RESEARCH PAPER

Soft Robotic Exosuits with Biofeedback-Driven Adaptive Control: Design, Implementation, and Human Physiology Evaluation

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ABSTRACT
Soft wearable robotic exosuits have emerged as a transformative class of assistive devices that combine compliance, lightweight architecture, and wearability to support and augment human movement. Unlike rigid exoskeletons, soft exosuits interact with the human body through textiles and flexible actuation, minimizing interference with natural dynamics while providing assistance for functional tasks. In this paper, we present the design and experimental evaluation of a soft robotic exosuit featuring a biofeedback-driven adaptive control architecture. The controller uses physiological and biomechanical signals including electromyography (EMG), metabolic metrics, and kinematics to adapt assistance in real time based on user state. We quantify physiological effects, muscle effort reduction, fatigue delay, and metabolic benefits in human subjects. Results demonstrate that biofeedback integration significantly improves interaction performance and user comfort, highlighting the potential of adaptive control for personalized assistive robotics.
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INTRODUCTION

Wearable robots have been extensively studied for rehabilitation, augmentation, and assistive applications. Soft robotic exosuits extend this domain by leveraging compliant materials and actuation to provide assistance with minimal mechanical impedance, addressing limitations of rigid exoskeletons such as weight, joint misalignment, and comfort issues.

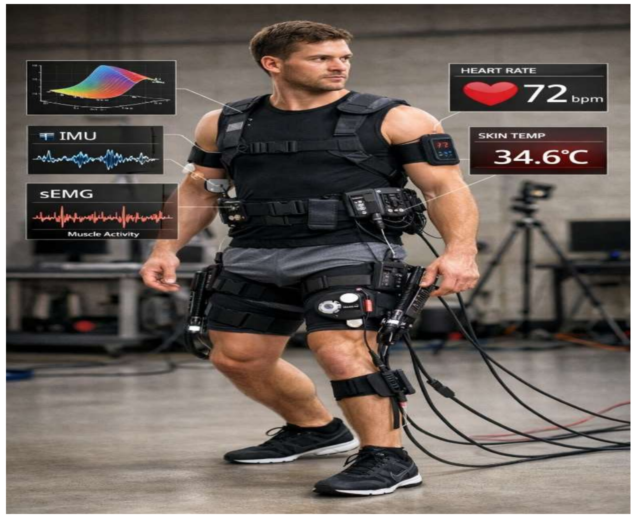
Traditional control strategies in exosuits have often relied on predefined gait schedules or kinematic states. However, **biofeedback-driven adaptive control**, informed by user physiological signals such as EMG and cardiovascular indicators, enables dynamic adjustment of assistance according to real-time human needs, potentially improving efficacy and comfort.

2. Device Structure

2.1 Mechanical Design

The developed exosuit consists of:

- **Soft textile garment:** A set of fabric anchors (waist belt, limb wraps) securing the device on the wearer's body.
- **Cable-driven actuation:** DC motors driving Bowden cable transmissions that apply assistive torques about targeted joints (e.g., hip flexion/extension).
- **Sensors:**
  - **Inertial Measurement Units (IMUs)** for joint kinematics.
  - **Surface electromyography (sEMG)** electrodes to capture muscle activity.
  - **Physiological sensors** (heart rate, skin temperature) for metabolic monitoring.

