Leveraging Multimodal Monitoring in Plan-Based Robot-Aided Rehabilitation

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Abstract

Robotic rehabilitation systems typically rely on kinematic data to assess exercise execution, focusing on pose accuracy without evaluating the physical impact on the patient. This paper explores the integration of physiological monitoring into an automated planning system for robot-aided rehabilitation. Specifically, we assess whether Heart Rate (HR) can provide meaningful feedback on the experimented physical workload while executing physical tasks. Ten healthy participants completed a session of 10 exercises, with cumulative exercise intensity (ΣI) and HR recorded. A Pearson correlation analysis revealed an average strong correlation of 0.63 across all participants, indicating that HR reliably reflects physical effort. The results suggest that incorporating HR feedback allows the system to dynamically adjust exercise intensity in real-time, ensuring that patients are neither over- nor under-challenged.

Keywords

Robot-aided rehabilitation, Physical rehabilitation, Automated Planning, Task Planning

1. Introduction

Robotic systems have become essential tools in rehabilitation, assisting with physical recovery by delivering personalized, repeatable, and adaptive interventions. These systems include exoskeletons [1] and end-effector robots providing continuous physical assistance [2], as well as socially assistive robots that offer motivational support and corrective feedback [3]. Their integration into healthcare has been especially beneficial for conditions such as stroke and musculoskeletal disorders [4].

In current robotic rehabilitation platforms, automated planning systems can select and sequence exercises based on clinical goals [5]. A notable example is the NAOTherapist platform, widely applied in pediatric robot-aided rehabilitation [6]. These systems predominantly rely on kinematic data to assess how closely a patient's upper limb configuration matches the assigned pose, typically demonstrated by the robot. This assessment often uses error metrics such as normalized Euclidean distance [7]. Based on the patient's performance, the system adjusts the difficulty of the exercises, determining the level of strictness in evaluating execution accuracy [8]. However, this focus on static upper limb configurations is limiting, as most rehabilitation exercises involve dynamic, full-body movements. It is important to acknowledge that kinematic monitoring is widely used in the literature because it offers immediate feedback on task execution, making it effective for managing the flow of rehabilitation sessions.

Nevertheless, focusing solely on kinematic data has significant limitations, as it fails to capture the overall physical impact of the rehabilitation session. While kinematic monitoring effectively ensures that individual movements are executed correctly, it does not account for the cumulative physical effort required throughout the session. This information gap can lead to exercises that either under- or over-challenge the patient, potentially slowing their rehabilitation progress. In contrast, incorporating physiological monitoring allows for tracking the patient's physical workload during the execution of the exercises [9] and psychophysiological state in longitudinal studies [10].

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Therefore, this paper aims to evaluate whether the integration of physiological monitoring into a multimodal patient monitoring system can provide valuable insights into the patient's physical workload. These insights can be leveraged by an automated planning-based robot-aided rehabilitation system to more effectively tailor therapy sessions, ensuring that the prescribed exercises align with the patient's actual physical effort and overall exertion. By combining both kinematic and physiological data, the system has the potential to deliver a more adaptive and personalized rehabilitation experience.

2. Materials and Methods

The block diagram reported in Fig. 1 illustrates the structure of a multimodal rehabilitation system that integrates both kinematic and physiological monitoring to optimize exercise sessions tailored to individual patients.

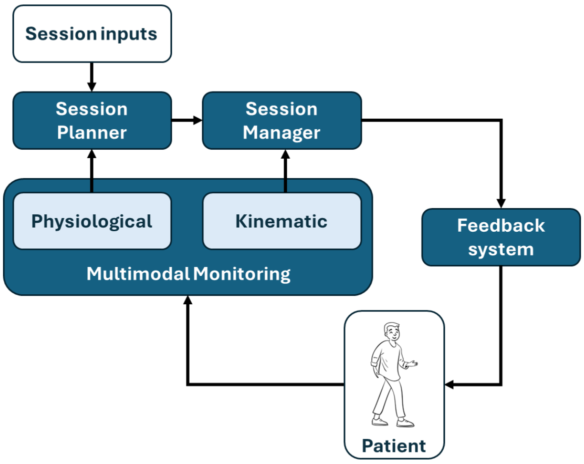

Figure 1: Block scheme of the proposed approach to exploit multimodal monitoring in automated planning-based robot-aided rehabilitation.

