FIT4MEDROB

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RTA4 - AI, CONTROL AND EXTENDED REALITY FOR HEALTHCARE ROBOTS #1

Piano Nazionale Complementare (PNC) – Decreto Direttoriale n. 931 del 6 giugno 2022 – Avviso per la concessione di finanziamenti destinati ad iniziative di ricerca per tecnologie e percorsi innovativi in ambito sanitario e assistenziale
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Duration: 44 months
Website: www.fit4medrob.it

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DISSEMINATION LEVEL OF DELIVERABLE		
PU	Public, fully open, e.g. web	**X**
CO	Confidential, restricted under conditions set out in Partners Agreement	

PNC

Piano nazionale per gli investimenti complementari al PNRR

Ministero dell'Università e della Ricerca

History of Changes

VERSION	SUBMISSION DATE	CHANGES
1.0	30/11/2023	First version
1.1	20/09/2024	Executive summary modified following reviewers' suggestions.

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1 Executive Summary

Mission 3 is devoted to support **frontier research topics** pertaining to physical and computational aspects of robot *bodies*, robot intelligence, and interfaces with the patient. Seven research topics (RTa1…RTa4, RTb1..RTb3) are articulated in 19 sub-projects, running in parallel and covering complementary enabling technologies in the field of robotics and biorobotics.

Research Topic a4 is defined by a convergence of artificial intelligence (AI), robot control methodologies, and extended reality (XR) in the design of next-generation healthcare robots. It combines four sub-projects —**IMPLANT**, **EXODAI4**, **DUAL-Cereb-Control**, and **COGBMI-XR**—each advancing complementary aspects of human-robot interaction for medical and assistive applications. All are characterized by the integrated use of artificial intelligence techniques, robot control approaches, and advanced human-robot communication technologies to power the next generation of health care robots.

RTa4 plays a *pivotal strategic role*: it is the interface between core robotic capabilities and human-centered applications. It transitions hardware advances (prototypes, materials, sensors) into intelligent, adaptive, and intuitive systems capable of effective integration into rehabilitation, surgical, and assistive contexts. RTa4 serves as the cognitive and interactive layer of the broader Fit4MedRob vision.

In **IMPLANT**, the focus is upper limb prosthetics (ULP), and in particular on developing novel control strategies leveraging force information and predicting user intentions to aid in the use of bimanual tasks. The main hypothesis of the study is that such information should improve the learning curve associated to the use of the prosthetic device.

EXODAI4 aims at the development of innovative control techniques to be implemented in commercial technologies and prototypes for the support and assistance of individuals with varying degrees and severities of motor difficulties.

DUAL-Cereb-Control is aimed at developing a neuro-inspired controller for sensorimotor learning and control, based on specific brain neural structures and their dynamics. The focus will be on a computational architecture employing a tandem configuration of forward and inverse internal models.

