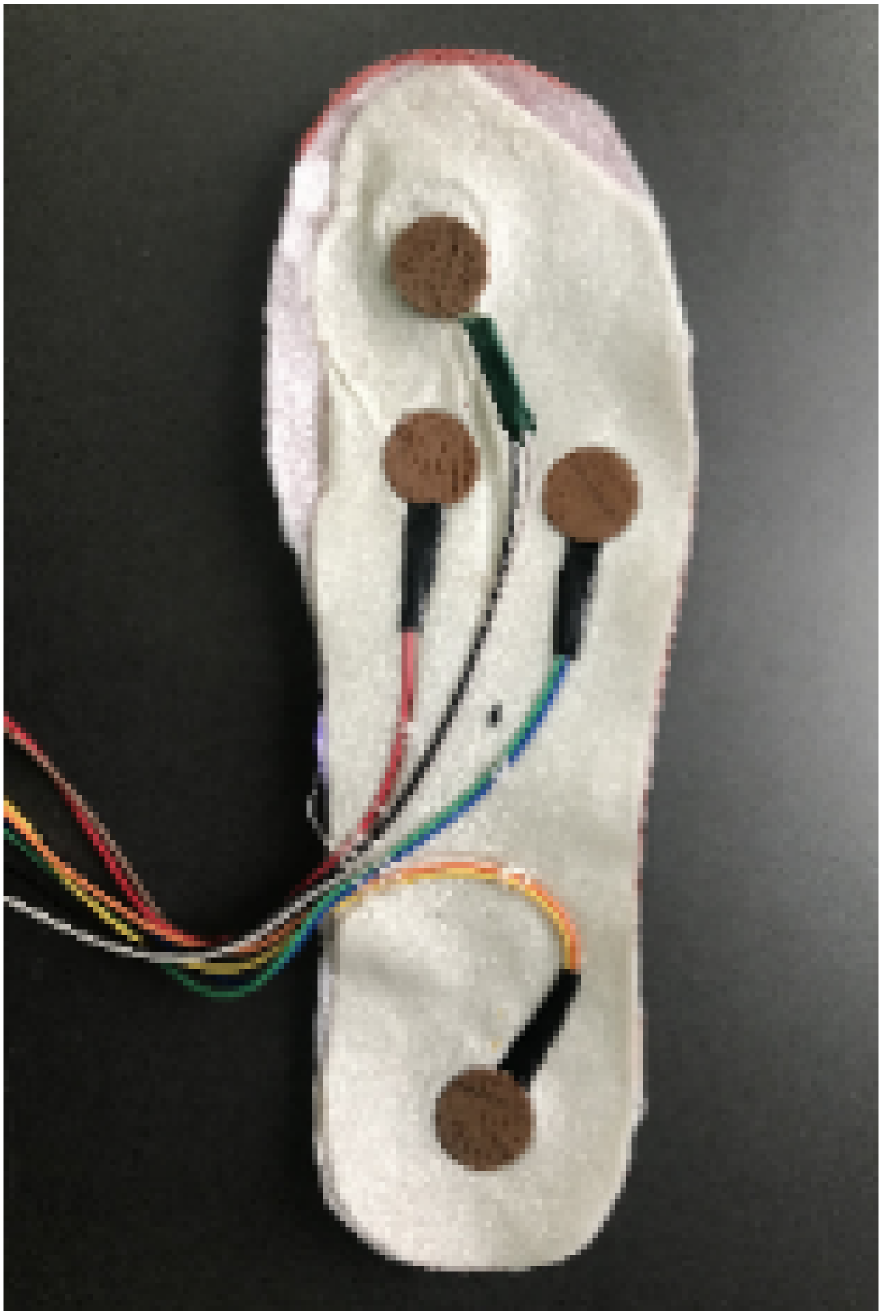

Fig.3 EEG recoding and additional sensing system

After the basic preprocessing, IMU data was filtered with a low-passed filter (cut-off frequency is 10Hz), and combing with the foot pressure signals from the heels, the onset of each standing and sitting action was determined. Then, all the data under the three conditions were segmented into the epochs lasting about 7s, including 4.5s prior and 2.5s post the onset of the motion action, and baseline correction were completed. Then the epochs which is greatly affected by artifacts were removed through visual detection, and the ICA decomposition of all signals was completed using runica. Artifact component which from eye movement, eye blink, muscle artifact and other artifacts mainly caused by the movement were removed with the help of SASICA toolbox. After the artifact remove, if necessary, the bad electrode was interpolated and the data was re-referenced. Finally, the 30 channels from the whole brain were divided into eight 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).

