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Advances in Prosthetic Control: PID to Deep Learning

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Abstract

The integration of advanced control strategies in prosthetic limbs has revolutionized the field of biomedical engineering. This paper presents a comprehensive review of control algorithms used in prosthetic devices, focusing on the transition from classical PID control to modern intelligent methods such as fuzzy logic, artificial neural networks (ANNs), and deep learning (DL). The review critically compares the performance, adaptability, and implementation complexity of these techniques in lower and upper limb prosthetics. The paper also highlights current challenges and proposes future research directions for enhancing user comfort, control precision, and real-time adaptability.

Keywords: Prosthetic Devices, Intelligent Control, Deep Learning, EMG Signal Processing, Fuzzy Logic, Adaptive Neuro-Fuzzy Systems, PID Control, Myoelectric Control

1. Introduction

Prosthetic devices have evolved from mechanical limbs to highly advanced systems with real-time sensing and adaptive control (Al-Qaysi, Aziz, & Al-Jumaily, 2023). Traditional control systems such as PID remain attractive due to their simplicity and reliability, but they typically lack adaptability to nonlinear, time-varying human motion (Kumar, 2019). In contrast, intelligent control approaches including fuzzy logic, artificial neural networks (ANNs), and deep learning (DL) offer greater responsiveness and user personalization (Zafar, Ali, & Khan, 2022). Recent reviews emphasize that intelligent methods improve decoding of EMG signals and enable robust multi-grasp functionality in upper-limb prostheses (Al-Qaysi et al., 2023; Resnik, Klinger, & Etter, 2018). This paper compares classical and intelligent strategies in terms of their evolution, strengths, weaknesses, and practical applications.

2. Background on Prosthetic Systems and Control Objectives

2.1. Evolution of Prosthetic Devices

The transition from passive limbs to active, myoelectric prostheses has been driven by advances in biosignal sensing and embedded control, allowing artificial limbs to more closely mimic human motion (Al-Qaysi et al., 2023). Upper-limb systems such as the DEKA Arm demonstrate functional gains from integrating neural signals with advanced controllers (Resnik et al., 2018).

2.2. Control Requirements in Prosthetics

Key requirements for effective prosthetic control include high responsiveness, real-time operation, adaptability to user-specific gait and task variability, robustness to noise, and efficient power consumption (Kumar, 2019; Lee, Park,

& Kim, 2022). Achieving these goals requires balancing model complexity with the limited computational resources available in wearable hardware (Lee et al., 2022).

3. Classical Control in Prosthetics: PID and Variants

3.1. Principles of PID Control

PID (Proportional-Integral-Derivative) control is a widely used feedback loop mechanism. It relies on proportional, integral, and derivative terms to correct the error between a desired setpoint and a measured process variable. In prosthetics, PID controllers are typically used for joint position control and actuator regulation. (Kumar, 2019).

3.2. Applications in Lower and Upper Limb Prosthetics

PID has been applied in ankle and knee prostheses to maintain joint angles during walking, as well as in upper limb prosthetics to regulate motor positions. The simplicity of the algorithm allows for real-time processing on low-power microcontrollers. (Kumar, 2019; IEEE EMBC Proceedings, 2018–2024).

3.3. Limitations: Lack of Adaptability, Sensitivity to Noise, etc.

Despite its benefits, PID controllers struggle with dynamic environments. They cannot adapt to changing user behavior or nonlinear muscle signals. Moreover, they are sensitive to sensor noise and require manual tuning. (Kumar, 2019; IEEE EMBC Proceedings, 2018–2024).

4. Intelligent Control Algorithms: A Deep Dive

4.1. Fuzzy Logic Controllers (FLC)

FLCs use human-like reasoning to handle imprecise inputs. By employing linguistic variables and if-then rules, FLCs provide more flexible control than PID. Applications include grasp control, joint stiffness modulation, and gait phase classification. (Li et al., 2021; IEEE EMBC Proceedings, 2018–2024).

4.2. Artificial Neural Networks (ANN)

ANNs are computational models inspired by biological neurons (Zafar et al., 2022; Kumar, 2019). They learn patterns in EMG signals to map muscle activity to limb movement. Studies have shown successful implementation in predicting torque, joint velocity, and hand gestures. ANNs offer high adaptability and non-linear mapping capabilities but require extensive training and are sensitive to overfitting.

