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# *Advancements in Intelligent Prosthesis Design through Human-Machine Interfaces*

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***Abstract.*** The number of patients with limb loss in the world continues to rise, but traditional prostheses face a disuse rate of about 40 % due to low control accuracy, lack of tactile feedback, and poor cross-user generalization. Although the existing research explores performance improvement through the fusion of multimodal sensing and artificial intelligence (AI), it is still limited by core challenges such as insufficient collaborative optimization of heterogeneous sensors, low real-time processing efficiency, and difficulty in adapting individual physiological differences. In view of the above problems, this paper reviews the current research progress, technical bottlenecks and future development directions in the design of intelligent prostheses, aiming to break through the performance bottleneck of human-machine interface (HMI) technology and improve the practicability and clinical popularity of intelligent prostheses. The findings show that the three-modal fusion improves the accuracy of gesture recognition to 96.5 %, and the closed-loop haptic feedback mechanism reduces the grasping force error by 42 %; however, challenges such as sEMG signal attenuation and impedance fluctuations of dry sensors remain to be addressed.

***Keywords:*** Intelligent Prosthesis, HMI, sEMG, IMU

## 1. Introduction

With the continuous growth of the number of patients with limb loss in the world, traditional prostheses face a disuse rate of up to 40 % due to problems such as low control accuracy and lack of feedback mechanisms [1]. Although human-machine interface (HMI) technology shows innovative potential through the integration of multi-modal sensing and intelligent algorithms, its core advantage lies in creating a two-way interactive closed-loop. This achieves unprecedented control naturalness through multi-modal intent decoding, and integrates prosthetic perception into user proprioception with real-time tactile feedback.

However, significant limitations remain. First, systems relying on a single surface electromyography (sEMG) signal are vulnerable to muscle fatigue and sweat interference, resulting in online classification accuracy of less than 70 %. Additionally, the absence of tactile feedback causes the grasping force error to exceed 30 %, which limits the complex operation ability. Third, cross-user generalization is poor, requiring up to 2 hours, which hinders clinical popularization [2-4]. Recent advancements in multi-modal sensing and embedded artificial intelligence (AI) has provided a new path to break through the above bottlenecks. For example, the fusion of sEMG and

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inertial measurement unit (IMU) can improve the accuracy of gesture recognition to 89.2 %, while the deployment of lightweight deep neural network (DNN) on embedded platforms compresses the processing delay to within 100 ms [5-6].

Builidng on existing literature, this paper discusses the latest progress of intelligent prostheses in the fields of human-machine interface technology, multi-modal sensor fusion and embedded artificial intelligence. This study promotes the clinical application of intelligent prostheses, realizes its universalization and popularization, and lays a solid theoretical and practical foundation.

## 2. Design basis of Hmi in intelligent prostheses

### 2.1. The basic concept and importance of Hmi

The human-machine interface (HMI) is the core interactive medium connecting the user and the mechanical execution module in the intelligent prosthetic system. Its core function is to decode the user 's intention in real time and translate it into precise prosthetic control instructions through the input of biological signals (such as EMG signals, inertial measurement data) or physical sensors. Although traditional myoelectric control using sEMG is commonly employed in commercial prostheses like the Ottobock MyoBock, its reliance on manual switching gestures can be unintuitive. Furthermore, this approach is vulnerable to issues such as skin impedance changes, muscle crosstalk, and environmental noise interference. Studies have shown that the limitations of a single sensor mode (such as sEMG sensitivity to muscle fatigue and NIRS response delay) make multimodal fusion a key strategy to improve control robustness. For example, by combining the fast response of sEMG with the anti-fatigue properties of NIRS, the offline classification accuracy can be increased from 70.7 % to 86.7 %, and the real-time control completion rate (CR) can also be increased from 89 % to 94 % [4]. The importance of HMI extends beyond improving action accuracy and response speed; it also significantly affects the user's psychological acceptance and long-term use compliance. This is particularly crucial during complex daily activities, where precise control of multi-degree-of-freedom movements is essential.

### 2.2. Hmi classification and sensor technology comparison

HMI technology in intelligent prostheses can be divided into sEMG, IMU, near infrared spectroscopy (NIRS) and other modes based on the type of sensor. sEMG achieves direct intention mapping by detecting muscle electrical activity (0.1-10mV, 0-500Hz), which has the advantage of high temporal resolution in milliseconds, but its signal stability is susceptible to electrode displacement or electromagnetic interference [5]. IMU captures limb motion trajectories through accelerometers and gyroscopes, which can assist dynamic motion prediction (such as gait phase recognition). However, its dependence on the residual motion ability of the residual limb limits its application in complete amputation scenarios. NIRS provides hemodynamic information by monitoring changes in muscle blood oxygen, with high spatial resolution, but its response delay (average 0.51 seconds) needs to be optimized by multi-wavelength modulation technology [4]. In addition, mechanical electromyography (MMG) detects muscle contraction through low-frequency vibration signals. Although it has strong anti-electronic interference ability, it is susceptible to motion artifacts. At present, multi-modal fusion (such as sEMG + IMU) has become a mainstream design strategy, which significantly improves the accuracy of gesture recognition through cascade classification or feature splicing [7].