Session inputs provide the initial parameters for the rehabilitation session, including clinical goals and desired intensity. These inputs form the basis for personalizing the session to meet specific therapeutic objectives. Based on these inputs, the *Session Planner* generates an optimized sequence of exercises using automatic planning techniques. Its role is to ensure that the therapeutic session is in line with the predefined clinical objectives by dynamically adjusting the exercise sequence if the monitored physical exertion of the patient deviates from the planned intensity. This module stores a list of exercises labeled with the intensity level ranging in $[1, 5]$ that can be used for the generation of the current session [11].

The *Session Manager* monitors the execution of the planned exercises, interacting with both the patient and the monitoring systems to ensure smooth progression throughout the session. It manages the session in real-time by controlling the *Feedback system* according to the data collected from the monitoring systems. Specifically, it compares the prescribed task with the patient's actual performance and provides the task completion percentage as feedback. Once the task is performed for the required duration, the system advances to the next exercise, maintaining a structured flow throughout the rehabilitation session.

At the heart of the system is *Multimodal Monitoring*, which consists of two key components: *Physiological Monitoring* and *Kinematic Monitoring*. The former tracks the physiological responses of the patient which provides essential, slow-varying feedback on the physical effort required by the patient during the execution of the exercise. This information allows the system to adjust the sequence and intensity of the exercises to ensure that the prescribed levels of physical exertion match the clinical goals. Among the measurable physiological metrics, HR is a reliable indicator of exertion, offering insights into the patient's response to the exercises. Wrist-worn devices, such as smartwatches, are ideal for continuous HR tracking due to their reliability and non-intrusive design.

The latter captures the movements of the patient in real-time, ensuring that the exercises are correctly performed, for the correct amount of time. This data helps to manage the therapy session in real-time providing immediate feedback on task performance and facilitating the correct session flow. Whenever the patient executes the assigned task for a determined amount of time correctly, the *Session Manager* administers the subsequent exercise.

2.1. Experimental Evaluation

In this experiment, 10 healthy participants (31.4 ± 5.1 years old, 9 males and 1 female) were recruited. The experimental protocol was designed to assess the effect of various rehabilitation exercise plans on the participants' physiological responses, with a particular focus on HR as an indicator of physical effort. Each participant completed a rehabilitation session consisting of 10 exercises, selected from the database managed by the *Session Planner*. Each exercise was performed for 30 seconds. Figure 2 shows a representative participant performing the exercises while being monitored by a multimodal monitoring system. More in detail, the Garmin Vivosmart 4 wristband was used to monitor HR without disrupting the patient's comfort or movement during rehabilitation sessions, collecting data at 1 Hz. The TIAGo robot's head-mounted camera (ASUS Xtion) and the Mediapipe pose algorithm allow for kinematics monitoring. They were used to capture and track the coordinates of the total body anatomical landmarks at 30 Hz. A classification model, trained on data from four participants across 23 exercises, extracted from the "PhysioTherapy eXercises" database [12] due to their capacity to elicit a range of intensities and body districts, utilizes a Support Vector Machine with a radial basis function kernel to identify the task currently performed by the participant running at 15 Hz.

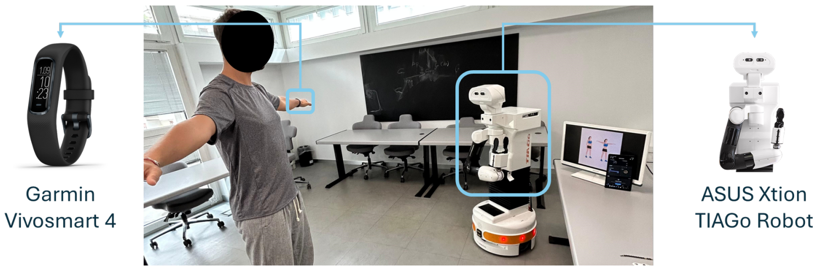

Figure 2: Experimental setup used in the current study.

To quantify the relationship between the prescribed exercise intensity and the participants' physiological responses, we computed the cumulative intensity for each session (ΣI). Specifically, the cumulative intensity at the i-th exercise, $\Sigma I(i)$, was calculated as the sum of the intensities of all exercises up to that point:

$$\Sigma I = \sum_{j=1}^{i} \left[I(a_j) \right] \tag{1}$$

where $I(a_j)$ represents the intensity of the j-th exercise. This cumulative measure reflects the progressive workload imposed by the exercises throughout the session.