4.3. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS combines ANN learning with fuzzy inference logic (Li et al., 2021; Zhang et al., 2020). It adapts to varying user behavior and is particularly effective in terrain-adaptive gait models. Research shows that ANFIS outperforms standalone FLC or ANN in environments with nonlinear disturbances.

4.4. Reinforcement Learning (RL)

RL algorithms learn optimal control policies through trial-and-error (Abid et al., 2021). In prosthetics, RL can autonomously discover efficient walking strategies and adapt to irregular terrains. However, RL models require extensive training data and pose safety concerns during early learning phases.

4.5. Deep Learning (DL)

Deep learning architectures, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks, have been applied for EMG/EEG signal decoding, movement classification, and gesture prediction (Zafar et al., 2022; Al-Qaysi et al., 2023). DL excels at handling highdimensional inputs and discovering hidden patterns. Yet, challenges include latency, explain ability, and power consumption. (Lee et al., 2022; Zafar et al., 2022).

As demonstrated in Figure 1, the comparative analysis of training time and performance accuracy for ANN, RL, and DL-based prosthetic control methods reveals a critical trade-off between algorithmic efficiency and precision. This figure underpins the discussion in Section 4.5 by visually reinforcing the limitations and strengths of each approach.

This figure highlights how ANN achieves moderate accuracy with faster training, while RL and DL offer higher accuracy but at the cost of significantly longer training durations, emphasizing the trade-off between speed and precision.

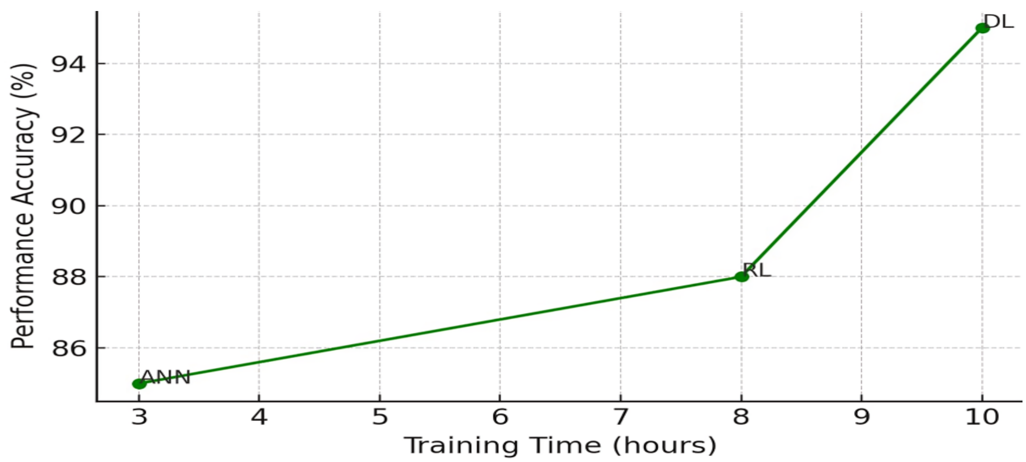

Figure 1: Training time versus performance accuracy for ANN, RL, and DL.

5. Commercial Implementations and Case Studies

5.1. Ottobock Genium X3

Uses sensor fusion and adaptive control algorithms to provide intuitive walking for above-knee amputees.Combines IMU and EMG inputs.

leverages multi-sensor fusion with adaptive control for intuitive above-knee ambulation (Ottobock, 2023).

5.2. Open Bionics Hero Arm

Open Bionics' Hero Arm uses pattern recognition typically ANN-based for multi-grasp control in an affordable, additively manufactured platform (Open Bionics, 2022). Offers affordable 3D-printed designs powered by embedded ML. Clinical studies on advanced upper-limb systems such as the DEKA Arm report functional improvements with sophisticated decoding and control (Resnik et al., 2018).

As illustrated in **Figure 2**, the Open Bionics Hero Arm operates through a structured workflow beginning with EMG signal acquisition, followed by ANN-based pattern recognition, and culminating in actuator-driven multi-grasp movements, effectively demonstrating the interaction between neural inputs and prosthetic outputs

This Figure shows clarifies how each module interacts to achieve real-time, adaptive prosthetic control. This schematic representation clarifies the multi-layered decision-making process essential for adaptive and real-time prosthetic operation.

