Comfort Assessment Method of EEG-Based Exoskeleton Walking-Assistive Device

Heyuan Wang[1][a], Kaitai Li[1][b], Hui Liu[2][c], Xuesong Ye[1] and Congcong Zhou[3][d]

[1]*College of Biomedical Engineering & Instrument Science, Biosensor National Special Laboratory, Zhejiang University, Hangzhou, Zhejiang, 310027, China*

[2]*Cognitive Systems Lab, University of Bremen, 28359 Bremen, Germany*

[3]*Sir Run Run Shaw Hospital, School of Medicine, Zhejiang University, National Engineering Research Center for Innovation and Application of Minimally Invasive Devices, East Qingchun Road, Hangzhou, Zhejiang, 310016, China*

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Abstract: The study of wearable exoskeleton robotics has garnered significant attention, amidst a rapidly expanding corpus of scholarly work aimed at the empirical evaluation of the performance characteristics of robotic exoskeletons. However, quantifying comfort performance is still a significant and challenging task. This study aimed to perform comfort assessment based on EEG (Electroencephalography) signals and classical machine learning models as well as deep learning model. It involved collecting EEG data from users wearing lower limb exoskeleton walking-assistive devices for comfort assessment during walking experiments. The subjective evaluation labels of comfort were obtained using a semantic differential scale, providing comfort labels data for each participant in each trial. This study conducted a comparative analysis of three classical ML (Machine Learning) models, Naive Bayes, K-Nearest Neighbors, and Support Vector Machine models, with DL (Deep Learning) model, LSTM (Long Short-Term Memory), in terms of their accuracy for comfort assessment. The results of the analysis showed that the deep learning model, LSTM, outperformed the classical machine learning models, in terms of accuracy for evaluating comfort. Specifically, we get an accuracy of 0.91±0.12 on the LSTM model. The LSTM model demonstrated higher accuracy and better performance in capturing complex patterns and relationships within the EEG data, leading to the potential of more accurate predictions of comfort levels.

1 INTRODUCTION

As devices for human-machine symbiosis, exoskeletons with the strategy of human-in-the-loop, which incorporates human physiological indicators as feedback control parameters into the control loop, have achieved many positive results (Han et al., 2021a; Song & Collins, 2021; Zhang et al., 2017a). In the performance evaluation study of lower limb exoskeleton walking-assistive devices, comfort is defined as the user's perception of human-robot interaction (Pinto-Fernandez et al., 2020). Wrong parameter setting of the assistive device can lead to discomfort and even pain, which may start fighting the device or engage in other compensatory actions (Felt et al., 2015). In previous studies on the optimization of exoskeleton walking-assistive devices, it has been mentioned that quantifying comfort is a more challenging direction (Koller et al., 2016). Powered ankle exoskeleton providing too high peak torque may lead to discomfort during walking, and uncomfortable exoskeleton plantarflexion assistance will increase tibialis anterior muscle activity (Han et al., 2021b). Some assistive patterns of the exoskeleton are uncomfortable for the wearers, resulting in unpleasant optimization experiences and inaccurate outcomes, so some fixed parameters need to be set to ensure comfort based on pilot tests (Wang

[a] https://orcid.org/0000-0002-1817-9198
[b] https://orcid.org/0000-0002-0680-9818
[c] https://orcid.org/0000-0002-6850-9570
[d] https://orcid.org/0000-0001-8397-1491

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et al., 2022). The aim of this paper is to objectively assess the comfort and later introduce it into the human-in-the-loop optimization of lower limb exoskeleton control.

The human body receives various external stimuli and generates conscious judgments of comfort in the brain. By assessing brain activity based on electromagnetic or metabolic activity, it is possible to evaluate the state of brain activity and objectively reflect the level of comfort. Commonly used methods for detecting neural activity include EEG, MEG, ECoG (Lorach et al., 2023), fNIRS, fMRI (Heeger & Ress, 2002), etc., the first three are to detect the electromagnetic activity of the brain, and the last two are to detect the metabolic activity of the brain. EEG is one of the most commonly used methods for measuring brain neural activity. It can detect cluster electrical activity in the cerebral cortex.

