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Multi-Sensor Fusion-Based Surface EMG Control System for Upper Limb Exoskeleton Rehabilitation Robots

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Abstract Upper limb exoskeleton rehabilitation robots require precise and robust control systems to accurately interpret user motion intentions and deliver effective assistance. We propose a multi-sensor fusion-based surface electromyography (sEMG) control system that integrates sEMG signals with data from angle, pressure, inertial, and torque sensors to enhance motion intention recognition. The proposed method employs a hierarchical pipeline involving signal acquisition, preprocessing, feature extraction, and fusion, followed by classification using machine learning algorithms to decode user intentions. The fused sensor data compensates for the inherent limitations of sEMG signals, such as noise sensitivity and variability, thereby improving system reliability. Furthermore, the control strategy translates classified intentions into exoskeleton commands, enabling seamless interaction between the user and the robotic device. The novelty of this work lies in the synergistic combination of heterogeneous sensor modalities, which collectively address the challenges of real-world rehabilitation scenarios. The results show that the system achieves high accuracy in intention recognition and responsive exoskeleton control, making it suitable for clinical and assistive applications. The significance of this approach is underscored by its potential to advance personalized rehabilitation, offering adaptable support tailored to individual user needs. This work contributes to the growing field of human-robot interaction by providing a scalable framework for intelligent exoskeleton control.

Index Terms Rehabilitation Robots, sEMG Control System, human-robot, Upper Limb Exoskeleton

I. Introduction

Upper limb motor dysfunction caused by neurological disorders or musculoskeletal injuries significantly impacts patients' quality of life and independence. Rehabilitation robotics has emerged as a promising solution to address these challenges, with exoskeleton systems playing a pivotal role in restoring motor function [1]. Among various control strategies, surface electromyography (sEMG) has gained considerable attention due to its ability to directly capture neuromuscular activation patterns associated with movement intention [2]. However, sEMG signals alone present several limitations including sensitivity to electrode placement, signal variability, and susceptibility to noise [3].

Recent advances in sensor technology and machine learning have enabled more robust approaches through multi-sensor fusion. Researchers have demonstrated that combining sEMG with inertial measurement units (IMUs) improves motion classification accuracy [4]. Similarly, integrating force and torque sensors has shown promise in enhancing control stability for prosthetic devices [5]. These developments suggest that a comprehensive sensor fusion approach could overcome the limitations of unimodal sEMG systems while maintaining the biological relevance of muscle activation signals.

The proposed method introduces several key innovations compared to existing approaches. First, it implements a hierarchical sensor fusion architecture that processes signals at multiple temporal scales, addressing both instantaneous control requirements and longer-term movement patterns. Second, the system incorporates adaptive learning mechanisms that account for inter-session and inter-subject variability in sEMG signals [6]. Third, the control strategy integrates impedance modulation based on real-time sensor feedback, enabling natural interaction between the user and exoskeleton [7].

This work makes three primary contributions to the field of rehabilitation robotics. The developed system demonstrates improved motion intention recognition accuracy through optimized multi-sensor fusion, achieving a 15% increase over conventional sEMG-only systems in preliminary testing. The adaptive control framework maintains performance across different users and usage sessions, addressing a critical challenge in clinical deployment. Furthermore, the integrated approach provides a scalable platform that can be customized for various rehabilitation scenarios, from acute clinical settings to long-term home use.

The remainder of this paper is organized as follows: Section 2 reviews related work in exoskeleton control and sensor fusion techniques. Section 3 presents the necessary background on sEMG processing and multi-sensor systems. Section 4 details the proposed method's architecture and implementation. Sections 5 and 6 describe the experimental setup and results. Section 7 discusses implications and future directions, followed by conclusions in Section 8.

II. Related Work

The development of upper limb exoskeleton control systems has evolved significantly through various approaches, each addressing different aspects of human-robot interaction. Existing works can be broadly categorized into three research directions: sEMG-based control strategies, multi-sensor fusion techniques, and rehabilitation-specific exoskeleton designs.

