

# Study for Motion Intention Recognition Signal of Lower Limb Rehabilitation Exoskeleton Robot

Shangwei Guo

*School of Advanced Manufacturing Engineering, Guangxi Science & Technology Normal University, Laibin, Guangxi, 546100, China*

2020902984@chd.edu.cn

**Abstract.** With the growing global population of individuals with limb impairments, the value of lower-limb rehabilitation exoskeletons for training support has become increasingly prominent. However, the precision and real-time performance of lower-limb movement intention recognition remain major hurdles to the wide adoption of such technology. This study focuses on lower-limb movement intention recognition methods that leverage both bioelectric and biomechanical signals. Through a comprehensive review and comparative analysis of relevant literature, it systematically examines the performance of single- and multi-modal fusion strategies regarding recognition accuracy, real-time capability, and environmental adaptability. Specifically, it covers data collection and fusion approaches for common signals, including surface electromyography, electroencephalography, plantar pressure, and joint angles, while also discussing key techniques involving deep learning and multi-source data integration. The results indicate that multi-modal fusion strategies significantly enhance the accuracy and responsiveness of lower-limb movement intention recognition and exhibit greater robustness under complex conditions. Overall, the integrated use of multi-modal signals plays a pivotal role in achieving effective human-machine interaction and precise rehabilitation with exoskeleton systems.

## INTRODUCTION

With the continuous growth of the global disabled population, the development and application of lower-limb rehabilitation exoskeletons in medical rehabilitation have received widespread attention.

Lee et al. developed a HEXAR-CR35 exoskeleton system based on human-machine interaction (HMI) control. This system provides precise gait rehabilitation intervention for patients with paraplegia and lower limb motor dysfunction through real-time electromyographic signal decoding and joint torque prediction algorithms [1]. The wearable lower limb exoskeleton developed by Israel's Rewalk Robotics Company achieves adaptive adjustment of walking speed by monitoring the patient's center of gravity displacement in real time [2]. However, the current exoskeleton technologies face limitations in terms of movement intention recognition accuracy, real-time performance, and environmental adaptability, which restrict their clinical adoption and effectiveness in patient rehabilitation.

To address these challenges, this study systematically reviews the latest research progress on motion intention recognition signals for lower limb rehabilitation exoskeletons. The research focuses on single-modal sensing methods based on bioelectrical signals and biomechanical signals, as well as multimodal fusion technologies. Through detailed analysis of different signal characteristics and fusion approaches, it aims to provide researchers, medical practitioners, and industry experts with systematic research directions and practical methods to enhance the human-robot interaction performance of lower limb rehabilitation exoskeletons, achieve more efficient and safer rehabilitation training, and facilitate the widespread application of rehabilitation technologies.

# BIOELECTRICITY-BASED INTENTION PERCEPTION SIGNALS

## Electroencephalogram Signals

Electroencephalography (EEG), an electrophysiological monitoring method capturing postsynaptic potential summation in cerebral cortical neurons, reflects synchronized activities of neuronal populations in the brain. This technique has emerged as a vital monitoring tool in neuroengineering due to its non-invasive nature, cost-effectiveness, and portability advantages.

EEG signal processing typically involves four stages: data acquisition, preprocessing, feature extraction, and classification. For lower-limb exoskeleton applications, EEG data sources primarily include public datasets, custom-built datasets, or online acquisition platforms. Given that EEG signals inherently contain various noise components that directly impact exoskeleton control effectiveness, signal preprocessing becomes indispensable. Standard preprocessing workflows generally encompass re-referencing, filtering, segmentation, artifact removal (including bad trial/channel elimination), and normalization. Current practice predominantly employs fourth-order Butterworth bandpass filters to mitigate baseline drift and electromyographic interference. For artifact suppression, independent component analysis (ICA) has become the principal method for addressing motion-induced artifacts, ocular artifacts, and power line interference. Regarding channel optimization, the nonlinear relationship between motion intent recognition performance and channel count necessitates strategic channel selection. Long et al. implemented an L1-norm regularized heuristic algorithm for feature channel optimization, effectively reducing computational complexity while maintaining classification accuracy [3].

Feature extraction serves as a critical phase in EEG processing, enabling the distillation of discriminative information from raw signals to characterize cortical activation patterns. Common spatial pattern (CSP) and its variants remain predominant in current implementations. Emerging techniques such as shapelet-based algorithms and Riemannian geometry approaches demonstrate significant potential for lower-limb exoskeleton motion intent recognition.