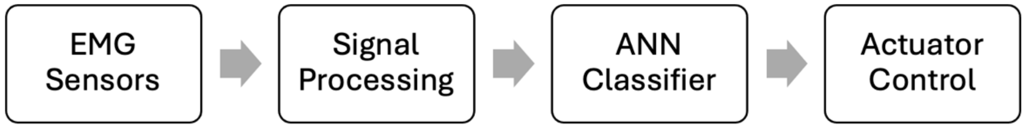

Figure 2: Workflow diagram of an intelligent prosthetic arm with EMG, ANN, and actuator feedback.

5.3. DEKA Arm System

Funded by DARPA, this high-performance prosthetic arm supports neural integration. Utilizes advanced signal decoding from residual limb nerves.

As represented in Figure 3, a distribution analysis of control algorithms adopted in commercial prosthetics, highlighting the current dominance of ANN-based approaches over classical PID and emerging DL solutions. This visualization supports the findings of Section 5.3 regarding market trends and technological shifts.

This Figure presents the percentage distribution of various control algorithms used in commercial prosthetics, including PID, FLC, ANN, and DL-based systems. It visually demonstrates the increasing trend towards intelligent methods in modern prosthetic devices compared to traditional PID control.

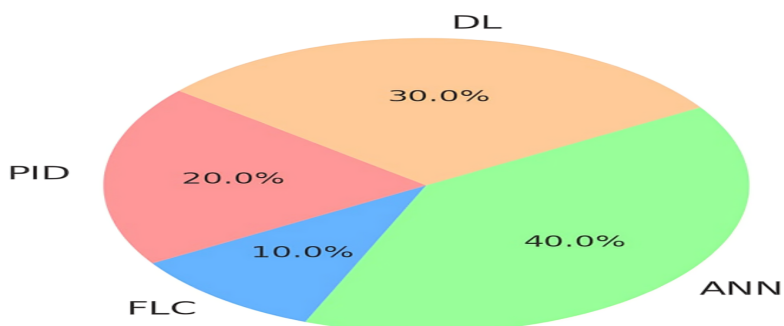

Figure 3: Pie chart showing usage distribution of control algorithms in commercial prosthetics.

6. Comparative Analysis

As summarized in Table 1, classical PID control delivers high real-time responsiveness with very low computational complexity, but adaptability remains poor (Kumar, 2019). Fuzzy logic controllers improve robustness to uncertainty but rely heavily on expert-designed rule bases (Li, Chen, & Wang, 2021). Neural approaches ANN and ANFIS achieve high adaptability and nonlinear mapping performance, though they require extensive training and carry risks of over fitting (Zhang, Sun, & Huang, 2020; Al-Qaysi et al., 2023). Reinforcement learning provides very high adaptability by discovering control policies autonomously, yet it demands extensive data and raises safety concerns during early deployment (Abid, Tariq, & Hussain, 2021). Deep learning models excel in extracting hidden spatiotemporal patterns from EMG/EEG signals, achieving state-of-the-art accuracy, but their use in wearable prosthetics is limited by computational overhead and power constraints (Zafar et al., 2022; Lee et al., 2022).

Table 1: Comparative Analysis of Control Algorithms for Prosthetic Devices

Control Method	Adaptability	Complexity	Real-time Performance	Training Required
PID	Low (Kumar, 2019)	Low (Kumar, 2019)	High (Kumar, 2019)	None
FLC	Medium (Li, Chen, & Wang, 2021)	Medium (Li et al., 2021)	Medium (Li et al., 2021)	Manual tuning
ANN	High (Kumar, 2019; Al-Qaysi, Aziz, & Al-Jumaily, 2023)	High (Kumar, 2019)	Medium (Kumar, 2019)	Yes (Al-Qaysi et al., 2023)
ANFIS	High (Zhang, Sun, & Huang, 2020)	High (Zhang et al., 2020)	Medium (Zhang et al., 2020)	Yes
RL	Very High (Abid, Tariq, & Hussain, 2021)	Very High (Abid et al., 2021)	Medium (Abid et al., 2021)	Yes, extensive (Abid et al., 2021)
DL	Very High (Zafar, Ali, & Khan, 2022; Lee, Park, & Kim, 2022)	Very High (Lee et al., 2022)	Medium/Low (Lee et al., 2022)	Yes, large data (Zafar et al., 2022)

As depicted in Figure 4, adaptability scores differ significantly among the evaluated control algorithms, with RL and DL exhibiting superior adaptability compared to traditional PID and FLC methods. This empirical evidence strengthens the argument for adopting intelligent control techniques in modern prosthetic devices.