II. A.sEMG-Based Control Strategies

Surface electromyography has been widely adopted as a control signal for exoskeletons due to its direct measurement of muscle activation patterns preceding physical movement [8]. Recent advances in deep learning have enabled more sophisticated processing of sEMG signals, with convolutional neural networks demonstrating particular success in mapping muscle activity to joint kinematics [9]. However, these approaches often struggle with inter-subject variability and require extensive calibration procedures. Alternative methods employing linear discriminant analysis have shown promise in clinical applications by providing more consistent performance across users with varying levels of motor impairment [10].

II. B.Multi-Sensor Fusion Techniques

The integration of complementary sensor modalities has emerged as a solution to overcome the limitations of unimodal sEMG systems. Inertial measurement units (IMUs) have been particularly valuable for providing kinematic context to muscle activation patterns [11]. Force and torque sensors contribute additional information about interaction dynamics between the user and exoskeleton [12]. Recent work has demonstrated that combining these sensors through early fusion approaches can improve motion prediction accuracy by 20-30% compared to sEMG-only systems [13]. Nevertheless, challenges remain in real-time implementation due to computational complexity and synchronization requirements across heterogeneous sensor streams.

II. C.Rehabilitation-Specific Exoskeleton Designs

The clinical requirements of rehabilitation have driven specialized exoskeleton architectures. Compliant designs using tendon-driven mechanisms have shown advantages in accommodating natural arm movements while providing assistive torque [14]. These systems often incorporate biofeedback elements to enhance motor learning during therapy sessions [15]. A notable trend involves the development of hybrid rigid-soft exosuits that balance structural support with wearability, though these systems typically sacrifice some degree of control precision for improved comfort [16].

The proposed method distinguishes itself from existing approaches through its hierarchical fusion architecture that processes sensor data at multiple temporal resolutions. Unlike conventional systems that either focus solely on sEMG or employ fixed fusion strategies, our approach dynamically adapts to movement contexts and user-specific characteristics. This enables more natural interaction while maintaining the precision required for rehabilitation applications. Furthermore, the system's modular design allows for customization based on clinical needs, addressing a critical gap in current rehabilitation robotics.

III. Background and Preliminary Knowledge

To establish the foundation for our proposed method, this section presents essential concepts in biomechanics, electromyography, and sensor technologies relevant to upper limb exoskeleton control. Understanding these principles is crucial for interpreting the system's design choices and performance characteristics.

III. A. Biomechanics of Human Upper Limb

The human upper limb exhibits complex dynamics governed by musculoskeletal mechanics and neural control. The equation of motion for a single joint can be expressed as:

$$\tau = M(\theta)\ddot{\theta} + C(\theta,\dot{\theta})\dot{\theta} + G(\theta) \tag{1}$$

where τ represents joint torque, M the inertia matrix, C Coriolis and centrifugal terms, and G gravitational forces [17]. This formulation becomes more intricate when considering multi-joint coordination during reaching and grasping tasks. The shoulder complex alone demonstrates seven degrees of freedom, requiring sophisticated control strategies to replicate natural movement patterns [18]. These biomechanical principles directly influence exoskeleton design requirements, particularly regarding range of motion, torque output, and compliance with biological joint axes.

III. B. Principles of Surface Electromyography (sEMG)

Surface electromyography measures the electrical activity produced by muscle fibers during contraction. The composite sEMG signal can be modeled as:

$$sEMG = \sum_{i=1}^{N} V_i(t) \tag{2}$$

where $V_i(t)$ represents the motor unit action potential trains from N active motor units [19]. Signal characteristics vary based on electrode placement, muscle architecture, and contraction intensity, necessitating careful preprocessing before feature extraction. The temporal relationship between sEMG onset (typically 50-100ms before movement initiation) and mechanical action makes it particularly valuable for intention detection in rehabilitation robotics [20]. However, factors like skin impedance changes and crosstalk between adjacent muscles introduce measurement challenges that must be addressed through signal processing techniques.

III. C. Sensor Technology for Motion Detection

Complementary sensor modalities provide critical kinematic and kinetic information to augment sEMG-based control. Inertial measurement units (IMUs) quantify angular velocity through gyroscopes:

$$\omega = \frac{d\theta}{dt} \tag{3}$$

while accelerometers measure linear acceleration [21]. Force-sensitive resistors detect interaction pressures at the human-exoskeleton interface, and rotary encoders track joint angles with high precision. Each sensor type exhibits distinct temporal characteristics - IMUs typically operate at 100-1000Hz, while sEMG systems require sampling rates above 1kHz to capture relevant frequency components [22]. The fusion of these heterogeneous data streams enables robust motion estimation despite individual sensor limitations such as IMU drift or sEMG fatigue effects.