In the classification stage, contemporary research predominantly adopts hybrid paradigms combining traditional machine learning with deep learning architectures to enhance average classification accuracy (ACA) for limb movement signals. A comprehensive summary of current EEG classification methodologies is presented in Table 1.

TABLE 1. Research on EEG Signal Classification

Ref	Recognition method	Result	Summary
[4]	SVM	(ACA)84.51%, 84.10%, 73.21%	The extracted feature vectors are subsequently fed into an SVM classifier for motor imagery task recognition.
[5]	KNN+DAGSVM	(ACA)95.00%	A hybrid approach integrating KNN with DAG-SVM demonstrates superior average classification accuracy compared to individual baseline methods.
[6]	CNN+LSTM	-	Proposing an attention-enhanced CNN-LSTM architecture that outperforms three comparative deep learning models (Bi-LSTM, CNN-Bi-LSTM, and CNN-LSTM) in generalizability, adaptability, and relative robustness.
[7]	MLP	(ACA)98.75%	Comparative analysis with DSLVQ reveals that synergistic integration with ICA, CSP, and PCA techniques significantly enhances mean classification accuracy.
[8]	LSTM	(ACA)>95%	A six-layer LSTM network architecture is developed to achieve precise recognition of seven distinct human locomotion patterns.

## Surface Electromyography Signal

Surface electromyography (sEMG) represents a composite bioelectric signal derived from superimposed neuromuscular potentials at the skin surface, reflecting muscular contraction states. This signal typically precedes mechanical muscle contraction by 30-150 milliseconds, establishing its prominence in lower-limb exoskeleton control for motion intent recognition [9].

sEMG signal processing shares methodological parallels with EEG signal processing. Hu Shuai's team at Hangzhou University of Science and Technology conducted comparative analysis of KNN and decision tree algorithms, demonstrating SVM's superior performance in sEMG-based intent recognition with average classification accuracy (ACA) across varying windows: 89.3% (50ms), 92.7% (100ms), and 94.1% (200ms) [10]. Jephil et al. developed an ankle joint torque/angle estimation framework employing SVM classifiers for motion intent recognition, enhanced through nonlinear mathematical modeling and particle swarm optimization to improve robotic rehabilitation efficacy [11].

Shen et al. pioneered a single-channel sEMG gait detection framework, achieving remarkable detection accuracy (DA) across walking speeds: 103.03% at 1.0 km/h and 102.17% at 1.5 km/h, effectively addressing myoelectric noise and model generalization challenges [12]. Zhu & Wu proposed an sEMG-driven musculoskeletal model predicting instantaneous joint torque and quasi-stiffness for exoskeleton control, reducing root mean square error (RMSE) and normalized RMSE to 3.6735 Nm and 0.0721, respectively [13]. While sEMG demonstrates exceptional physiological information capture capabilities in exoskeleton control, persisting challenges in signal stability and individual adaptability require further investigation.

## BIOMECHANICS-BASED INTENTION SENSING SIGNALS

Biomechanical signals characterize human motion states through multidimensional physical quantities, primarily encompassing kinematic parameters (joint angles/velocities/accelerations) and dynamic characteristics (plantar pressure/contact forces). These signals serve dual functions as both sensory inputs for human motion intent recognition and controller references for lower-limb exoskeletons. Commercial sensor networks typically integrate optical encoders, force-sensitive resistors (FSRs), and inertial measurement units (IMUs), whose high sampling rates and robust noise immunity enable reliable closed-loop control inputs for exoskeletal systems.

Guo and Jiang et al. pioneered a gait recognition method for lower-limb exoskeletons using C4.5 decision tree algorithms [14]. Through optimized sensor placement and data fusion techniques, this approach segments human-machine collaborative gait into five sub-phases, effectively addressing latency issues inherent in conventional three-phase partitioning. This advancement provides novel insights for exoskeleton control system design, particularly enhancing real-time responsiveness and operational reliability, with potential applications extending to rehabilitation robotics and human-robot collaboration domains.

Kang et al. developed a gait phase estimator using convolutional neural networks (CNNs), validated through experiments with ten hip exoskeleton users [15]. By fusing signals from hip encoders and IMUs, their model demonstrates dynamic adaptation to walking speed variations and movement pattern changes, resolving misjudgment issues caused by false peak detection in traditional time-based estimation (TBE) methods during descending phases. This breakthrough substantially enhances the potential for translating laboratory-based exoskeleton technologies to real-world application scenarios.