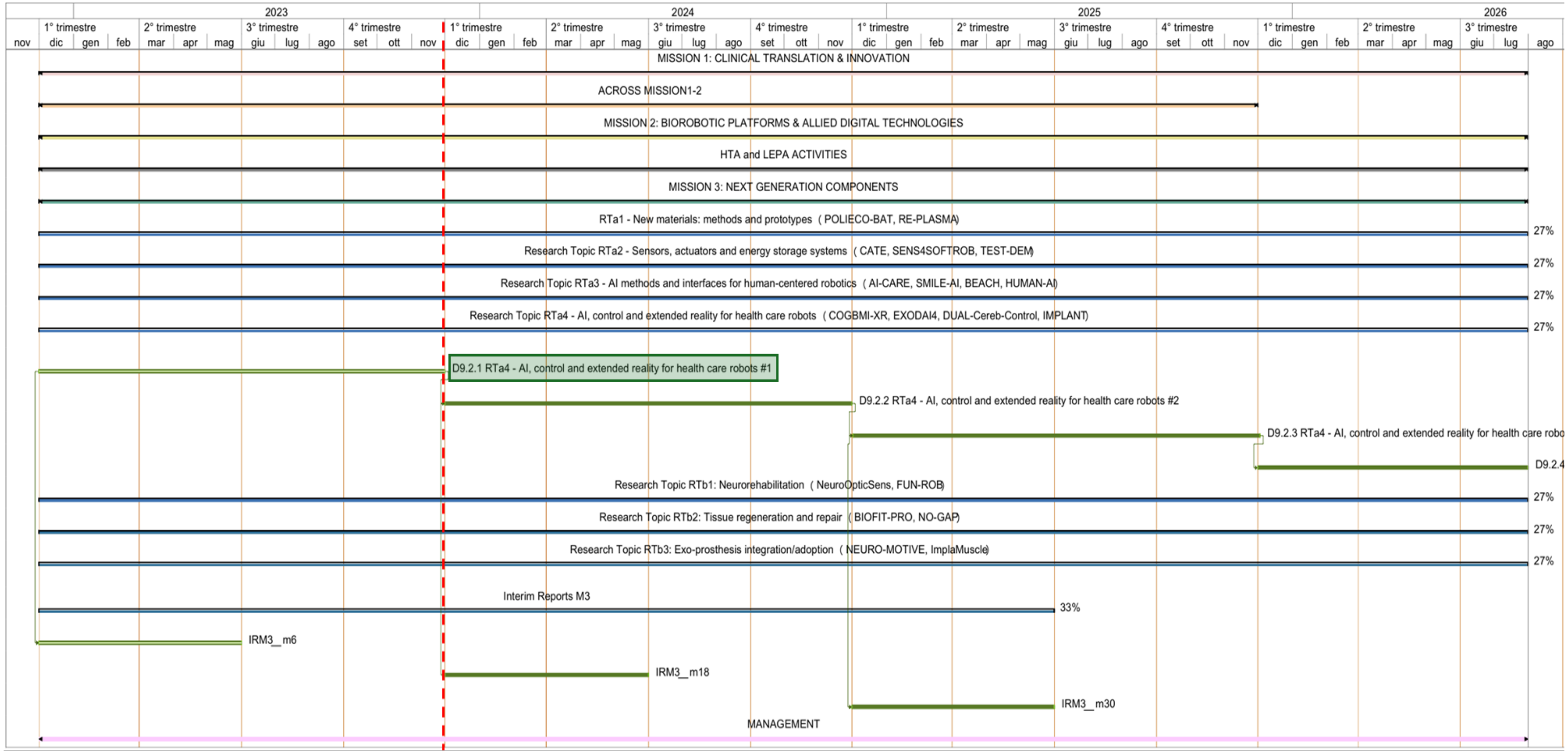
Finally, **COGBMI-XR** aims at designing a hardware and software platform intrinsically leveraging XR technology to support human-robot communication using body-machine and/or brain-computer interfaces. In this context, it will be necessary to design and implement techniques for modulating control actions leveraging principles related to physical and cognitive ergonomics, which are informed by state-of-the-art techniques to measure the stress level of the person controlling the robot. Therefore, it will be necessary to develop robot-agnostic control techniques.

Each of the RT4 projects advances a core pillar of the Fit4MedRob vision:

Project	**Focus Area**	**Strategic Pillar**
IMPLANT	Motor recovery and neuroplasticity	Rehabilitation Technology
EXODAI4	Adaptive exoskeleton control	Personalization & Data-Driven Design
DUAL-Cereb-Control	Bioinspired cognition & learning	Neuroscience-AI Convergence
COGBMI-XR	BCI, XR, stress-aware control	Cognitive Human-Robot Interfaces

Together, they act as the connective tissue between the initiative’s technical capabilities and its clinical, ethical, and societal impact. Moreover, they align with the PNC’s priorities of translational innovation, accessibility, and digital health infrastructure. This Deliverable hence represents a strategic map outlining how robotics, AI, neuroscience, and human factors will converge to transform healthcare. The integration of cutting-edge computational paradigms with human-centered design underlines RTa4’s role as the intelligence core of Fit4MedRob.

In the following page is provided the Gatt chart.