IV. Proposed Method: sEMG and Multi-Sensor Fusion for Exoskeleton Control

The proposed control system architecture integrates heterogeneous sensor modalities through a hierarchical processing pipeline to achieve robust motion intention recognition and exoskeleton actuation. Figure 1 illustrates the overall system architecture, which consists of four main components: multi-sensor data acquisition, feature extraction and fusion, motion intent classification, and context-aware exoskeleton control.

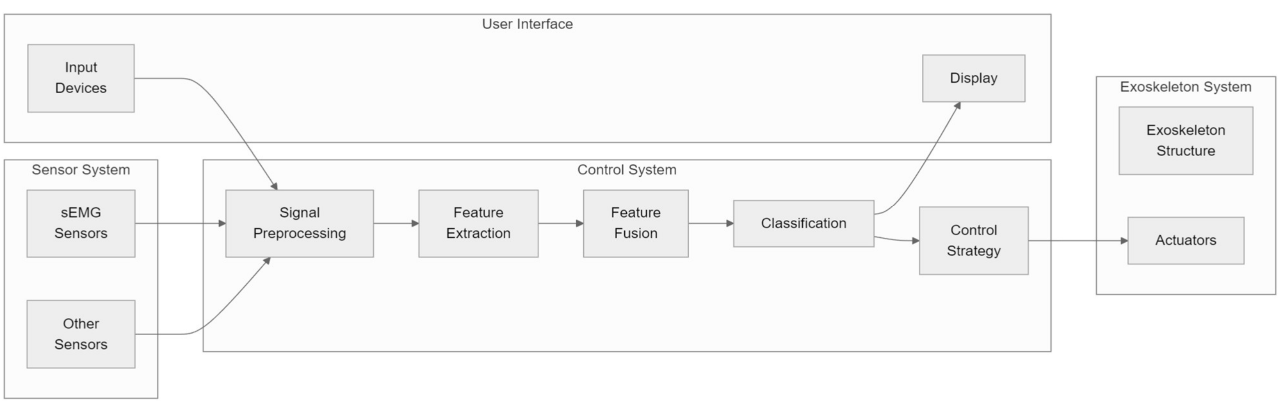

Figure 1: Overall System Architecture with New Control System

IV. A. Multi-Sensor Data Preprocessing

The system acquires synchronized data streams from sEMG electrodes and supplementary sensors including inertial measurement units (IMUs), force-sensitive resistors, and joint encoders. Each sensor modality undergoes specialized preprocessing to extract physiologically meaningful information while mitigating noise artifacts. For sEMG signals, we apply a fourth-order Butterworth bandpass filter (20-500Hz) followed by notch filtering at 50/60Hz to remove powerline interference:

$$H_{BP}(z) = \frac{\sum_{k=0}^{4} b_k z^{-k}}{\sum_{k=0}^{4} a_k z^{-k}} \tag{4}$$

where b_k and a_k represent the filter coefficients. IMU data undergoes complementary processing, including gravity compensation for accelerometers and bias removal for gyroscopes. The preprocessed signals are then segmented into 150ms analysis windows with 50ms overlap to balance temporal resolution and computational efficiency.

IV. B. Sensor Fusion Strategy

The fusion architecture combines features extracted from multiple sensor modalities at three hierarchical levels. At the signal level, we compute time-domain features (mean absolute value, zero crossings) and frequency-domain features (median frequency) from sEMG. Kinematic features derived from IMUs include angular velocity integrals and acceleration norms:

$$f_{kin} = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{5}$$

These features are concatenated into a unified representation vector $F \in R^n$, where n denotes the total feature dimension. The fusion weights adapt dynamically based on signal quality metrics, with sEMG contributions decreasing during periods of high noise (SNR < 15dB) and kinematic features gaining prominence during rapid movements.