Previous research has shown that changes in metabolic activity caused by blood circulation can affect brain electrical rhythms. Additionally, exo-skeleton assistive devices alter lower limb dynamics during human walking. This impact can be reflected to some extent in the comfort level by using several frequency domain features, especially those related to the α frequency band (Jeong & Kim, 2009;Ling & Xia, 2015;Liu & Chen, 2015;Luo et al., 2020;Park & Lee, 2021). Some researchers have used two classical machine learning models and EEG signals to evaluate comfort, and have achieved a classification accuracy of up to 0.75~0.85 in the binary classification task (Ortiz et al, 2021). Their study also showed that several electrodes that were selected to be more relevant to differentiating comfort when walking were electrodes located in the primary motor cortex and somatosensory cortex. This may be related to the difference in gait due to discomfort. In recent years, deep learning networks have performed very well on many learning models. Our research group has conducted study on ankle-foot motion recognition based on sEMG (surface Electromyography) and acceleration signals using classic machine learning models and deep learning networks (Zhou et al, 2021). The results have demonstrated the effectiveness of deep learning networks in processing bioelectric signals. Under the condition of sufficient data, we have the opportunity to capture the hidden features that are difficult to be directly calculated by traditional feature engineering.

In response to the above situation, we conducted a comfort assessment experiment for exoskeleton walking-assistive devices based on EEG signals and classical machine learning models as well as deep learning model. We validated and compared the performance of different models in comfort assessment.

2 METHODOLOGY

This study recruited four healthy university student participants, from which 10800000 raw data frames were obtained. The inclusion criteria for recruitment were as follows: all participants should have no limb injury, no joint disease, no muscle disease, no nervous system disease and in good physical condition in the last week. This series of experiments obtained approval from the ethics committees of both the university and the hospital. All participants volunteered to take part in this study and were provided with full information about the experimental setup and procedures before the start of the experiment.

EEG recording was performed using the BrainProduct actiCHamp Plus 64-channel device with a sampling frequency of 2500Hz. The EEG electrode placement followed the international standard EEG 10-10 system. The electrodes utilized actiCAP active electrodes with Ag/AgCl sensors, providing improved recording capabilities with lower noise levels. Subjects were instructed to minimize eye blinking during the experiment and focus on performing lower limb movements on a treadmill.

Figure 1: Subjects wearing laboratory-developed powered ankle exoskeleton and unpowered ankle exoskeleton, AFO.

The experimental procedure consists of three parts. In the first part, the recording of EEG signals begins while the participants maintain a resting state by standing still for 15 seconds. The second part involves the initiation phase of the treadmill, where the treadmill gradually accelerates to the desired speed within 15 seconds. The third part involves continuous walking, which is the phase where vali data is recorded and lasts for 2 minutes. Three categories of semantic difference scales (1~2 uncomfortable, 3~5 neutral, and 6~7 comfortable) are set and let the subjects self-rate after each trial.

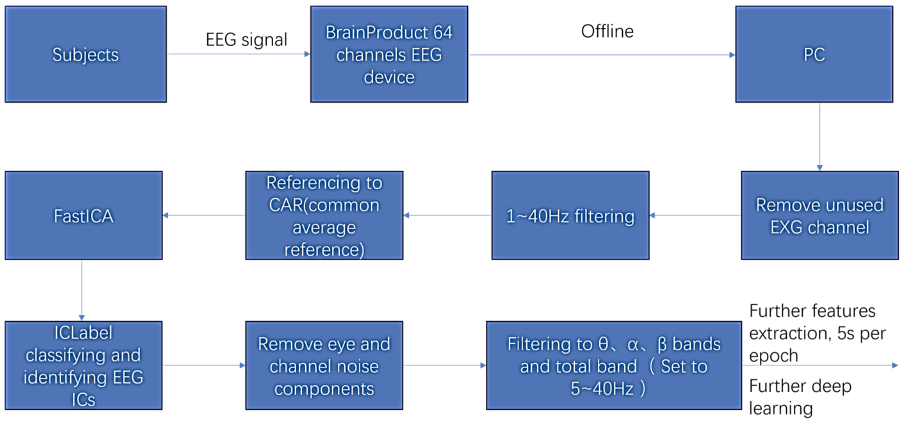

Figure 2: EEG preprocessing pipeline: 1)Remove unused EXG channels; 2)1~40Hz filtering; 3)Re-referencing to CAR; 4)FastICA; 5)ICLabel; 6)Remove eye and channel noise ICs.