Complexity analysis is an important tool to reveal the characteristics of a nonlinear system. In recently years, more and more researchers began to evaluate the activity state of the brain through the nonlinear dynamic analysis [11]. Among them, entropy is one of the most widely used analysis methods. At present, various entropy analysis have been used for the neural signal analysis [11,12]. In order to more comprehensively discuss the representation of various entropy on EEGs during motion, this study calculated 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 representing time-frequency characteristics were also discussed. In addition, we also discussed the Hurst index, Kurtosis index and Hjorth parameters. 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 shows significant differences among the three conditions to form the feature vector and several machine learning classifiers were used to achieve the recognition of the sitting and standing condition.

Results and Discussion: In order to conduct quantitative analysis of the complexity measures in each brain region under the three conditions, ten complexity measures were calculated for averaged EEGs of each brain region respectively. We found that the values of various parameters in the eight regions are very closed and these parameters in LO and RO region are the largest, followed by the LC and RC region. Statistical analysis found that PeEn, ShEn, SpEn and Kurtosis in RT region were significantly different (t-test, $p < 0.05$) between standing and sitting, and 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 shows significant difference between standing and quiet. 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 shows significant different between sitting and quiet.

Based on the above discussed complexities of the EEGs in each region, combined with the statistical analysis results, the feature vector was constructed with these parameters which has significant difference among the three conditions. Three machine learning algorithms, including support vector machine (SVM), logistic regression (LR) and linear discriminant analysis (LDA), were used to test these features to complete the recognition of two types of motion condition. As show in Fig.4 is the averaged classification accuracy obtained after five-fold cross validation. It can be seen that all the classification accuracies are over 81% and the SVM has the best effect. The classification accuracy of standing and sitting, standing and quiet, and sitting and quiet are 83.3%, 87% and 82.5% respectively, which proves the effectiveness of this method.

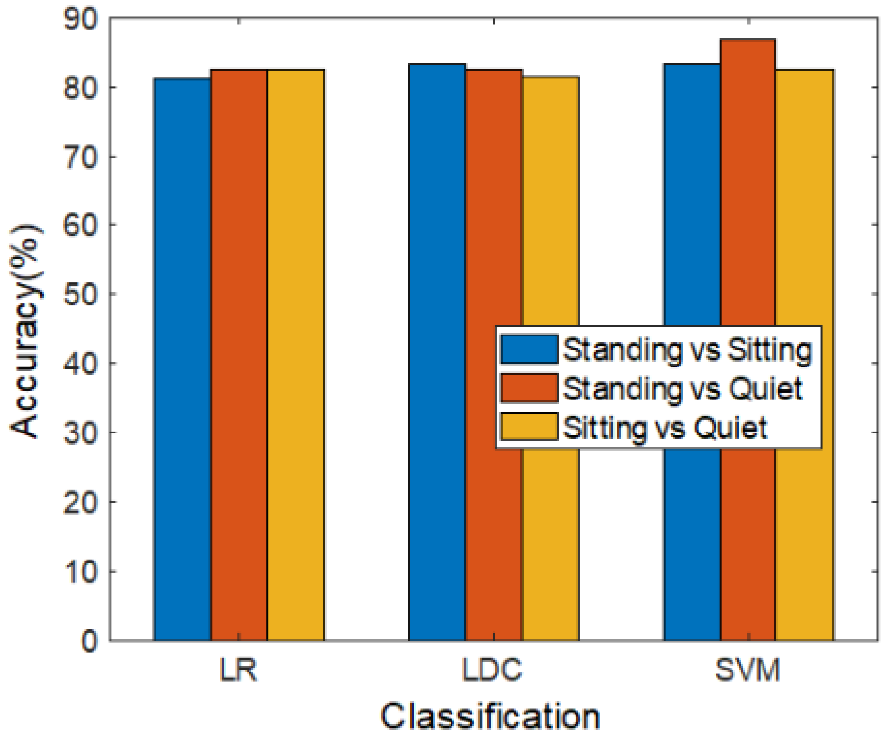

Fig.4 Classification accuracy of different classifiers in the three conditions

Conclusion : The active rehabilitation system based on BCI is an important tool in the future process. In this study, we proposed an effective method to detect the motion intention of low limbs using EEG signals. Firstly, a movement experiment was designed with the EEG signal synchronously recorded and the brain was divided into eight regions. Then, a series of entropy features and complexity parameters were discussed respectively for the grand averaged EEGs from each brain region. Finally, through the statistical analysis, relevant features with significant differences among the three motion conditions are screened out, combined with SVM, LDA and LR to realize the classification of standing, sitting and quiet. The highest classification accuracy is up to 87%, which proves the feasibility of detecting and recognizing the lower limb motion intention based on the complexity parameters of EEGs. This study also provides a new insight for EEG based motion intention detection, and has a certain reference value for the development of BCI based lower limb walking aid and rehabilitation robot.

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