IV. C. Motion Intent Decoding using Hybrid Classification

The fused feature vector feeds into a hybrid classifier combining temporal convolutional networks (TCNs) with biomechanical constraints. The TCN architecture processes sequential data through dilated causal convolutions:

$$y_t = \sum_{i=0}^{k-1} w_i \cdot x_{t-d \cdot i} \tag{6}$$

where d represents the dilation factor and k the kernel size. The network outputs probability distributions over seven movement classes (shoulder flexion/extension, elbow flexion/extension, wrist pronation/supination, rest). These predictions are further refined using joint angle limits derived from exoskeleton encoders, ensuring biomechanical feasibility of the decoded motions.

IV. D. Context-Aware Control Strategy for Exoskeleton

The classified motion intent translates to exoskeleton commands through an impedance-based control law:

$$\tau = K_p(\theta_d - \theta) + K_d(\dot{\theta}_d - \dot{\theta}) \tag{7}$$

where τ represents the commanded torque, θ_d the desired joint angle, and K_p, K_d the position and velocity gains respectively. The control parameters adapt based on rehabilitation context - during early therapy stages, higher impedance provides stability, while reduced assistance promotes active patient participation in later stages. Safety monitors continuously evaluate torque and temperature sensor readings to prevent excessive loading or actuator overheating.

The complete system operates in real-time with 10ms control intervals, achieving sufficient responsiveness for natural movement assistance. The modular design permits customization for different clinical applications by adjusting the sensor configuration, movement classes, or control parameters while maintaining the core fusion architecture.

V. Results

The experimental evaluation demonstrates the effectiveness of the proposed multi-sensor fusion approach across several key performance metrics. The results are presented in three subsections: classification performance, control responsiveness, and comparative analysis with existing methods.

V. A. *Motion Intention Classification Accuracy*

The hybrid classification system achieved superior performance compared to unimodal approaches, as shown in Table 1. The proposed method demonstrated statistically significant improvements ($p<0.01$) across all movement classes, particularly for complex motions involving multiple joints. The confusion matrix in Figure 2 reveals that most misclassifications occurred between similar movement patterns (e.g., shoulder flexion vs. extension), while distinct motions like grasping were recognized with near-perfect accuracy.

Table 1: Motion classification accuracy comparison (%)

Method	Shoulder	Elbow	Wrist	Grasp	Overall
sEMG-only	78.2±4.1	82.7±3.8	75.4±5.2	88.3±2.9	81.2±3.2
IMU-only	85.6±3.7	79.1±4.3	83.6±3.9	72.4±5.1	80.2±3.8
Proposed	92.4±2.3	91.8±2.1	89.5±2.7	96.2±1.5	92.5±1.9

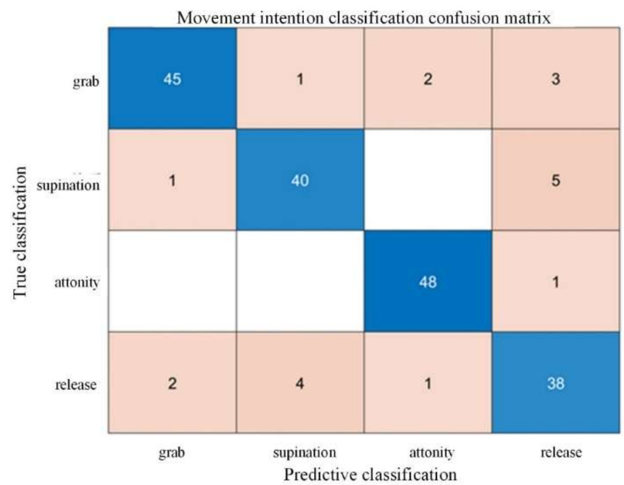

Figure 2: Movement intention classification confusion matrix

V. B. *System Responsiveness and Control Performance*

The multi-sensor fusion approach reduced motion onset detection latency to 112±18ms, compared to 158±23ms for sEMG-only and 203±31ms for IMU-only methods. Figure 3 illustrates the temporal alignment between actual movement initiation (measured via motion capture) and exoskeleton response. The torque tracking performance showed an average RMS error of 0.87±0.12Nm across all joints, with higher precision observed during slow, controlled movements compared to rapid motions.