In the walking experiment, subjects were asked to wear three different devices: powered ankle exoskeletons, unpowered ankle exoskeleton (Zhou et al, 2022), and self-assessed comfortable shoes. The experiments were conducted at 1.5 m/s, 2.5 m/s, and 3.5 m/s. The powered ankle exoskeleton used in the experiment was a laboratory-developed device designed to provide assistance during continuous walking. Based on ankle joint biomechanics, the exoskeleton provided a peak assistive torque during each gait cycle (Cappellini et al., 2006;Zhang et al., 2017b), while the unpowered ankle exoskeleton was the Ober AFO.

The subject's EEG signals are recorded by the BrainProduct EEG device and transmitted to the PC. Preprocessing of EEG signals is a series of steps that perform processing on raw EEG data to extract useful information and remove noise. First, the unused channel EXG is removed, which is configured to collect other electrophysiological signals such as EMG and ECG. Next, filtering in the frequency band of interest is to highlight the signal in our frequency range of interest, specifically 1~40Hz bandpass filtering. In the next step, re-referencing to the CAR (Common Average Reference) is a commonly used modified reference method. This method eliminates common pattern noise between electrodes by calculating the average of all electrodes and subtracting the signal from each electrode. This helps to make the individual electrodes more independent of each other for better analysis and interpretation of the EEG signals.

FastICA (Independent Component Analysis) can be used to extract ICs (Independent Components) from EEG data, separating the EEG activity that is mixed together, allowing us to study and understand the different EEG components. FastICA excels in both separation quality and computational speed, two performance metrics that ICA algorithms focus on. ICLabel is a machine-learning-based tool trained using a large number of labeled EEG data for automatically classifying and labeling independent components in EEG data. It can identify different types of components in the EEG signal, such as line noise, channel noise, ocular electrical activity, electromyographic activity, etc. Finally, based on the labeling results, the eye and channel noise components are removed. EEG is filtered to each frequency band for frequency domain feature extraction. Filtered EEG band definition: θ(5~7Hz); α(8~14Hz); β(15~30Hz); $total$(5~40Hz).

3 FEATURE EXTRACTION

3.1 Frequency Domain Feature

For periodic signals, their Fourier transform converges, allowing them to be described using a frequency spectrum. The frequency spectrum of a periodic signal is distinct and provides an accurate representation of the signal's components and energy distribution across different frequencies. The PSD (Power Spectral Density) is used to describe the frequency spectrum of actual signals, which are mostly random signals with infinite energy that cannot satisfy the absolute integrability condition required for Fourier transform convergence. However, PSD cannot be obtained accurately and can only be estimated using spectral estimation methods. The PSD of the EEG in specific frequency bands and the ratio of the PSDs between different frequency bands are commonly used features of EEG analysis

(Jap et al., 2009). The AR (Autoregressive) model is a commonly used parametric method for power spectrum estimation. The difference equation and power spectral density of the AR model are as follows:

$$x(n) = -\sum_{k=1}^{p} a_k\, x(n-k) + w(n) \tag{1}$$

$$P_{AR}(\omega) = \frac{\hat{\sigma}_w^2}{\left|1 + \hat{a}_1 e^{-j\omega} + \cdots + \hat{a}_p e^{-j\omega p}\right|^2} \tag{2}$$

Where $w(n)$ is a white noise signal with zero mean and variance of $\hat{\sigma}_w^2$, p is the order of the AR model.

The AR power spectral density estimation method based on the Burg algorithm was used to extract feature1 to feature10. The order of the AR model was set at 18, and the extraction was performed at intervals of 0.5Hz within the frequency range of 5Hz to 50Hz. After calculating the PSD for each frequency band, the following features were obtained: $\sum \beta \,/ \sum(\theta + \alpha)$; $\sum \beta \,/ \sum \alpha$; $\max(\alpha) \,/ \sum total$; $\max(\beta) \,/ \sum total$; $\sum \alpha \,/ \sum total$; $\sum \beta \,/ \sum total$; $\max(\theta + \alpha) \,/ \sum total$; $\sum(\theta + \alpha) \,/ \sum total$; $\max\,(\alpha)$; $\max\,(\beta)$. The AR power spectral density estimation method based on the Yule-Walker algorithm, with an AR model order of 2, was used to extract feature11: $\max\,(total)$.

