Proceedings on Automation in Medical Engineering
Proc AUTOMED, 2026, Vol. 3, No 1, Article ID 2477, 2 Pages

Infinite Science Publishing

Clinically Informed Adaptive Control for Rehabilitation Robots: A Framework for Improved Patient Interaction

Z. Shahrbaf[1,2*], L. Budde [2], T. Seel[2], A. Turolla[3], and I. Jakob[1]
[1] *Tyromotion, GmbH, 8020 Graz, Austria*
[2] *Leibniz University Hannover, Institute of Mechatronic Systems, Hanover, Germany*
[3] *Department of Biomedical and Neuromotor Sciences (DIBINEM), Alma Mater Studiorum, University of Bologna, Bologna (Italy)*
[*] *Corresponding author, email: zahra.shahrbaf@tyromotion.com*

Abstract: Lower-limb rehabilitation robots often provide limited assessment of patient performance and personalized training. This paper proposes a conceptual framework that integrates multi-sensor data fusion with an adaptive assistance-as-needed (AAN) control approach. The framework consists of three steps: selecting clinically relevant parameters, fusing multi-sensor data into a performance score, and adjusting robotic assistance based on an adaptive AAN rule. This approach aims to improve therapy personalization, provide more informative feedback, and support evidence-based clinical decision-making. Future work will implement and evaluate the framework on a robotic gait trainer to assess its technical and clinical impact.

© 2026 Zahra Shahrbaf; licensee Infinite Science Publishing
This is an Open Access article distributed under the terms of the Creative Commons Attribution License CC-BY 4.0., which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

I. Introduction

Robotic-assisted gait rehabilitation has become a crucial approach for supporting the recovery of patients with impairments in walking and mobility [1]. Personalized and patient-centered rehabilitation has been shown to improve functional outcomes and promote long-term motor learning [2], and achieving such personalization requires a reliable assessment of the sensorimotor function of the individual. To provide this, a comprehensive view of the movement performance of the patient is needed.

However, existing robotic assessment methods typically rely on a single data modality (such as kinematic or force data alone), providing only a partial view of the movement performance of the patient. Integrating heterogeneous data sources (such as force sensors, motion capture, and robotic system parameters) can enable multi-sensor data fusion for a more comprehensive and clinically meaningful assessment [3]. Despite significant progress in rehabilitation robotics, many robotic systems still provide only basic feedback, rely on pre-defined therapy parameters, and use conventional PID control schemes that lack adaptability to variations in patient behavior [4].

Using an adaptive controller while ensuring robust performance offers opportunities to enhance rehabilitation outcomes [5]. Data fusion assessment has been used on the lower limb, and assistance-as-needed (AAN) control has been implemented on lower-limb exoskeleton robots [6], but these approaches were implemented independently. Recent work such as combining adaptive control with multi-source sensing but does not explicitly integrate multi-sensor fusion into an AAN update strategy. Therefore, current methods do not yet provide a unified approach.

To better understand the options for adaptive and patient-centered control, the main controller strategies are compared in Table 1 [1], which summarizes the advantages and limitations of commonly used control strategies in robotic rehabilitation. Within this paper, we propose a framework that extends previous work by providing a fully integrated system that combines multi-sensor performance scoring with an adaptive AAN control loop in a single real-time system. The goal is to improve patient-centered outcomes in lower-limb rehabilitation.

Table 1 Comparison between the main control schemes used in robot-assisted rehabilitation

Control Type	Main Advantages	Main Limitation/Challenges
PID	Simplicity, stability, easy to implement	Limited to linear dynamics, no adaptivity
Force	Realistic feedback, safety	Requires precise sensors, instability with delays
Impedance	Flexibility, natural human–robot interaction	Fine tuning, noise sensitive
Adaptive	Adapts to the patient in real time	Increased complexity, risk of instability
AI/ML/RL-based	Prediction, personalization, learning from data	Lack of transparency (XAI), computational cost
Hybrid	Combines the benefits of multiple methods	Complex implementation, difficult tuning

II. Proposed Controller Design

The proposed framework is designed for a commercial robotic gait trainer. To improve current rehabilitation robots, the primary focus is on upgrading the control system, which forms the core of the framework. As shown in Table 1, conventional PID, force, and impedance controllers lack adaptability, while AI/ML/RL-based and hybrid methods require large datasets and high computational cost. These limitations motivate the need for an adaptive AAN controller that adjusts based on the abilities of patients.

AAN controller adjusts parameters according to the performance of patients. To achieve this goal, the first step is to define the walking performance of patient. This value becomes more accurate and comprehensive when it includes various parameters such as force, kinematic, or physical data. Therefore, we need to determine which parameters are most relevant and influential. Outputs from a focus group and a literature review will be combined, ensuring results are clinically and practically meaningful.

The focus group will include both experienced therapists with and without expertise in robotic gait training.

To fuse the various parameters into a single scalar performance metric that represents walking performance, a weighted-sum formulation is used. In the initial stage, all parameters are assigned equal weights. In subsequent phases, data-driven methods such as random forest will be used to tune the weighting parameters of the scalar metric, thereby optimizing its alignment with clinical outcome measures (e.g., 10m walk test), which serve as target variables. The exact model architecture and dataset will be defined during pilot data collection. This performance metric will track progress across sessions, giving a clear overview of improvements. The walking performance is defined as:

$$S(t) = \omega_1 f_1(t) + \omega_2 f_2(t) + \cdots + \omega_n f_n(t) \quad (1)$$

where $f_i(t)$ represent force, kinematic, or physically based measurements and ω_i are their corresponding weights. To ensure comparability between components and to prevent any single parameter from dominating the others, all input values and weights are normalized prior to computing $S(t)$, with the weights scaled so that their sum equals 1. Consequently, the resulting $S(t)$ is also normalized.