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## 2.3. The theoretical basis of HMI

The theoretical basis of HMI covers three aspects: signal processing, classification algorithm and real-time performance evaluation. In the signal processing stage, the sEMG needs to be band-pass filtered (20-450 Hz) to suppress the baseline drift and high-frequency noise, and the 300 ms sliding window is used to balance the signal stability and real-time performance [4]. Feature extraction includes time domain (such as mean absolute value MAV, waveform length WL) and frequency domain (such as power spectral density) methods, while NIRS needs to extract hemodynamic features (such as HbO2 concentration slope) through light source modulation and demodulation techniques. In terms of classification algorithms, linear discriminant analysis (LDA) is widely used in low-dimensional feature space because of its high computational efficiency, while support vector machine (SVM) deals with nonlinear classification problems through kernel functions. In recent years, deep learning models such as convolutional neural networks (CNN) have shown potential in multi-modal feature fusion, but their dependence on a large amount of labeled data limits real-time applications. Performance evaluation indicators include selection time (ST, target < 0.3 seconds), completion rate (CR) and real-time accuracy (RA). Experiments show that EMG-NIRS fusion can reduce ST from 0.38 seconds to 0.27 seconds, and increase CR from 89 % to 94 % [4].

## 2.4. The application strategy of Hmi in the design of intelligent prosthesis

The design of HMI needs to take into account multimodal complementarity, clinical adaptability and dynamic environment robustness. In terms of multimodal complementarity, the fusion of sEMG and IMU can compensate for the interference of limb position on EMG signals through kinematic data. Clinical adaptation optimization needs to use lightweight wireless sensors and transfer learning techniques to reduce cross-user performance differences for the problem of residual limb muscle degradation. The robustness in the dynamic environment can suppress the power frequency interference by band-pass filtering, or dynamically adjust the signal gain in combination with IMU data to compensate for motion artifacts. In addition, user feedback mechanisms (such as tactile vibration or visual interface) can form a closed-loop control, such as adjusting the grip strength in real time through a prosthetic fingertip force sensor. In order to achieve clinical practicality, HMI needs to achieve high-performance computing on resource-constrained embedded platforms (such as Arduino BLE 33). The hardware selection should give priority to the energy efficiency ratio, and the ARM Cortex-M series microcontroller is used to balance the computing power and power consumption. At the software level, data acquisition, feature extraction and classification decision are processed in parallel through multi-thread scheduling mechanism to ensure that the end-to-end delay is less than 100 ms. Model compression techniques (such as Edge Impulse quantization tool) can reduce memory usage by 35-55 %, so that complex models (such as DNN) can run on micro devices with 256 KB RAM. This optimization allows the system to maintain > 97 % accuracy while costing less than 10 % of the high-end solution, significantly improving the accessibility of intelligent prostheses [4-6].

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## 3. Collaborative application and case analysis of intelligent prosthesis and human-machine interface

### 3.1. Multi-modal sensor fusion mechanism and performance improvement

Multi-modal sensor fusion is the core strategy to improve the robustness of intelligent prosthetic control. As a mainstream means of intention perception, sEMG has high temporal resolution (< 100ms), but it is susceptible to electrode displacement, sweat interference and muscle fatigue [8]. In order to make up for its limitations, the inertial measurement unit (IMU) is introduced to capture the trajectory of the limb. For example, Lu et al. developed a sEMG + IMU hybrid system, which improves the accuracy of gesture recognition from 85 % of a single sEMG to 95 % through a cascade classification strategy. Its core is to use IMU to quantify the body posture and eliminate the EMG signal attenuation caused by forearm pronation [7].

Furthermore, the three-modal fusion system shows stronger environmental adaptability. The sEMG + EIT + IMU framework proposed by Wu et al.achieved 96.5 % recognition accuracy through a decision-level fusion strategy. Among them, sEMG is responsible for fast intention classification, electrical impedance tomography (EIT) verifies gesture type, and IMU corrects spatial pose. The system is stable in electromagnetic interference scenarios, and the accuracy rate is more than 5 % higher than that of a single mode [9]. In addition, the introduction of force-muscle graph (FMG) enhances the low-frequency mechanical perception. The co-located sEMG + FMG sensor developed by Jiang et al., which measures the contact pressure through a gas pressure sensor, has an accuracy rate of 91.6 % in complex gesture classification tasks, which is significantly better than a single mode [10].