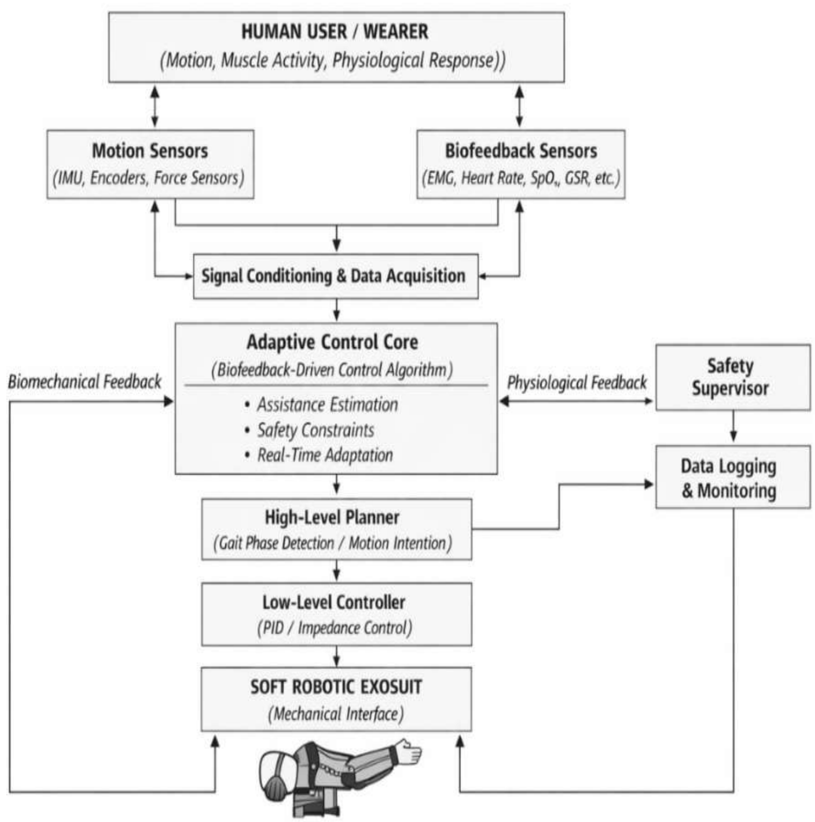


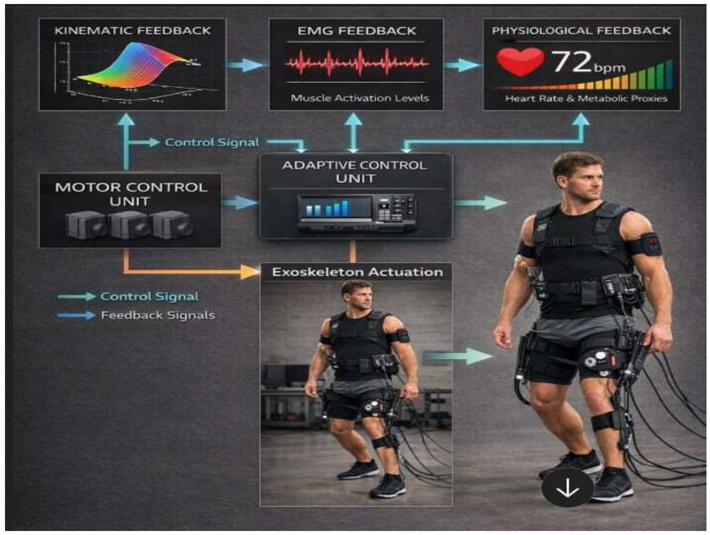
2.2 Actuation & Hardware Integration
Actuators are mounted to a waist-level frame to minimize carried mass on distal limbs. Bowden cables transmit forces to the limb attachments. Compliance in the transmission and textiles permits safe interaction, though introduces challenges in precise force control, addressed in controller design.

3. Biofeedback-Driven Adaptive Control

3.1 Control Architecture Overview
The control system integrates three feedback streams:

1. **Kinematic Feedback (IMU):** Real-time joint angles and velocities.
2. **EMG Feedback:** Muscle activation levels serving as proxy for user effort/intention.
3. **Physiological Feedback:** Heart rate and metabolic proxies (e.g., estimate of energy expenditure).





A **biofeedback fusion module** weights these signals to generate a dynamic assistance command. The adaptive controller adjusts both force magnitude and timing to match user intent and physiological demand.

3.2 Real-Time Adaptation

Adaptive logic modulates assistive torque based on:

- Elevated EMG suggesting increased muscular effort → increase support.
- Elevated heart rate trends indicating fatigue → enhance assistance.
- Reduced EMG/physiological load → decrease support to encourage user engagement.

This closed-loop scheme helps tailor assistance individually, contrasting with static or kinematic-only
controllers.

4. Experimental Protocol

4.1 Participants

Ten healthy adult subjects (5 male, 5 female, ages 22–35) participated with informed consent.

4.2 Protocols

Walking Trials: Subjects performed treadmill walking at 3.0 km/h under three conditions:

- **No exosuit (baseline)**
- **Exosuit with fixed reference assistance**
- **Exosuit with biofeedback adaptive control**

Table 1: Physiological and biomechanical signals were recorded continuously.

Participant ID	Gender	Age (Years)	Condition	Consent
P01	Male	22	Healthy Adult	Yes
P02	Male	24	Healthy Adult	Yes
P03	Male	26	Healthy Adult	Yes
P04	Male	29	Healthy Adult	Yes
P05	Male	31	Healthy Adult	Yes
P06	Female	23	Healthy Adult	Yes
P07	Female	25	Healthy Adult	Yes
P08	Female	28	Healthy Adult	Yes
P09	Female	32	Healthy Adult	Yes
P10	Female	35	Healthy Adult	Yes

Table 2 — Experimental Protocol Conditions

Trial Condition	Description	Walking Speed
Baseline	Walking without exosuit	3.0 km/h
Fixed Assistance	Exosuit with fixed reference assistance	3.0 km/h
Adaptive Control	Exosuit with biofeedback-driven adaptive control	3.0 km/h