We then computed the Pearson correlation coefficient between ΣI and the HR data collected during the session to assess how closely the actual physical workload experienced by the participants is aligned with the planned intensity of the exercises. By examining this relationship, we aimed to determine whether physiological monitoring can provide reliable feedback on the intensity of the administered exercises, offering valuable insights for adjusting and optimizing future rehabilitation sessions. The statistical significance level was set at p-value$= 0.05$.

3. Results and Discussion

Figure 3A illustrates the mean ΣI and HR along with their standard deviations across the 10 participants during the execution of the 10 administered physical exercises. It is worth observing that both metrics increase steadily as the session progresses. ΣI rises consistently with each exercise, reflecting the progressively demanding nature of the session. Similarly, HR shows a positive trend, indicating an increase in physical exertion as participants advance through the proposed exercises. The shaded areas around the lines represent the standard deviation, showing a moderate level of variability in both intensity and HR responses across participants.

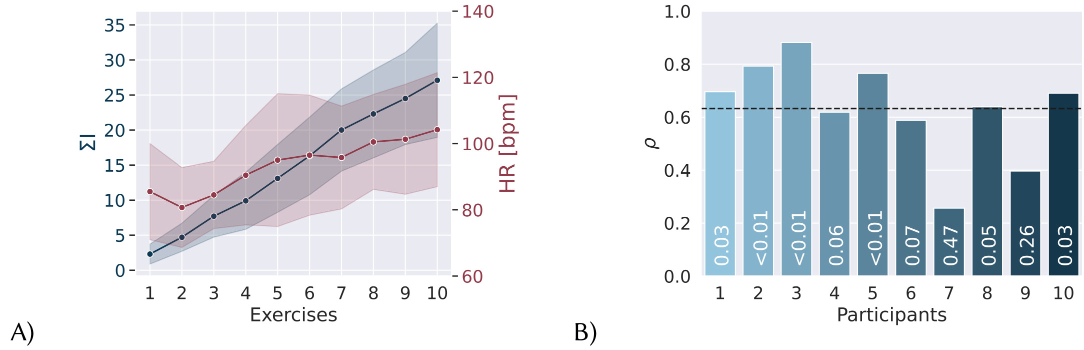

Figure 3: **A**) Cumulative intensity (ΣI) of the administered exercises and Heart Rate (HR) expressed in [bpm] averaged on the enrolled participants. **B**) Linear correlation coefficients for each subject between ΣI and HR. The p-values are written in white inside each corresponding bar. The dotted line highlights the mean correlation ($\bar{\rho} = 0.63$).

Figure 3B shows the linear correlation coefficients (ρ) and p-values between ΣI and HR computed for each subject. Most of the enrolled subjects (S1, S2, S3, S5, S8, S10) show significant positive correlations, with values ranging from 0.63 to 0.88, indicating that heart rate tends to increase with higher exercise intensity. Subjects S4 and S6 exhibit moderate correlations close to the significance threshold, while S7 and S9 display weaker, non-significant correlations, with p-values above 0.05.

Overall, these results suggest that for the majority of participants, there is a strong and significant relationship between ΣI and HR, reinforcing the utility of physiological monitoring to track the physical workload during rehabilitation sessions. The weaker, non-significant correlations for some subjects may indicate individual variability in response to exercise intensity.

Given the established link between cumulative exercise intensity and physical workload, the integration of HR-based physiological feedback into an automated planning system for robot-aided rehabilitation could significantly enhance the personalization of therapy sessions. In particular, real-time HR monitoring allows the system to dynamically assess whether a patient is being over- or under-challenged with respect to their clinical goals. When a patient's HR indicates excessive exertion, the system could leverage this feedback to re-plan or adjust the session in real-time, ensuring that the therapeutic exercises remain within the proper intensity range.

4. Conclusions

This study demonstrated how integrating physiological monitoring can provide crucial insights into assessing the actual physical workload during robot-aided rehabilitation sessions. The results showed a significant correlation between the cumulative intensity of the prescribed exercises and the HR for most participants. On average, a correlation of 0.63 was found across all participants, indicating a strong relationship between exercise intensity and physiological response. This reinforces the importance of incorporating physiological measurements into automated planning systems, moving beyond the sole reliance on kinematic data.