2023
2024
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1° trimestre
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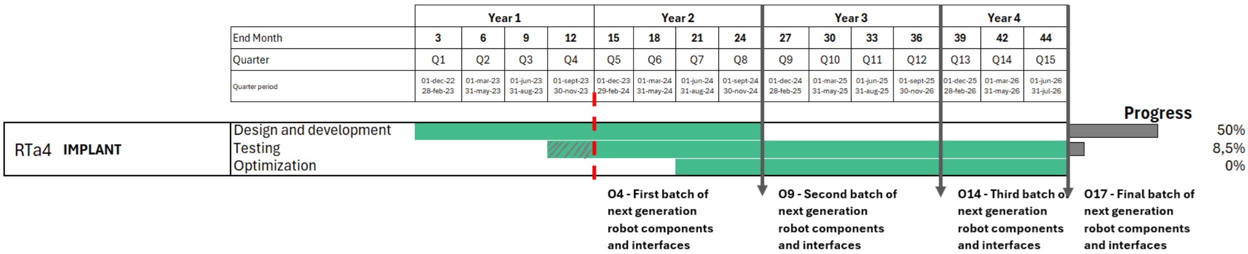
nov dic gen feb mar apr mag giu lug ago set ott nov dic gen feb mar apr mag giu lug ago set ott nov dic gen feb mar apr mag giu lug ago set ott nov dic gen feb mar apr mag giu lug ago
MISSION 1: CLINICAL TRANSLATION & INNOVATION
ACROSS MISSION1-2
MISSION 2: BIOROBOTIC PLATFORMS & ALLIED DIGITAL TECHNOLOGIES
HTA and LEPA ACTIVITIES
MISSION 3: NEXT GENERATION COMPONENTS
RTa1 - New materials: methods and prototypes (POLIECO-BAT, RE-PLASMA)
27%
Research Topic RTa2 - Sensors, actuators and energy storage systems (CATE, SENS4SOFTROB, TEST-DEM)
27%
Research Topic RTa3 - AI methods and interfaces for human-centered robotics (AI-CARE, SMILE-AI, BEACH, HUMAN-AI)
27%
Research Topic RTa4 - AI, control and extended reality for health care robots (COGBMI-XR, EXODAI4, DUAL-Cereb-Control, IMPLANT)
27%
D9.2.1 RTa4 - AI, control and extended reality for health care robots #1
D9.2.2 RTa4 - AI, control and extended reality for health care robots #2
D9.2.3 RTa4 - AI, control and extended reality for health care robo
D9.2.4
Research Topic RTb1: Neurorehabilitation (NeuroOpticSens, FUN-ROB)
27%
Research Topic RTb2: Tissue regeneration and repair (BIOFIT-PRO, NO-GAP)
27%
Research Topic RTb3: Exo-prosthesis integration/adoption (NEURO-MOTIVE, ImplaMuscle)
27%
Interim Reports M3
33%
IRM3_m6
IRM3_m18
IRM3_m30
MANAGEMENT

IMPLANT progress

The timeline of the project IMPLANT is represented by the blue lines in the Gantt below.

The “Design and Development” Task is devoted to i) develop the stiffness modulation strategy for prosthesis joints through EMG, ii) introduce virtual reality and non-invasive brain modulation for improving the learning process of the prosthesis users, iii) investigate cortical organization in prosthesis users and the effects of different rehabilitation interventions through MRI. The **“Design and Development”** phase is **50%** advanced compared to the planned Gantt (green line). A literature review of human joint stiffness estimation methods was carried out to identify the most appropriate methods for the intended application. The **"Testing"** phase is about **8,5%** ahead of the planned activities according to the Gantt.

The **“Optimization”** activity has **not yet started**, according to the Gantt.

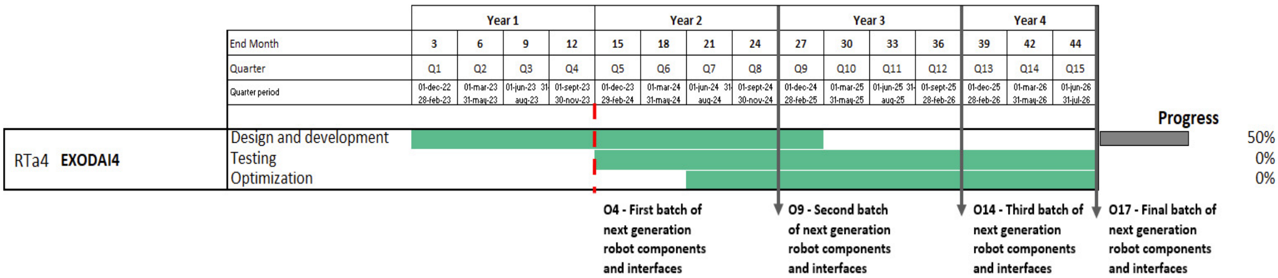


There are no deviations on the original plan and the research is progressing as originally foreseen.