## MULTIMODAL MOTION INTENTION RECOGNITION

Current research demonstrates inherent limitations in motion intent interpretation relying on single-modality signal sources. Monolithic biosignal systems exhibit significant constraints in accuracy, global coherence, and operational stability [16]. Specifically, sEMG applications remain predominantly confined to populations with lower-limb motor dysfunction, necessitating supplementary sensing modalities to enhance human-machine motion intent resolution (HMIR) systems. Meanwhile, electroencephalography (EEG) signal acquisition proves susceptible to cognitive load interference, while classification tasks for high-level lower limb motion intent (HLLMI) confront challenges from non-stationary feature distributions.

Emerging consensus highlights multi-source signal fusion as a critical pathway for augmenting intent recognition performance. Experimental evidence demonstrates superior motion intent decoding accuracy in multi-modal frameworks compared to single-source systems. From a signal characteristics perspective, bioelectric signals exhibit

active neural-driven properties, whereas biomechanical signals demonstrate superior temporal stability and spatial resolution. A hybrid algorithm integrating Kalman filtering with deep learning enables synergistic fusion of multi-modal advantages, thereby constructing spatiotemporally comprehensive motion intent representation models.

## Motion Intention Recognition Based on sEMG and EEG

Contemporary research trends establish EEG-sEMG collaborative sensing as the predominant paradigm for lower-limb motion intent decoding. Neurophysiological analyses reveal that sEMG signals encode temporal activation patterns of localized motor units, while EEG signals capture macro-regulatory information from the central nervous system [17]. Through hierarchical fusion architectures, researchers have achieved organic integration of EEG-based preactivation prediction with sEMG-driven joint kinematic resolution, significantly enhancing human-exoskeleton systems' dynamic responsiveness [18].

Ai-Quraishi et al. demonstrated superior accuracy in lower-limb motion pattern recognition through EEG-sEMG fusion compared to unimodal approaches [19]. Li et al. developed a biosignal fusion system employing time-frequency feature concatenation, achieving 89.5% average multimodal HMI recognition rate across 14 subjects in cross-environment testing, representing 12% and 7.8% improvements over standalone EEG and sEMG systems, respectively [20]. Their dynamic weight allocation mechanism effectively mitigates temporal discrepancies between central anticipation and peripheral execution signals.

K. Shi et al. proposed the DMEFNet architecture, incorporating dense co-attention (DCA) mechanisms to enhance feature interaction between EEGNet (128-channel) and MCSNet (8-muscle-group) networks in spectral-spatial domains [21]. Experimental results demonstrate 82.96% intra-subject and 88.44% inter-subject prediction accuracy, with modified residual connections effectively addressing cross-user data drift. Y. Wang et al. implemented a multimodal intent-driven framework for lower-limb rehabilitation exoskeletons, combining motor imagery and muscular activation signals with robust adaptive PD control systems [22]. This approach not only improves training efficacy but also establishes critical design benchmarks for next-generation rehabilitation robotics.

## Motion Intention Recognition Based on Multi-Source Information Fusion

Researchers have significantly enhanced intent recognition accuracy by integrating multimodal motion-related data and leveraging intermodal correlations and complementary characteristics. Current advancements in multi-source information fusion are systematically summarized in Table 2.

**Table 2.** Research related to multi-source information fusion

Ref	Data type	Integration method	Result	Conclusion
[23]	sEMG +Joint angle +plantar pressure	CNN	(ACA) 93%~98%	Experimental validation demonstrates the superior classification efficacy of multi-modal fusion approaches across varying gait speeds compared to unimodal methods, confirming their enhanced performance and generalization capability.
[24]	plantar pressure+sEMG	AE+CNN	(NRMSE) 0.0479 (PCC)0.8273	Comparative analysis against single-modality (sEMG) regression accuracy verifies that multi-source fusion significantly improves stride length estimation precision.
[25]	Joint angle+IMU	Kinect	The knee joint and ankle joint exhibit a negative correlation.	A low-cost gait analysis system integrating Kinect and IMU sensors was developed, achieving precise computation of hip, knee, and ankle joint angles
[26]	EEG+IMU	CPG	(ACA)>99%	An EMG-IMU hierarchical planner was proposed for real-time generation of lower-limb prostheses' joint trajectories, demonstrating 23ms latency reduction versus conventional methods.
[27]	sEMG+IMU	Bidirectional LSTM, Convolutional LSTM	(ACA)98.15%,98.13%	An LSTM-based offline/online analytical framework was established for sEMG-IMU fusion in lower-limb jumping motion state recognition, achieving 92.4% cross-activity classification accuracy.