### 3.2. Embedded system design and real-time optimization

The practical application of intelligent prostheses needs to solve the bottleneck of computational delay and power consumption. Traditional PC-side solutions (such as SVM) are difficult to meet portable requirements due to high power consumption (> 10W) and delay (120ms). Ahsan Rafiq et al.proposed an embedded DNN model based on Arduino BLE 33, which uses a lightweight network architecture (3 hidden layers, 64 neurons / layers). After quantization and compression to 150 kB Flash, the end-to-end delay is ≤ 100 ms, and the power consumption is only 50 mW. Experiments show that the system has a classification accuracy of > 99.6 % for basic gestures such as fist holding and hand opening, and 93.2 % for complex gestures (index finger movements) [6].

The hierarchical control architecture further optimizes real-time performance. Wang et al.proposed a three-layer planner : high-level intent decoding combined with sEMG and IMU data to identify five gait patterns through a cascade classifier (SVM / LDA) (accuracy > 99 %) ; the mid-level step frequency estimation is based on Newton iteration method to realize phase domain mapping (error is only 2.3 %). The underlying trajectory is generated by the central pattern generator (CPG) to synchronize hip, knee, and ankle movements (RMSE < 6.5 in the variable pace scenario). The architecture verified cross-terrain adaptability in 8 healthy subjects. For example, the hip flexion angle was dynamically adjusted by 8 ° during the uphill transition, and the response delay was ≤ 455 ms [11].

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### 3.3. Clinical challenges and future technological breakthroughs

However, the current system still faces multiple challenges. Firstly, the problem of insufficient individual adaptability is prominent. The sEMG signal of amputees is attenuated by 50 % -80 % due to muscle atrophy. The existing transfer learning model has limited adaptability to extreme physiological differences. It is necessary to combine brain-computer interface (BCI) to predict intentions or introduce adaptive dynamic calibration algorithms. Secondly, the environmental robustness needs to be improved urgently. For example, the contact impedance of the dry sensor changes up to 10kΩ ~ 1MΩ when sweating, resulting in signal drift. It is necessary to develop a dynamic impedance matching circuit or adopt flexible self-healing electrode materials. In addition, the long-term stability of embedded systems is limited by power consumption (50mW) and hardware design. In practical applications, lightweight algorithms and low-power architectures (such as RISC-V processors) need to be further optimized. Finally, aiming at the problem of insufficient recognition ability of complex terrain, Sheng et al.proposed a sEMG + MMG + NIRS three-mode system. Through the fusion of muscle vibration (MMG) and blood oxygen metabolism (NIRS) features, the accuracy rate was still 94.01 % after 1 minute of continuous contraction, which was 15 % higher than that of single mode [11].

The future development direction focuses on multi-modal database construction and new interactive technologies. The establishment of the Ninapro database provides a standardized data set for algorithm generalization, and the introduction of brain-computer interface (BCI) is expected to further shorten the response delay. For example, the sEMG-EEG hybrid system developed by Pancholi et al.compresses the delay to 80 ms by predicting the intention of the motor imagery signal [12]. In addition, 3D printing technology can customize the personalized receiving cavity, optimize the sensor layout and wear comfort [10].

## 4. Conclusion

This paper systematically reviews the latest developments of intelligent prostheses in the fields of human-machine interface technology, multi-modal sensor fusion and embedded artificial intelligence. It is found that the collaborative optimization of multi-modal sensor fusion and embedded artificial intelligence algorithm significantly improves the control accuracy, response speed and clinical adaptability of prostheses. The sEMG provides millisecond-level intent capture capabilities. The IMU compensates for the interference of limb pose on the EMG signal through kinematics data, while the carbon nanotube tactile sensor monitors the contact pressure in real time to form a closed-loop tactile feedback mechanism. Furthermore, findings indicate that the three-modal fusion enhances gesture recognition accuracy to 96.5% and the closed-loop tactile feedback lowers the gripping force inaccuracy by 42%, all at a cost that is just 1/ten of the conventional method.

However, this study is limited by the nature of the literature review and fails to carry out experiments to verify the effectiveness of these technologies in practical applications. In addition, some emerging technologies can only be discussed theoretically based on existing literature, and there is a lack of in-depth empirical research.

Looking ahead, future research needs to expand the sample size and cooperate with clinical institutions to build a dynamic evaluation system. In addition, it is necessary to break through the deep coupling of the neural-machine interface. On the one hand, the brain-computer interface ( BCI ) is used to predict the user 's intention to cope with the attenuation of muscle signals, and a dynamic impedance matching circuit is developed to solve the environmental interference. On the other hand,

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it is necessary to integrate flexible electronics and adaptive algorithms to realize real-time perception and collaborative optimization of prosthetic limbs on users ' physiological states (such as fatigue and motion mode migration). Through multi-center clinical verification, a long-term stability database is constructed to promote the basic application of laboratory high-precision models to the inclusive landing of more complex life scenes.

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