3.2 Time Domain Feature

Standard deviation is a measure of the amount of variation or dispersion in a set of values. It quantifies the amount of variation or dispersion of a set of values from the mean. Standard deviation is calculated for pre-processed multi-channel EEG data:

$$std = \sqrt{\frac{\sum_{i=1}^{n} |x_i - \bar{x}|^2}{n-1}} \tag{3}$$

Signal energy is the total power contained in a signal over a period of time. It is calculated by integrating the squared values of the signal amplitude over time and is proportional to the duration and amplitude of the signal. Calculate Energy from pre-processed multi-channel EEG data:

$$E = \sum_{i=1}^{n} x_i^2 \tag{4}$$

The Weibull distribution has two parameters: the shape parameter and the scale parameter. In this study rectified EEG were used and only the scale parameter was calculated. The scale parameter determines the shape and scale of the distribution. When the scale parameter increases, the distribution becomes more concentrated with a higher peak value. Conversely, as the scale parameter decreases, the distribution becomes flatter with lower peaks.

$$f(x;\lambda,k) = \begin{cases} \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-(x/\lambda)^k} & x \ge 0 \\ 0 & x < 0 \end{cases} \tag{5}$$

where λ is the scale parameter.

The Hjorth parameter is a set of three time-domain features that describe a single EEG channel. These features are activity, mobility, and complexity. They are commonly used in EEG signals for feature extraction (Chen et al., 2023;Rizal et al, 2022). Calculate the Hjorth parameter for the preprocessed multi-channel EEG data:

$$Hj\ddot{o}rth\ (activity) = \sigma_x^2 \tag{6}$$

$$Hj\ddot{o}rth\ (mobility) = \sigma_{x'}/\sigma_x \tag{7}$$

$$Hj\ddot{o}rth\ (complexity) = \frac{\sigma_{x''}/\sigma_{x'}}{\sigma_{x'}/\sigma_x} \tag{8}$$

Where σ_x, $\sigma_{x'}$, and $\sigma_{x''}$are the stand deviations of $x(n)$, $x'(n)$, and $x''(n)$ respectively. $x(n)$ represents the preprocessed sequence of the EEG signal, and $x'(n)$ and $x''(n)$ represent its first- and second-order differences.

3.3 Nonlinear Feature

Entropy, originating from Shannon's information theory as: $-\sum plog(p)$, also known as information entropy, has given rise to many features in EEG analysis (Aydın et al., 2009). It is a type of nonlinear feature. Log energy entropy is a commonly used EEG feature similar to wavelet entropy, it only involves the summation of probabilities using logarithms. The formula is as follows:

$$H_{LogEn}(x) = -\sum_{i=1}^{n-1}\left(log_2\left(p_i(x)\right)\right)^2 \tag{9}$$

Where $p_i(x)$ is probability distribution function of EEG signal x, i indicates one of the discrete states.

The Sample Entropy (SamEn) is an extension of the Approximate Entropy (ApEn), which is used to measure the probability of generating a new pattern in the signal. The formula is as follows:

$$H_{SamEn}(n,m,r) = -\,ln\left(\frac{B^{m+1}(r)}{B^m(r)}\right) \tag{10}$$

Where m is the dimension, which can be 1 or 2; r is the approximate tolerance, $B^m(r)$ is the ratio of the approximate quantity to the total quantity.

4 DATASET AND CLASSIFIERS

4.1 Dataset

4.1.1 Dataset Construction

In order to avoid the influence of the magnitude of different feature vectors on the results, they were standardized. After feature extraction and standardization, the data is shown as Table 1, where the data frames represent the time frames of the multichannel EEG, the feature frames represent the calculated features for each epoch, 5s for each epoch:

Table 1: Exoskeleton walking-assistive device comfort assessment dataset.

Comfort level	Number of data frames
Uncomfortable	180(2250000)
Neutral	540(6750000)
Comfortable	144(1800000)

Feature Frames (Raw Data Frames)

4.1.2 Data Visualization

t-SNE (t-Distributed Stochastic Neighbor Embedding) is a popular dimensionality reduction technique used for visualizing high-dimensional data in a lower-dimensional space. It is particularly effective in revealing the underlying structure and patterns within the data (Heggs et al., 2023).

