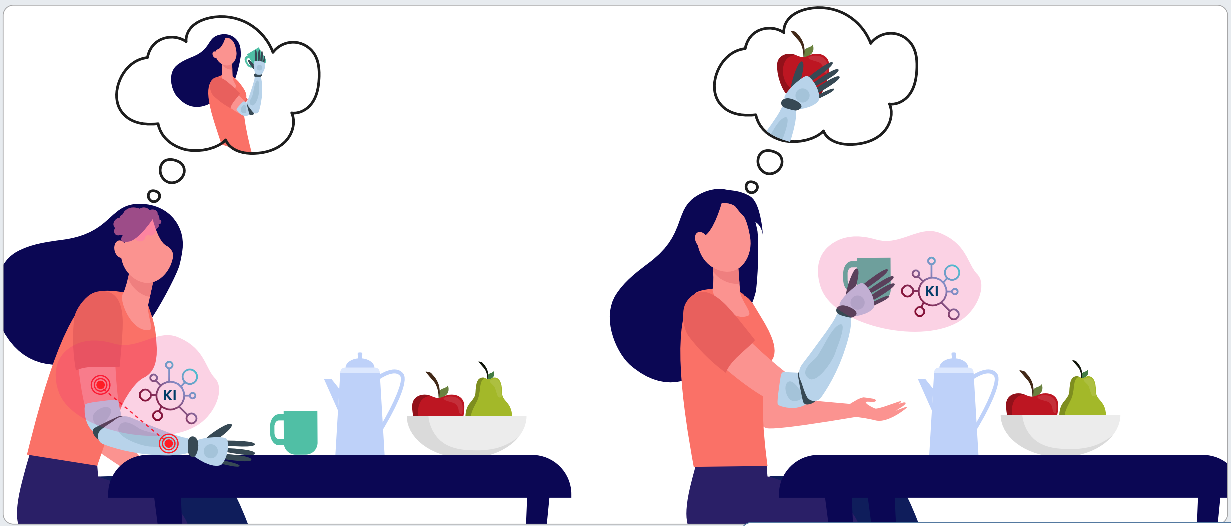
LEARNING FROM INTERACTION

Wearable Robotics: Personalized support and physical rehabilitation



Overview

Industry: Health sector

Task: Supporting the human body as needed

Method: Classification, regression, (deep) reinforcement learning, active learning, evolutionary algorithms, and more

General information

"Wearable Robots" refers to robots that are worn on the body, such as active exoskeletons and orthoses, or robotic arm and leg prostheses. These devices must be highly adaptive to the human body and are designed to provide support that is as situationally appropriate and personalized as possible – either to enable movement in the first place or to reduce strain during movement or posture. Ideally, the support should follow the principle of "as much as necessary, as little as possible" ("assist-as-needed"). The robotic system itself detects the required level of assistance. Furthermore, it should be capable of learning how much support is appropriate in each situation, based on the user's residual strength. In essence, a properly designed prosthesis can help enhance the autonomy of individuals with impairments.

Status quo

Currently, exoskeletons can be instructed via interfaces (e.g., input through a smartwatch or control unit) to support specific movements such as "walking straight" or "climbing stairs". They can also provide support in an "assist-as-needed" manner, aiding the human body only as much as the person's current strength requires in a given situation. The individually required level of assistance can be customized by therapists or adjusted by the users themselves.

In practice, human specifications and predefined rules are used to operate the system. There are also approaches to adapt learned behaviors through interaction. For instance, models for pattern recognition from biosignals are developed to control robotic prostheses, helping to recognize and interpret the user's movement intentions. Users can further refine the control through an app, optimizing it according to their needs. These solutions are already integrated into the product in compliance with current regulations.

Future perspectives with AI

Researchers are using machine learning to determine the level of support a patient requires based on the remaining activity of their muscles. The AI models developed in this way can also be retrained during use. In wearable robotics research, learning systems of this kind are already emerging.
In the future, these systems could autonomously detect, via feedback loops, whether they need retraining during operation, eliminating the need for users to initiate the retraining themselves. The system could adjust independently, providing more personalized support. Additionally, it could also learn context-specific preferences through user feedback, determining which type and intensity of assistance is perceived as comfortable in different situations without the user having to specify this explicitly. Researchers investigate what kinds of feedback are meaningful for machine learning (even including brain activity). Furthermore, future exoskeletons could learn to differentiate between intended muscle activation and activation caused by pathological conditions (e.g., spasticity, rigidity, or tremor) and automatically adjust the level of support (such as movement strength and speed) or the type of therapeutic exercise accordingly.