EXODAI4 progress

The timeline of the project EXODAI4 is represented by the blue lines in the Gantt below. Specifically, “Design and Development” is referred to the design of the experimental protocol to test the exoskeleton technology and its advantages on subjects affected by SLA (flair leg and flair arm). One of the objectives of the project is to improve the state-of-the-art experimental protocols used for the specific pathology treated with different kind of rehabilitation technologies and to introduce innovative performance metrics from both exoskeletons and users to evaluate the goodness of robot-assisted rehabilitation. The **“Design and Development”** phase is **50%** advanced compared to the planned Gantt (green line). We have performed a literature review to select clinical cases to study and technologies to use.

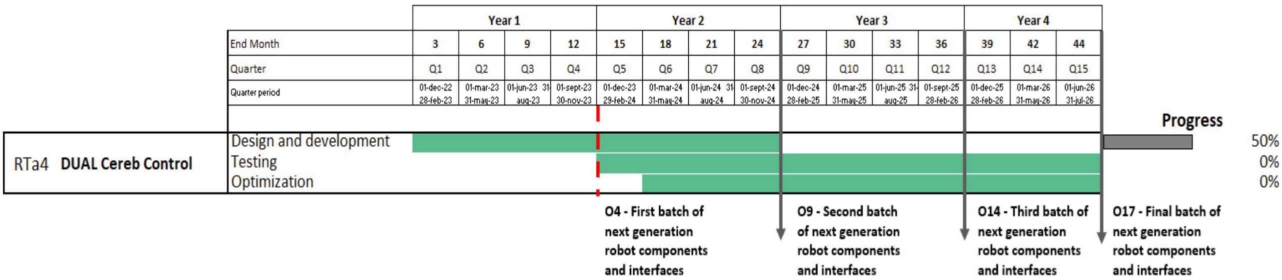
The **“Testing”** and **“Optimization”** activities have **not yet started** from Gantt.



There are no deviations on the original plan and the research is progressing as originally foreseen.

DUAL-Cereb-Control progress

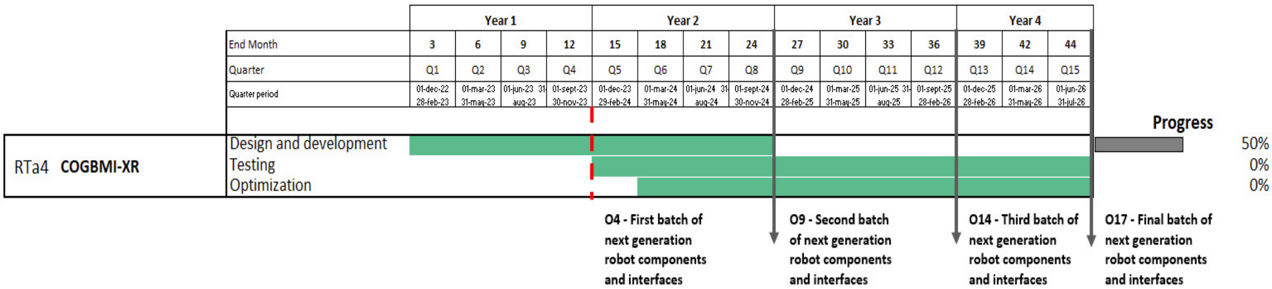
The timeline of the project DUAL-CEREB-CONTROL is represented by the blue lines in the Gantt. Specifically, “Design and Development” has been mainly focused on the architecture design and implementation of single spiking components of the brain-inspired sensorimotor control system. Ad-hoc long-term plasticity rules for cerebellar blocks, with labeling of specific spike types, are under refinement. The **“Design and Development”** phase is **50%** as planned by Gantt. The **“Testing”** phase, focused on a preliminary version of the control system, and the **“Optimization”**, focused on tuning parameters regulating plasticity rule rates and initial synaptic weights, **have to start**.