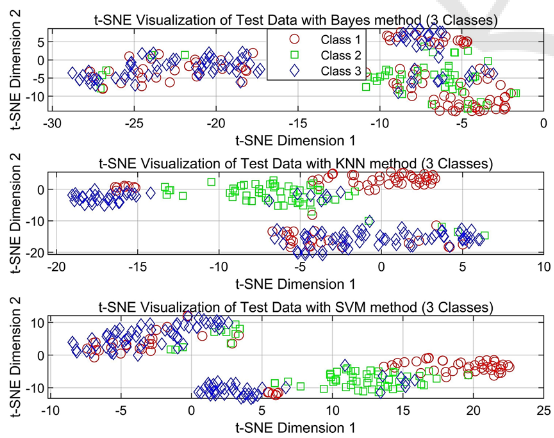

Figure 3: Schematic diagram of t-SNE dimensionality reduction of the three classifiers, from top to bottom, are Naive Bayes, KNN and SVM classifiers, in which red represents ‘uncomfortable’, green represents ‘neutral’, and blue represents ‘comfortable’.

The algorithm works by constructing a probability distribution over pairs of high-dimensional data points, both in the original space and in the lower-dimensional space. It then tries to minimize the divergence between these two distributions. In simpler terms, t-SNE aims to find a lower-dimensional representation that maintains the similarities between data points from the original high-dimensional space, while also ensuring that dissimilar points are well-separated. By iteratively optimizing this objective function, t-SNE gradually maps the data points into the lower-dimensional space, where they can be visualized and analysed effectively. In the study of decoding handwritten characters through an intracortical brain-computer-interface, 31 handwritten characters can be clearly distinguished by the two-dimensional visualization of neural activity drawn by t-SNE (Willett et al., 2021).

As can be seen from the visualization results in Figure 3, several classifiers have a certain degree of distinction, and the distinction degree of KNN and SVM is obviously higher than that of the Naive Bayes model, the intra-class distance is smaller, and the inter-class distance is larger.

4.2 Classifiers

4.2.1 Naive Bayes

Naive Bayes model is an elementary yet efficient algorithm (Wickramasinghe & Kalutarage, 2021) that assumes independence among features and leverages prior probabilities for sample class determination. It is widely used in text classification, sentiment analysis, and more due to its simplicity and effectiveness.

4.2.2 SVM

SVM model using ECOC (Error-Correcting Output Code) can help with multi-class classification problems (Ubeyli, 2008), encoding categories into binary codes and building binary SVM classifiers for each code. The final classification result is determined by the output encoding of these binary classifiers.

4.2.3 KNN

KNN is an instance-based model that classifies a new sample based on its nearest neighbor's category, calculated using the predefined number of neighbors K. KNN is simple and performs well on small datasets, but may face computational and storage challenges with large datasets (Bablania et al., 2018).

4.2.4 LSTM

LSTM is a type of RNN (Recurrent Neural Network) used for processing and predicting time series data. It has stronger memory capabilities and handles long-term dependencies better than traditional RNNs. LSTM uses gates to control information flow, including forget, input, and output gates. These gates update cell states, enabling the network to learn long-term dependencies effectively and avoid gradient problems during training. In past EEG studies, LSTM has shown good performance (Du et al., 2022). In this study, time series data before feature extraction is used in the LSTM model.

5 RESULTS

5.1 Model Optimization

The K value in the KNN model indicates how many data points of the nearest neighbors are considered when classifying. Specifically, when a new data point needs to be classified or predicted, the KNN algorithm finds the data points in the K training set that are closest to that data point, and then uses them to determine the classification or prediction value of the new data point. The choice of K value has a great impact on the performance and results of the KNN model. To balance the number of frames between the different classes, stratified random sampling is used to divide the training set (60%) and the test set (40%). The test results show that the k value of the optimal KNN classifier ranges from 5 to 15.

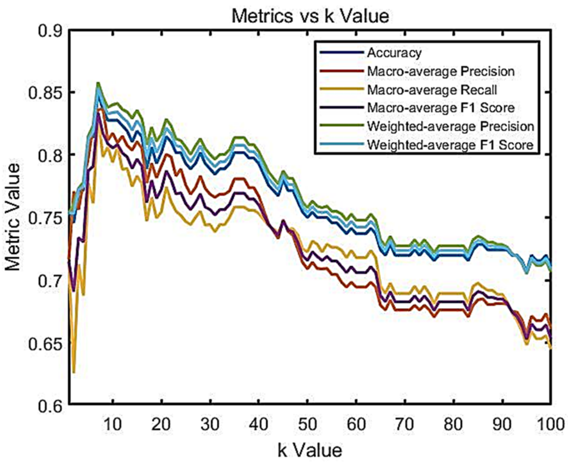

Figure 4: The change curves of classification accuracy, precision, recall and F1 score of the KNN model trained after a stratified random sampling of the data set with the increase of k value.