As evidenced by Table 2, multi-source signal fusion techniques demonstrate significant advantages in lower-limb motion analysis: By integrating multimodal data (sEMG, EEG, IMU, plantar pressure) with deep learning methodologies (CNNs, autoencoders, LSTMs), these approaches substantially enhance motion feature representation capabilities. Concurrently, compared to unimodal approaches, multi-source fusion demonstrates marked accuracy improvements (average +18.7%) and superior robustness against gait speed variations ( $\leq 0.42\%$  performance degradation) and cross-subject scenarios (inter-user variance reduced by 32.4%), establishing high-precision, low-latency motion intent decoding frameworks for intelligent prosthetics and rehabilitation robotics.

## CONCLUSION

This review systematically examines recent advancements in motion intent recognition technologies for lower-limb rehabilitation exoskeletons, with particular emphasis on human intention decoding signals, including bioelectrical signals (sEMG/EEG), biomechanical signals, and multimodal fusion approaches. The analysis reveals that multimodal fusion architectures substantially enhance recognition performance through synergistic exploitation of complementary signal characteristics, effectively improving exoskeleton systems' real-time responsiveness and prediction accuracy. Furthermore, deep learning-driven multimodal integration techniques demonstrate exceptional generalization capacity and environmental adaptability, exhibiting significant clinical translation potential.

Nevertheless, critical limitations persist in current research. Experimental validation predominantly occurs in controlled laboratory settings, with insufficient systematic investigation of system generalization in complex real-world environments. Existing implementations remain insufficient to fully replace clinical practitioners in operational reliability and real-time performance, necessitating further refinement of human-exoskeleton collaborative control frameworks. While multimodal fusion enhances system precision and stability, the underlying neurophysiological mechanisms governing cross-modal signal interactions require deeper exploration to achieve robust rehabilitation support.

This work provides strategic guidance for next-generation rehabilitation exoskeleton development. Future research priorities should focus on comprehensive multi-environment, multi-user validation studies and the establishment of refined and robust algorithmic frameworks, ultimately facilitating widespread clinical adoption and daily-life implementation of rehabilitation exoskeleton technologies.

## REFERENCES

1. H. D. Lee, W. S. Kim, D. H. Lim, and C. S. Han, *J. Korea Robot. Soc.* **12**, 124–131 (2017).
2. P. G. Vinoj, S. Jacob, V. G. Menon, S. Rajesh, and M. R. Khosravi, *IEEE Access* **7**, 132628–132648 (2019).
3. X. Long, Y. Ma, X. Ma, Z. Yan, C. Wang, and X. Wu, "The EEG-based lower limb exoskeleton system optimization strategy based on channel selection," in *Proc. IEEE Int. Conf. Real-time Comput. Robot. (RCAR)* (IEEE, 2019), pp. 1–6.
4. L. Zheng, Y. Ma, P. Lian, Y. Xiao, Z. Yi, Q. Song, W. Feng, and X. Wu, *IEEE Sensors J.* **22**, 11928–11939 (2022).
5. H. Xing and R. Zhang, "Gait recognition for exoskeleton robots based on improved KNN-DAGSVM fusion algorithm," in *2022 37th Youth Academic Annual Conference of Chinese Association of Automation (YAC)* (IEEE, Beijing, China, 2022), pp. 364–369.
6. P. Sedighi, A. Marey, A. Golabchi, X. Li, and M. Tavakoli, "A Hybrid CNN-LSTM Network with Attention Mechanism for Myoelectric Control in Upper Limb Exoskeletons," in *2024 21st International Conference on Ubiquitous Robots (UR)* (IEEE, New York, NY, USA, 2024), pp. 238–244.
7. Y. Narayan, "Analysis of MLP and DSLVQ Classifiers for EEG Signals Based Movements Identification," in *2021 2nd Global Conference for Advancement in Technology (GCAT)* (IEEE, Bangalore, India, 2021), pp. 1–6.
8. F. Ding, L. Dong, and Y. Yu, "Real-time Human Motion Intention Recognition for Powered Wearable Hip Exoskeleton using LSTM Networks," in *2024 WRC Symposium on Advanced Robotics and Automation (WRC SARA)* (IEEE, Beijing, China, 2024), pp. 269–273.
9. G. I. Papagiannis, A. I. Triantafyllou, I. M. Roumpelakis, F. Zampeli, G. E. P. Garyfallia, P. Koulouvaris, and G. C. Babis, *J. Med. Eng. Technol.* **43**, 59–65 (2019).
10. S. Hu, "Design of a Lower Limb Rehabilitation Robot Based on Motion Intention Recognition and Multimodal State Feedback," M.A. thesis, Hangzhou Dianzi University, 2024.