Sources of learning

Wearable Robots can learn using various methods, including:

- Biosignals from the human body (e.g., muscle and brain activity, eye-tracking, or motion data)
- Explicit human feedback (e.g., speech, manual manipulation)
- Information or data from the environment (e.g., location, objects, interaction possibilities)

The exoskeleton or robotic prosthesis analyzes these biosignals and data during interaction with the user. Depending on the situation and context, different AI models can be learned or applied.

Required data

The data are collected via various sensors and can be gathered from different sources, for example, through the sensory capture of…

- the environment in terms of observable data
- the human body, such as biosignals that can only be obtained using specialized methods and devices (e.g., users' attention focus)
- data from the interaction with users, such as interaction forces
- data from the exoskeleton regarding its own state

Learning methods

Using classification or regression, biosignals can be interpreted regarding the strength of muscular remaining activity. More complex AI models, such as deep neural networks, are particularly effective for distinguishing which movements should be supported when and how. To utilize the data for adaptation, methods such as classification, regression, (deep) reinforcement learning, and even evolutionary algorithms are necessary. With these methods, the robotic system learns how to behave based on the remaining activity of specific muscle groups, types of movement, or situational context. Due to the large amounts of data required and the time-consuming training processes, deep learning methods like deep reinforcement learning are rarely used (if at all). More recent approaches are exploring ways to train generic large AI models that are no longer trained on a person-specific basis. Despite their generality, these models can still be adapted to specific persons using corresponding individual data.

Quality assurance

Quality assurance depends on human feedback. A key research question is how this feedback can be systematically and automatically evaluated and utilized. The feedback can come from laypersons (users, patients) or professionals (from field such as medicine, orthopedics, biomechanics) and can vary significantly in quality and subjectivity. The easiest approach is to rely on explicit feedback for evaluation; however, it is challenging to derive the source of potential errors or quality issues from this alone. Implicit feedback can provide more timely insights. Additionally, it is crucial to assess the quality of the training data for the robotic system: poor training data should not be used to adapt AI models. To detect and avoid errors, a "safty net" should be implemented, and systems (robot control engineering plus robot learning methods, etc.) should be designed with user safety as a priority.

System requirements

- User data must be used in compliance with data protection regulations.
- Ideally, the learning capability should be implemented within the system itself (cf. Edge AI).
- When wearable robots utilize generic AI models, the individuality of the users must always be considered.
- Increasingly, systems need to be able to analyse and learn from data about the user and the environment. With regard to (self-)learning systems, safety concepts need to be reviewed, adapted, or newly developed.

Further requirements

- People should be able to engage in interactive robot learning.
- Safety mechanisms must be established and recognized as sufficient by both experts and users.
- Therapists, doctors, and caregivers should understand the processes involved.
- All participants should have or develop some level of digital literacy (e.g. in the case of the elderly).

Realization and possible obstacles

On the technological level, it is possible to use wearable robots with learning capabilities today.

However, there are hurdles and uncertainties regarding authorisation, certification, legal frameworks (e.g., AI Act, MDR – Medical Device Regulation, GDPR – General Data Protection Regulation), and reimbursement practices:

- AI components of wearable robots can be designed with safety in mind by implementing constrains based on control engineering. While already trained models are certifiable, there is currently no official procedure for certifying continuously self-learning systems.

- Regarding the AI Act, there are uncertainties in the application of risk classes: Are wearable robots with learning capabilities inherently classified as high-risk? The entire robotic system must be considered (including the safeguards for AI based on control engineering) rather than individual learning methods or algorithms.

- Uncertainty about reimbursement inhibits the technology transfer to the rehabilitation sector. Although reimbursement is theoretically possible under current regulations, there are significant practical hurdles. While the cost of acquisition is high, the benefits and savings will outweigh this from a purely economic point of view

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Further Information on Wearable Robots Projects:

- **Recupera REHA Exoskelett:** Robot-assisted rehabilitation using a mobile full-body exoskeleton.
- **MRock:** Utilizes an assist-as-needed approach, where the level of support patients require is determined through their interaction with the system based on EMG data, while subjective comfort is evaluated using EEG data.
- **Expect:** Deriving human intentions for collaboration, particularly through EEG data (as well as multimodal approaches).
- **NoGravEx:** Development of a learning approach to compensate the individual arm weight for creating a sensation of microgravity.
- **Q-Rock:** Robots learn to perform correct actions based on feedback during interactions, using EEG data to avoid errors.
- **NOE-EMY:** An adaptive foot orthosis capable of recognizing movement intentions through multi-electrode systems on the thigh.
- **RoSylerNT:** Interactive robotic training systems designed for physical and cognitive stimulation, adapting through biomechanical models.
- **PhysioMio:** Adaptive soft exoskeleton to assist physiotherapy following a stroke.