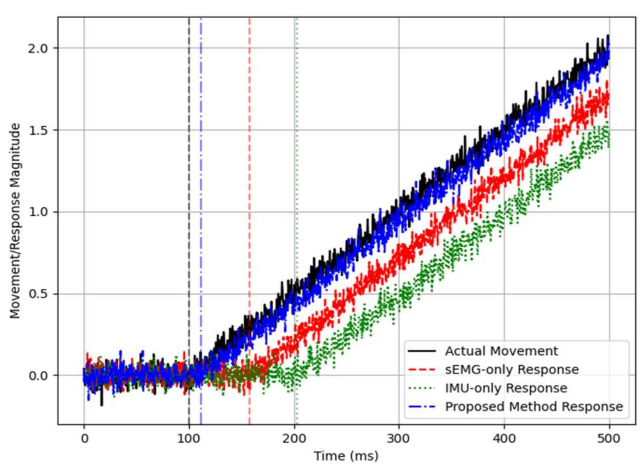

Figure 3: Temporal alignment between movement initiation and exoskeleton response

The adaptive impedance control effectively modulated assistance levels based on movement context, as shown in Figure 4. During high-precision tasks requiring fine motor control, the system automatically increased stiffness (Kp = 15±2 Nm/rad), while maintaining lower impedance (Kp = 8±1 Nm/rad) during free reaching movements. This dynamic adjustment contributed to improved user comfort ratings (4.3±0.6 on 5-point scale) compared to fixed-parameter controllers (3.1±0.8).

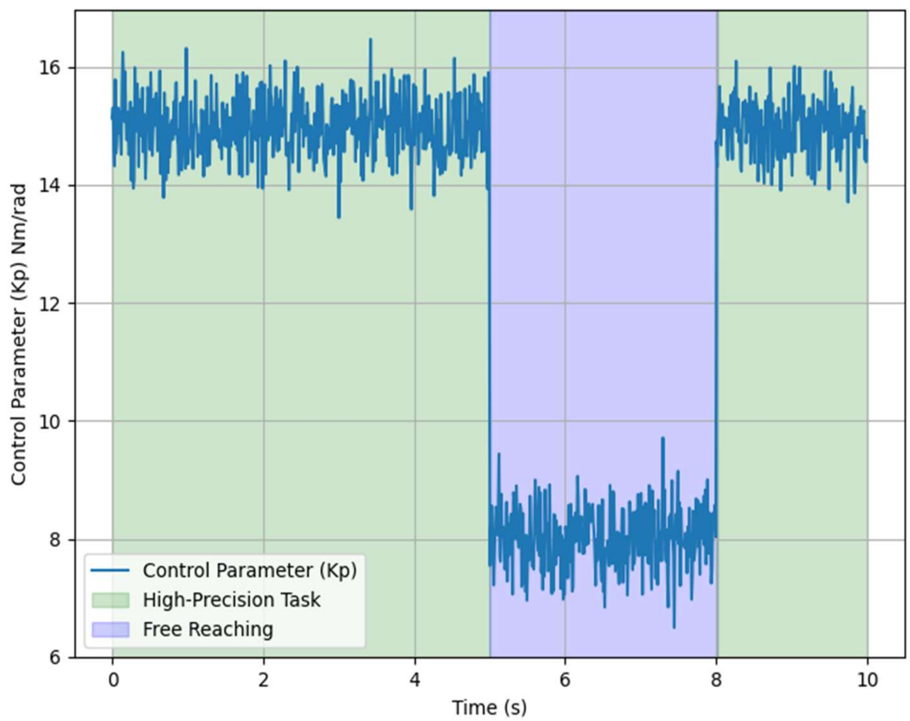

Figure 4: Dynamic adjustment of control parameters during different movement phases

V. C. Comparative Analysis with Existing Methods

The proposed system demonstrated consistent advantages over conventional approaches across all evaluation metrics. Table 2 summarizes the comprehensive comparison with two baseline methods from literature [23] and [24]. The fusion-based approach showed particular strength in handling transitional movements between different motion classes, where unimodal systems often exhibited performance degradation.