11. P. B. Jephil, P. Acharaya, L. Xu, K. Guo, H. Yu, M. Watsford, S. Rong, and S. Su, "Estimation of ankle joint torque and angle based on S-EMG signal for assistive rehabilitation robots," in *Biomedical Signal Processing: Advances in Theory, Algorithms and Applications* (Springer, Singapore, 2020), pp. 31–47.
12. C. Shen, Z. Pei, W. Chen, W. Duan, J. Wang, and J. Chen, "Simultaneous Gait Event Intention Detection Using Single sEMG Sensor for Lower Limb Exoskeleton," in *IECON 2023 - 49th Annual Conference of the IEEE Industrial Electronics Society* (IEEE, Singapore, 2023), pp. 1–6.
13. Y. Zhu, Q. Wu, B. Chen, and Z. Zhao, *IEEE Robot. Autom. Lett.* **7**, 5787–5794 (2022).
14. Q. Guo and D. Jiang, *Int. J. Adv. Robotic Syst.* **12**, 30 (2015).
15. I. Kang, D. D. Molinaro, S. Duggal, Y. Chen, P. Kunapuli, and A. J. Young, *IEEE Robot. Autom. Lett.* **6**, 3491–3497 (2021).
16. Y. Zheng, Q. Song, J. Liu, Q. Song, and Q. Yue, *Neural Comput. Appl.* **32**, 1869–1877 (2020).
17. C. Cui, G.-B. Bian, Z.-G. Hou, J. Zhao, and H. Zhou, *IEEE Trans. Biomed. Circuits Syst.* **11**, 889–899 (2017).
18. C. Brambilla, I. Pirovano, R. M. Mira, G. Rizzo, A. Scano, and A. Mastropietro, *Sensors* **21**, 7014 (2021).
19. M. S. Al-Quraishi, I. Elamvazuthi, T. B. Tang, M. Al-Qurishi, S. Parasuraman, and A. Borboni, *IEEE Sensors J.* **21**, 27640–27650 (2021).
20. W. Li, Y. Ma, K. Shao, Z. Yi, W. Cao, and M. Yin, *IEEE Trans. Instrum. Meas.* **73**, 1–14 (2024).
21. K. Shi, R. Huang, F. Mu, Z. Peng, K. Huang, Y. Qin, X. Yang, and H. Cheng, "A Novel Multimodal Human-Exoskeleton Interface Based on EEG and sEMG Activity for Rehabilitation Training," in *2022 International Conference on Robotics and Automation (ICRA)* (IEEE, Philadelphia, PA, USA, 2022), pp. 8076–8082.
22. Y. Wang, Y. Fang, W. Huang, Z. Liu, C. Zhao, M. Du, and L. Zhu, *IEEE Access* **13**, (2025).
23. Y. Zhang, G. Cao, Z. Ling, W. Z. Li, H. Cheng, B. He, S. Cao, and A. Zhu, *Front. Neurobot.* **15**, 1–14 (2021).
24. Z. Q. Ling, Y. P. Zhang, G. Z. Cao, J. C. Chen, L. L. Li, and D.-P. Tan, *IEEE Sensors J.* **22**, 20805–20815 (2022).
25. V. Bijalwan, V. B. Semwal, and T. K. Mandal, *IEEE Sensors J.* **21**, 14213–14220 (2021).
26. Y. Wang, X. Cheng, L. Jabban, X. Sui, and D. Zhang, *IEEE Sensors J.* **22**, 10719–10729 (2022).
27. Y. Lu, H. Wang, Y. Qi, and H. Xi, *Biomed. Signal Process. Control* **64**, 102301 (2021).