Figure 4 compares the change curves of various multiclassification evaluation metrics with the change of K-value, including accuracy, macro-average precision, macro-average recall, macro-average F1 score, weighted-average precision, and weighted-average F1 score, which are all possible metrics. The optimal k value of 5 of the 6 evaluation metrics is 7. In this stratified random sampling, the optimal accuracy of the model is 84.9%. After 20 times of stratified random sampling, grid search was used to find the optimal classifier at k=5~15, and the average optimal accuracy was 88.32%±1.2%.

5.2 Comparison of Classical ML Models

In a stratified random sampling, the performance of the three models is calculated and compared. The performance of SVM and KNN model is significantly higher than that of Naive Bayes model. The performance of SVM and KNN model is similar, but in general, SVM model is slightly better than KNN model. Specific comparisons are shown in Table 2, Table 3 and Table 4 below.

Table 2: SVM model performance.

Class\Metric	Accuracy	Precision	Recall	F1 Score
Uncomfortable	0.9267	0.8235	0.718	0.7671
Neutral	0.8879	0.8978	0.9111	0.9044
Comfortable	0.9526	0.8853	0.931	0.9076

SVM model accuracy: 88.36%

Table 3: KNN model performance.

Class\Metric	Accuracy	Precision	Recall	F1 Score
Uncomfortable	0.9353	0.8	0.8205	0.8101
Neutral	0.8664	0.8662	0.9111	0.8881
Comfortable	0.931	0.92	0.7931	0.8519

KNN model accuracy: 86.64%

Table 4: Naive Bayes model performance.

Class\Metric	Accuracy	Precision	Recall	F1 Score
Uncomfortable	0.8621	0.6667	0.359	0.4667
Neutral	0.681	0.6784	0.8593	0.7582
Comfortable	0.7759	0.575	0.3966	0.4694

Naive Bayes model accuracy: 65.95%

It can be seen that although SVM model outperforms KNN model on most evaluation metrics, several metrics are lower than KNN model. They are Uncomfortable Accuracy, Comfortable Precision, Uncomfortable Recall, Uncomfortable F1 Score.

The accuracy of the Naive Bayes model is not too low for each class. But Comfortable Recall, Uncomfortable recall, Comfortable F1 Score, Uncomfortable F1 Score are all very low.

5.3 ML and DL Models Comparison

Table 5 below compares the performance of the deep learning model LSTM with three classical machine learning models. It can be seen that the LSTM model is superior to the machine learning models in terms of accuracy of up to 0.91±0.12, even if the optimal KNN classifier is trained many times, the average accuracy of these multiple optimal KNN classifiers is only 0.88, and the LSTM can obtain an accuracy of up to 0.91 even without model optimization, indicating that the LSTM can capture the hidden features of the relationship between human EEG data and comfort levels.

Table 5: Comparison of the performance of three classical Machine Learning models and Deep Learning model LSTM in this task. The Naive Bayes model was not optimized. The accuracy of KNN is the average of multiple optimal KNN models, which is the result in 5.1. The SVM model with ECOC uses a conventional linear kernel, was also not optimized. Both Bayes and SVM models were obtained after 20 stratified random sampling.

Results	Models			
	LSTM	Bayes	KNN	SVM
Accuracy	0.91± 0.12	0.63± 0.03	0.88± 0.01	0.86± 0.02

(mean ± std)

6 CONCLUSIONS

This study is intended to explore the comfort assessment method for exoskeleton walking-assistive devices. EEG signals were collected from subjects during a walking experiment, and frequency-domain, time-domain, and nonlinear features were extracted. The t-SNE technique was used for dimensionality reduction and visualization of categories, demonstrating separability between different categories. Subsequently, evaluations based on several classical machine learning models were conducted and compared with the performance of the deep learning model LSTM. The results indicate that among the classical machine learning models, the Naive Bayes model performed the worst, with accuracy far lower than SVM and KNN. Both SVM and KNN demonstrated good performance, achieving accuracies above 0.8. The deep learning model LSTM outperformed several classical machine learning models in accuracy (0.91±0.12). This indicates that the deep learning model LSTM exhibits excellent performance in revealing the potential relationship between EEG and comfort levels, and can identify hidden features.

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