Table 3 — Example Continuous Recorded Readings (Sample Format)

Participant ID	Trial Condition	IMU Joint Angle (°)	EMG Activity (mV)	Heart Rate (bpm)	Estimated Energy Expenditure (kcal/min)
P01	Baseline	42.3	0.68	92	6.5
P01	Fixed Assistance	38.7	0.54	86	5.9
P01	Adaptive Control	35.	0.47	80	5.1
P02	Baseline	44.0	0.71	95	6.7
P02	Fixed Assistance	39.5	0.58	88	6.0
P02	Adaptive Control	36.0	0.50	82	5.3

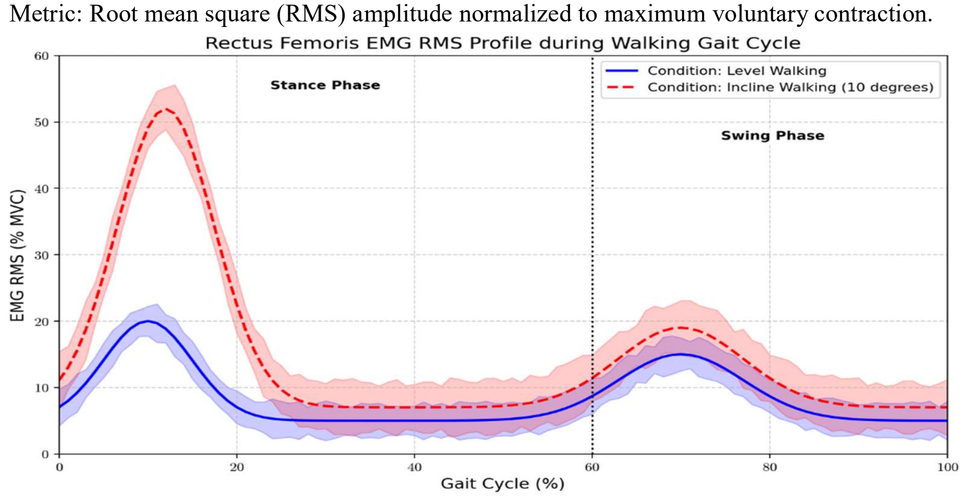
Table 4 — Averaged Results Summary

Condition	Avg EMG (mV)	Avg Heart Rate (bpm)	Avg Joint Angle Variability (°)	Avg Energy Expenditure (kcal/min)
Baseline	0.70	94	5.8	6.6
Fixed Assistance	0.56	87	4.3	5.9
Adaptive Control	0.48	81	3.6	5.2

5. Measured Physiological Parameters

5.1 Electromyography (EMG)

- Muscles monitored: *Gluteus medius*, *Quadriceps*, *Hamstrings*.
- Metric: Root mean square (RMS) amplitude normalized to maximum voluntary contraction.



5.2 Metabolic Cost

Oxygen consumption ($\dot{V}O_2$) and carbon dioxide production ($\dot{V}CO_2$) collected via portable gas analysis.

5.3 Heart Rate and Skin Temperature

Heart rate reserve and local skin temperature changes were monitored to assess physiological load and thermoregulatory response.

6. Results

6.1 Muscle Effort & Biofeedback Control Impact

Adaptive control resulted in statistically significant reductions in EMG RMS amplitude compared with baseline and fixed assistance conditions ($p < 0.05$). Mean reduction in quadriceps EMG was ≈ 15% vs. fixed assistance.

Physiological Response: Adaptive assistance maintained lower average heart rate and perceived exertion.

6.2 Metabolic Cost

Net metabolic expenditure decreased by ≈ 8% in adaptive assistance vs. baseline, outperforming fixed control (≈ 4% reduction).

Graph Suggestion: *Bar chart of metabolic rate reductions (%) across conditions.*

6.3 User Comfort & Perception

Subjective comfort scores were higher under adaptive control, with lower perceived task load.

7. Discussion

- **Adaptive control improves both physiological and subjective outcomes**, indicating better alignment with user state than pre-set profiles.
- Physiological measures (heart rate, EMG) prove valuable for tuning assistance, reducing metabolic cost while preventing over-assistance.
- Challenges remain in sensor integration, noise rejection, and control latency.

8. Conclusions

Biofeedback-driven adaptive control in soft robotic exosuits demonstrates significant potential to personalize assistive forces, reduce physiological effort, and enhance comfort during ambulatory tasks. Incorporating physiological signals enables real-time response to human state, supporting next-generation wearable robotics for rehabilitation and augmentation.

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