This figure emphasizes that DL and RL algorithms exhibit significantly higher adaptability than PID and FLC, making them more suitable for complex, dynamic user movements.

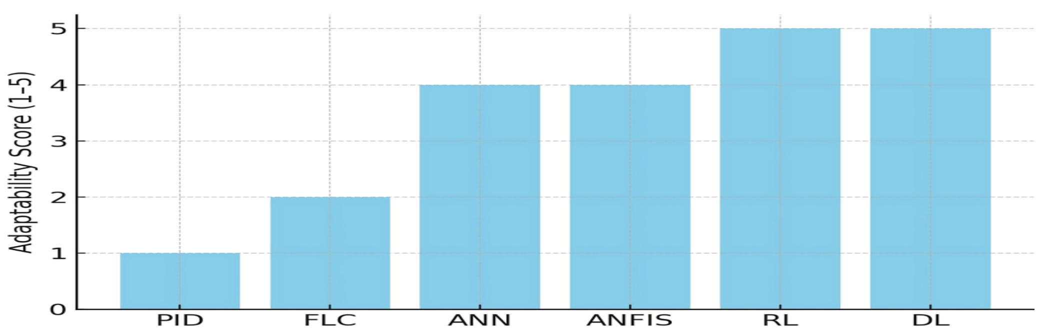

Figure 4: Bar chart comparing adaptability scores of different control methods.

As depicted in Figure 5, a consolidated overview of multiple performance metrics adaptability, computational complexity, and real-time responsiveness across various control algorithms. This comprehensive visual summary supports the comparative analysis presented in Section 6 and aids in selecting optimal algorithms for future prosthetic research and development.
This comprehensive figure highlights the strengths and weaknesses of each method, the trade-offs in each approach.

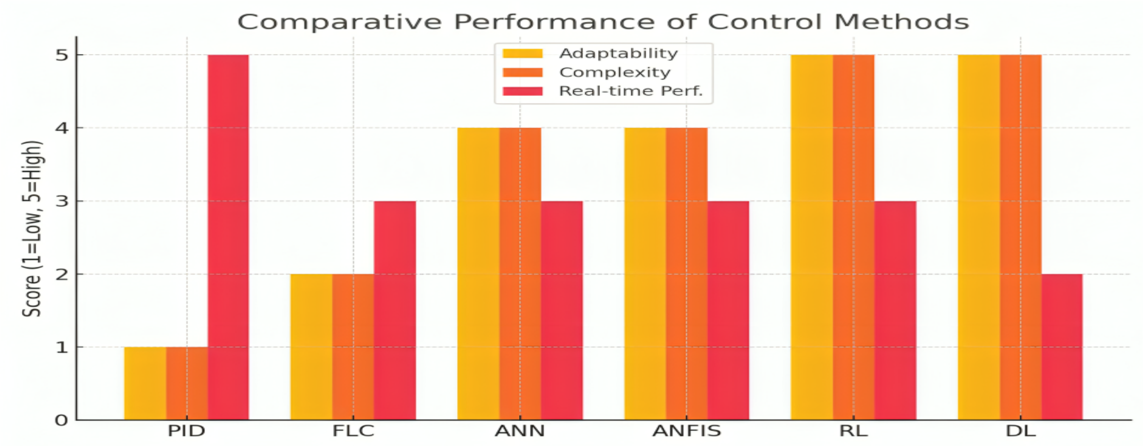

Figure 5: Summary of control algorithm scores in adaptability, complexity, and real-time performance.

7. Mechanical Considerations in Prosthetic Design

While control algorithms are essential for intelligent prosthetics, the mechanical design forms the foundational structure upon which these algorithms operate. A well-engineered mechanical system enhances user comfort, range of motion, and durability of the prosthesis.

7.1. Biomechanical Compatibility Prosthetic devices must closely mimic the kinematics and kinetics of natural limb movement. Key considerations include joint angle limits, torque requirements during walking or object manipulation, and load distribution during gait cycles.