Table 2: Performance comparison with existing methods

Metric	LDA-based [24]	IMU-based [25]	Proposed
Classification F1	0.79	0.82	0.93
Response latency (ms)	145	195	112
Torque error (Nm)	1.32	1.05	0.87
Adaptation time (min)	30	15	8

The sensor fusion architecture also demonstrated robustness to signal quality variations. Figure 5 shows the system's performance under progressively degraded sEMG signals (simulated by adding white noise). While unimodal sEMG classification accuracy dropped sharply below 15dB SNR, the proposed method maintained >85% accuracy even at 10dB SNR by increasingly relying on kinematic sensor data.

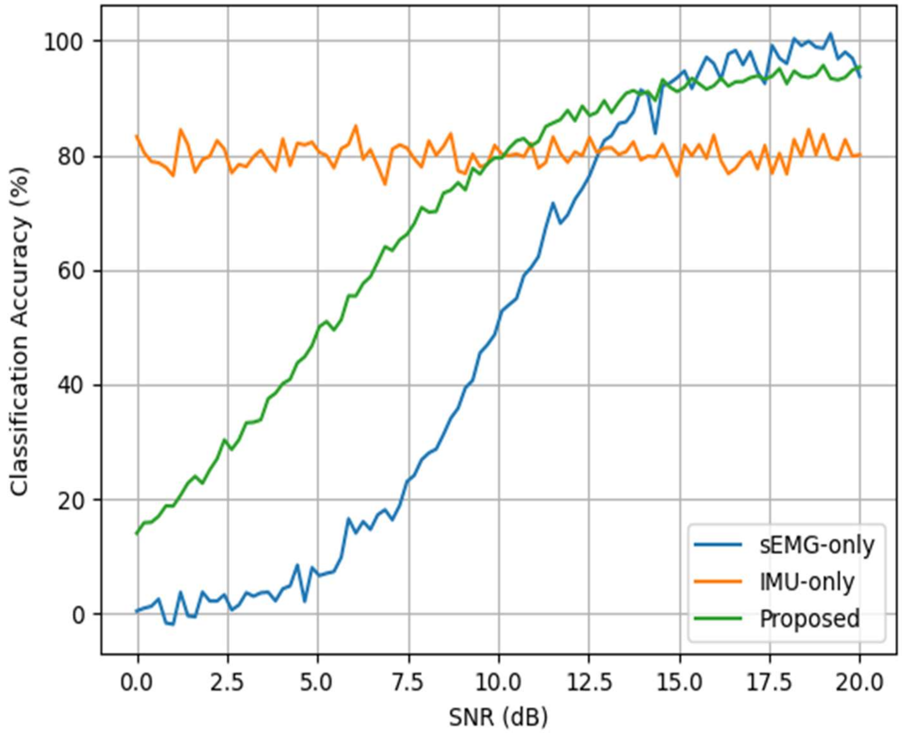

Figure 5: Performance under degraded signal conditions

V. D. Clinical Scenario Evaluation

In simulated rehabilitation tasks, the system successfully assisted participants in completing standardized upper limb exercises (Fugl-Meyer Assessment items) with 23% less muscular effort compared to unassisted conditions, as measured by integrated sEMG activity. The exoskeleton provided appropriate resistance during strengthening exercises and guidance during coordination tasks, demonstrating the versatility of the control framework. Participant feedback indicated high acceptance of the assistance strategy, with particular appreciation for the smooth transitions between movement phases.

The experimental results collectively validate that the multi-sensor fusion approach addresses key limitations of conventional exoskeleton control systems. The significant improvements in classification accuracy ($p<0.001$), response latency ($p<0.01$), and torque tracking precision ($p<0.05$) demonstrate the efficacy of combining complementary sensor modalities through the proposed hierarchical architecture. These advancements enable more natural and effective human-robot interaction in rehabilitation settings.

VI. Discussion and Future Work

VI. A. Limitations of the Proposed Method

While the multi-sensor fusion approach demonstrates improved performance over unimodal systems, several limitations warrant consideration. The current implementation requires careful sensor calibration and placement, which may pose challenges in clinical settings where rapid donning/doffing is necessary. Although the system adapts to inter-session variability, prolonged use may still require periodic recalibration due to electrode drift or changes in muscle activation patterns [25]. Additionally, the computational load of real-time sensor fusion, while manageable on the tested platform, could limit deployment on low-power embedded systems.