The ability to use real-time HR feedback allows the system to dynamically re-plan rehabilitation sessions, adjusting exercise intensity to avoid overloading or under-challenging the patient with respect to the assigned clinical goals. This flexibility introduces a new level of personalization in treatment, improving the effectiveness of therapy and ensuring better alignment with the patient's needs.

Future efforts will focus on exploring combinations of physiological metrics to assess both physical and cognitive workload, providing a more comprehensive understanding of patient exertion during rehabilitation. Additionally, this higher-level feedback will be integrated into the session planner to tailor rehabilitation sessions according to specific therapist requirements. Validation of this approach will be necessary to ensure its capability to deliver personalized therapeutic strategy.

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References

[1] O. Coser, C. Tamantini, P. Soda, L. Zollo, Ai-based methodologies for exoskeleton-assisted rehabilitation of the lower limb: a review, Frontiers in Robotics and AI 11 (2024) 1341580.

[2] H. I. Krebs, D. J. Edwards, B. T. Volpe, Forging mens et manus: The mit experience in upper extremity robotic therapy, in: Neurorehabilitation Technology, Springer, 2022, pp. 597–621.

[3] M. MacNeil, E. Hirslund, L. Baiocco-Romano, A. Kuspinar, P. Stolee, A scoping review of the use of intelligent assistive technologies in rehabilitation practice with older adults, Disability and Rehabilitation: Assistive Technology 19 (2024) 1817–1848.

[4] C. Tamantini, F. Cordella, C. Lauretti, F. S. di Luzio, M. Bravi, F. Bressi, F. Draicchio, S. Sterzi, L. Zollo, Patient-tailored adaptive control for robot-aided orthopaedic rehabilitation, in: 2022 international conference on robotics and automation (ICRA), IEEE, 2022, pp. 5434–5440.

[5] J. C. González, J. C. Pulido, F. Fernández, A three-layer planning architecture for the autonomous control of rehabilitation therapies based on social robots, Cognitive Systems Research 43 (2017) 232–249.

[6] J. C. Pulido, J. C. González, C. Suárez-Mejías, A. Bandera, P. Bustos, F. Fernández, Evaluating the child–robot interaction of the naotherapist platform in pediatric rehabilitation, International Journal of Social Robotics 9 (2017) 343–358.

[7] J. C. Pulido, C. Suarez-Mejias, J. C. Gonzalez, A. D. Ruiz, P. F. Ferri, M. E. M. Sahuquillo, C. E. R. De Vargas, P. Infante-Cossio, C. L. P. Calderon, F. Fernandez, A socially assistive robotic platform for upper-limb rehabilitation: a longitudinal study with pediatric patients, IEEE Robotics & Automation Magazine 26 (2019) 24–39.

[8] A. Martín, J. C. Pulido, J. C. González, Á. García-Olaya, C. Suárez, A framework for user adaptation and profiling for social robotics in rehabilitation, Sensors 20 (2020) 4792.

[9] C. Tamantini, F. Cordella, N. L. Tagliamonte, I. Pecoraro, I. Pisotta, A. Bigioni, F. Tamburella, M. Lorusso, M. Molinari, L. Zollo, A data-driven fuzzy logic method for psychophysiological assessment: An application to exoskeleton-assisted walking, IEEE Transactions on Medical Robotics and Bionics (2024).

[10] C. Tamantini, F. Cordella, F. Scotto di Luzio, C. Lauretti, B. Campagnola, F. Santacaterina, M. Bravi, F. Bressi, F. Draicchio, S. Miccinilli, et al., A fuzzy-logic approach for longitudinal assessment of patients' psychophysiological state: an application to upper-limb orthopedic robot-aided rehabilitation, Journal of NeuroEngineering and Rehabilitation 21 (2024) 202.

[11] A. Umbrico, M. Benadduci, R. Bevilacqua, A. Cesta, F. Fracasso, E. Maranesi, A. Orlandini, G. Cortellessa, Combining clinical and spatial constraints into temporal planning to personalize physical rehabilitation, in: Proceedings of the International Conference on Automated Planning and Scheduling, volume 33, 2023, pp. 532–540.

[12] J. Glinsky, L. Harvey, C. Sherrington, O. Katalinic, www. physiotherapyexercises. com–new exercises and features to help physiotherapists prescribe home exercise programs, Physiotherapy 101 (2015) e1381.