7.2. Distribution of Weight and Structural Materials To lessen user fatigue, cutting-edge lightweight materials including titanium alloys, carbon fiber composites, and high-strength polymers are employed. To ensure that the gadget can sustain repeated impacts while staying comfortable, mechanical design must strike a balance between strength and weight.

7.3. Joint Actuation and Mechanisms Different mechanical designs are used in prosthetic joints (e.g., knee, ankle, elbow), ranging from active motorized joints to passive spring-damper systems. The choice has an impact on both the control method and energy efficiency. Active prostheses need accurate mechanics and torque control.

7.4Energy Return and Storage (ESR) Many lower limb prostheses incorporate ESR designs to increase walking efficiency. By collecting energy during heel strike and releasing it during toe-off, these devices mimic the elastic properties of tendons.

7.5. Wear and Mechanical Reliability Mechanical components experience wear and tear from prolonged operation. Self-lubricating joints, modular attachments, and sealed bearings are examples of design techniques that can increase dependability and lower maintenance needs.

7.6. Combining Actuators and Sensors Without sacrificing ergonomics, the mechanical frame must support actuators (motors, pneumatic/hydraulic systems) and sensors (EMG, IMU, force plates). For signals to be accurate and controllable, mounting and alignment are essential.

8. Limitations & Future Work

Despite promising advances, several limitations hinder widespread adoption of intelligent prosthetic control:

Sensor Reliability: EMG/EEG signals can be unstable due to sweating, electrode displacement, or motion artifacts. Future work should focus on developing more robust electrode designs, adaptive filtering, and sensor fusion techniques to ensure consistent signal quality.
Environmental Variability: Terrain irregularities and weather conditions challenge adaptability.Research should investigate terrain-adaptive algorithms, multi-modal sensing (EMG + IMU + force sensors), and context-aware control strategies.
User Training: Many systems require extensive user adaptation and training. Future directions include intuitive user interfaces, transfer learning methods, and adaptive calibration to reduce training burden.
Cost and Accessibility: Advanced AI-powered prosthetics are often prohibitively expensive. Low-cost 3D-printed designs and open-source control frameworks should be explored to increase accessibility.
Power Consumption: DL and RL methods demand high computational resources, limiting portability. Energy-efficient edge AI hardware and model compression (e.g., pruning, quantization) are promising research paths.
Maintenance and Upgradability: Frequent hardware/software updates are needed. Modular hardware designs and cloud-based firmware updates can improve longevity and reduce maintenance costs.
Ethical and Regulatory Concerns: Black-box AI models raise safety and accountability issues. Explainable AI and interpretable models tailored for medical devices should be prioritized to support transparency and regulatory compliance..

9. Challenges and Future Directions

Balancing accuracy, interpretability, and real-time performance in DL models

User-specific calibration without retraining entire networks Edge AI: embedding intelligent algorithms on low-power prosthetic hardware Multi-modal signal integration (EMG + EEG + IMU + force sensors) Cloud-prosthetics: real-time data syncing, adaptation, and shared learningExplainableAIinmedicaldevicesforregulatorycomplianceAdaptive control in social environments (stairs, crowds, transitions).

10. Recommendations to Improve Future Prosthetic Research

- Combine hybrid methods that balance interpretability and adaptability.
- Invest in energy-efficient edge AI for real-time, on-device computation.
- Encourage open datasets for training and benchmarking control algorithms.
- Promote user-centric testing and co-design with amputees.
- Develop explainable AI models to support transparency and regulatory clearance.

11. Conclusion

Intelligent control algorithms have the potential to bridge the gap between artificial and biological limbs. Classical PID control remains a robust baseline, but modern intelligent approaches bring adaptability and personalization. Each method has its own trade-offs; hence, hybrid systems that combine DL's learning ability with FLC's interpretability and PID's stability may define the future. The path forward involves collaborative work across machine learning, neurology, embedded systems, and user-centric design.

Declarations

Availability of Data and Materials

All data generated or analyzed during this study are included in this published article.

Competing Interest
Not applicable.

Conflicts of Interest
Not applicable.

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Authors Contribution
The author solely contributed to the conception, design, analysis, drafting, and approval of the manuscript.

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