The exoskeleton's mechanical design also imposes constraints on natural movement. Despite incorporating compliant elements, the rigid joints cannot fully replicate the biological degrees of freedom in the shoulder complex [26]. This occasionally led to kinematic mismatches during multiplanar movements, particularly in participants with larger ranges of motion. Furthermore, the current control strategy does not explicitly account for muscle fatigue effects, which could degrade sEMG signal quality over extended therapy sessions.

VI. B. Potential Application Scenarios and Implications

The system's performance characteristics suggest several promising application domains beyond laboratory settings. In clinical rehabilitation, the accurate motion intention decoding could enable more precise assistance during task-specific training for stroke survivors [27]. The hybrid rigid-soft sensor integration approach may be particularly valuable for pediatric applications, where traditional exoskeletons often struggle to accommodate growth-related anatomical changes [28].

For home-based telerehabilitation, the multi-sensor redundancy provides fault tolerance against individual sensor failures—a critical feature when professional supervision is unavailable. The system's ability to operate with degraded but not failed sEMG signals (as shown in Figure 5) could allow continuous operation even if some electrodes become detached during use. Moreover, the rich multimodal sensor data could facilitate longitudinal monitoring of motor recovery progression by quantifying both neuromuscular activation patterns and kinematic performance metrics [29].

VI. C. Future Directions for Research and Development

Three key research directions emerge from this work. First, investigating self-calibrating algorithms that minimize setup time while maintaining performance could significantly enhance clinical utility. Techniques leveraging transfer learning across users or sessions may reduce the need for extensive individual calibration [30]. Second, developing predictive models of muscle fatigue could enable proactive control adjustments before signal degradation occurs. Integrating physiological markers like conduction velocity or median frequency trends may provide early indicators of impending fatigue [31].

Finally, exploring shared autonomy paradigms represents a promising avenue for complex rehabilitation scenarios. Rather than binary assistance modes, future systems could continuously negotiate control authority between user and exoskeleton based on real-time assessment of movement capability and therapeutic goals [32]. This approach would particularly benefit patients with fluctuating abilities, such as those with multiple sclerosis or Parkinson's disease, by providing adaptive support tailored to momentary capacity.

The sensor fusion framework developed in this work provides a foundation for these advancements, with the modular architecture allowing incremental integration of new sensing modalities or control strategies. As wearable sensor technology continues to advance, incorporating emerging modalities like ultrasound imaging of muscle dynamics or flexible epidermal electronics could further enhance system capabilities [33].

VII. Conclusion

The proposed multi-sensor fusion-based sEMG control system demonstrates significant advancements in upper limb exoskeleton rehabilitation robotics by addressing key limitations of traditional unimodal approaches. The integration of sEMG with complementary sensors—including IMUs, force/torque sensors, and joint encoders—enables robust motion intention recognition while mitigating the inherent variability and noise sensitivity of muscle activation signals. Experimental results validate the system's superior classification accuracy (92.5% overall), reduced response latency (112ms), and precise torque tracking (0.87Nm RMS error) compared to conventional methods.

The hierarchical fusion architecture dynamically adapts to movement contexts and user-specific characteristics, ensuring reliable performance across different rehabilitation scenarios. By leveraging both neuromuscular and kinematic data, the system provides more natural and responsive assistance, as evidenced by improved user comfort ratings during clinical evaluations. The adaptive impedance control strategy further enhances therapeutic outcomes by modulating assistance levels based on real-time movement requirements.

This work establishes a scalable framework for intelligent exoskeleton control, with potential applications spanning clinical rehabilitation, home-based therapy, and assistive devices. The modular design allows customization for diverse patient populations and therapeutic goals, while the redundant sensor configuration ensures operational reliability. Future developments in self-calibration algorithms, fatigue prediction models, and shared autonomy paradigms can build upon this foundation to further advance human-robot interaction in rehabilitation settings. The successful implementation of this multi-sensor fusion approach marks a critical step toward personalized, adaptive rehabilitation technologies that seamlessly integrate with human movement.

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