The normalized performance metric $S(t)$ guides real-time adaptations of exercise parameters in the robotic gait trainer. To achieve a structured progression through AAN, the system gradually increases exercise intensity as patient performance improves. If performance parameters exceed the upper thresholds while the heart rate remains within a safe range, walking speed and step length are increased in a controlled manner.

To ensure patient safety and maintain dynamic stability, parameters are updated at predetermined intervals or movement cycles, allowing the patient's neuromuscular system sufficient time to adapt to each training load.

On the other hand, if patient performance fall below predefined lower thresholds, or if the heart rate exceeds the safe target range, the system considers the current activity level to exceed the patient's capacity. In this case, training parameters are adjusted to reduce the motor load, including a gradual reduction in both walking speed $V(t)$ and step length $L(t)$. This approach provides patient-centered, adaptive assistance while minimizing the risk of instability or excessive fatigue. To formalize the decision-making logic and how to adapt the training parameters, control rules were defined as follows:

$$V(t+1) = V(t) + \alpha\Delta_V(t) \quad (2)$$

$$L(t+1) = L(t) + \alpha\Delta_L(t) \quad (3)$$

Where, Δ_V and Δ_L denote the step sizes that constrain how fast the assistance parameters are allowed to change. The thresholds, represent clinically informed ranges, determined jointly with physiotherapists and tailored to patient-specific factors such as diagnosis and cardiopulmonary tolerance. Here, α represents the adaptation direction (harder, easier or unchanged), and is defined as:

$$\alpha = \begin{cases} -1, & if\ \ HR > HR_{Max}\ or\ RoM < RoM_{Min} \\ & or\ \ S < S_{Min} \\ +1, & if\ \ HR_{Min} < HR < HR_{Max}\ and\ S_{Low} < S \le S_{Normal} \\ & and\ RoM_{Min} < RoM \le RoM_{Normal} \\ 0, & Otherwise \end{cases} \quad (4)$$

where HR, RoM, and S denote heart rate, joint range of motion, and performance score respectively. For example, if $S(t)$drops below the lower clinical threshold ($S(t) < S_{Min}(t)$), the system decreases speed by a small preset increment ($V(t+1) = V(t) - \alpha\Delta_V(t)$).

The overall control architecture is illustrated in Fig. 1, where the AAN controller adapts exercise parameters based on the performance score $S(t)$.

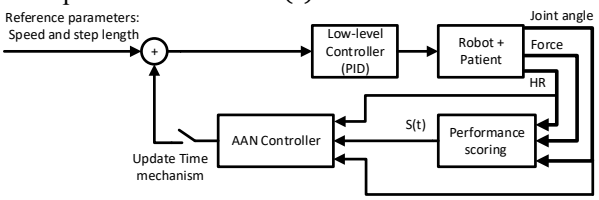

Figure 1Control architecture of the proposed adaptive AAN framework.

III. Conclusions

This paper proposes a clinically informed framework for adaptive control in lower-limb rehabilitation robots. The framework integrates parameter selection based on clinical expertise, multi-sensor performance fusion, and an AAN adaptation rule. Force-, kinematic-, and physics-based measurements are combined into a normalized scalar score $S(t)$, which serves as the decision variable for adaptive updates across sessions. This work defines the controller structure, thresholds, and update rules for implementation. Compared with fixed-trajectory PID control, the proposed framework introduces adaptive parameter updates to support personalization and more meaningful assessment during robotic gait training. The feasibility and clinical impact of this conceptual framework will require experimental validation. Future work will therefore focus on implementing the framework on the Lexo (robotic gait trainer, Tyromotion, Austria) and evaluating its technical and clinical performance.

AUTHOR'S STATEMENT

Research funding: This project has received funding from the European Union's EU Framework Program for Research and Innovation Horizon Europe under Grant Agreement No. 101169197
Conflict of interest: Authors state no conflict of interest.
Informed consent: Not applicable, as no human subjects were involved .
Ethical approval: This study did not involve human participants or clinical data, and therefore did not require ethical approval.

REFERENCES

[1] O. L. Rad and C. Brisan, "Control Algorithms in Robot-Assisted Rehabilitation: A Systematic Review," *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/app15169184.
[2] M. Maier, B. R. Ballester, and P. F. M. J. Verschure, "Principles of Neurorehabilitation After Stroke Based on Motor Learning and Brain Plasticity Mechanisms," *Frontiers Media S.A.* doi: 10.3389/fnsys.2019.00074.
[3] D. Novak and R. Riener, "Sensor fusion in assistive and rehabilitation robotics," *MDPI AG*. doi: 10.3390/s20185235.
[4] S. Maggioni, L. Lünenburger, R. Riener, A. Curt, M. Bolliger, and A. Melendez-Calderon, "Assessing walking ability using a robotic gait opportunities and limitations of assist-as-needed control in spinal cord injury," *J Neuroeng Rehabil*, vol. 20, no. 1, doi: 10.1186/s12984-023-01226-4.
[5] Y. Du, H. Wang, S. Qiu, W. Yao, P. Xie, and X. Chen, "An advanced adaptive control of lower limb rehabilitation robot," *Frontiers Robotics AI*, vol. 5, no. doi: 10.3389/frobt.2018.00116.
[6] S. M. Campbell, C. P. DIduch, and J. W. Sensinger, "Autonomous Assistance-as-Needed Control of a Lower Limb Exoskeleton with Guaranteed Stability," *IEEE Access*, vol. 8, pp. 51168–51178, 2020, doi: 10.1109/ACCESS.2020.2973373.