There are no deviations on the original plan and the research is progressing as originally foreseen.

COGBMI-XR progress

In the Gantt below, the current timeline of COGBMI-XR is represented using a dashed red line. The first activity **"Design and development"**, is focused on the design and implementation of the whole software framework, specifically focusing on open and interoperable components. The software architecture, entirely open-source, leverages the ROS/ROS2 frameworks and integrates non-ROS components through multiple Kafka-based interface adapters. This setup allows seamless communication with XR systems like the Microsoft HoloLens 2 and custom hardware such as IMU-equipped devices using serial connections. It is also compatible with various robotic platforms, including the Tiago++ by PAL Robotics and Franka Emika manipulators. This phase is complete at **50%** according to the Gantt. The second activity, namely **"Testing"** is aimed at a validation of the whole architecture, both in terms of functional and non-functional design specifications, and **is going to start**. The **"Optimization"** activity **has yet to start**: the plan is to update and improve the whole architecture also on the basis of the outcome of the "Testing" activity.



There are no deviations on the original plan and the research is progressing as originally foreseen.

2 IMPLANT: UPPER LIMB PROSTHESIS CONTROL AND TRAINING

The upper limbs let the human being interacting physically with the environment, in terms of execution of the Activities of Daily Living (ADLs) and social connections (Jang et al., 2011). Therefore, traumatic events which lead to the loss of upper extremities, generate severe consequences from a functional and social point of view.

Myoelectric prostheses constitute one of the most promising solutions for regaining hand functionality after upper limb amputation. They rely on the collection of electromyographic (EMG) data obtained by the contraction of stump muscles. These data are processed and then used to decode gestures (such as hand opening/closing, wrist flexion/extension, and wrist pronation/supination), allowing for the control of the prosthetic device.

Despite several advancements have been made in the field of prosthetic devices, myoelectric prostheses are still far to replace the complete functionality of the lost limbs, especially in cases of proximal amputation, such as transhumeral amputation or shoulder disarticulation, where the simultaneous control of multiple joints should be performed (Leone at al., 2022). Bimanual tasks are particularly challenging since the prosthesis user must control the artificial limb to coordinate its movements with the ones of the sound limb also changing its stiffness during task execution.

One of the main drawbacks of myoelectric prosthesis consists in the training procedure, which requires the collection of a great amount of data and that severely affects the performance of the device. This step is crucial to obtain high and reliable performance of the decoder, thus user engagement during this phase is critical.

2.1.1 Main goals

IMPLANT aims at advancing upper limb prosthetics for above elbow amputations by proposing new strategies to address current limitations. The project will use muscular activity to estimate joint stiffness and to develop a control strategy using force information, that is, force level intention retrieved from muscles, to adapt joint stiffness during bimanual tasks. Furthermore, IMPLANT will improve the learning process of prosthetic users, by exploiting techniques specifically aimed at maximizing user engagement (for example, virtual reality) and at promoting neuroplasticity (for example, non-invasive brain modulation). The prosthetic device used will be a poly-articulated myoelectric prosthesis jointly developed by the Italian Institute of Technology (IIT) and the Istituto Nazionale per l'Assicurazione contro gli Infortuni sul Lavoro (INAIL).

2.1.2 Literature analysis

2.1.2.1 Joint stifness estimation methods

For many individuals who have undergone transhumeral amputation, the experience of living with a prosthetic limb can be marked by a persistent frustration and dissatisfaction with the functionality of their artificial limb. One of the key factors contributing to this discontent is the inherent limitations in control that prosthetic arms often present. The ability to seamlessly and intuitively control a prosthetic arm remains a significant challenge, hindering the full integration of these devices into the daily lives of amputees. To address this problem a potential solution is an online modulation of prosthesis stiffness to naturally manage interaction with external environment, especially when performing bimanual tasks or interacting with people. By implementing this method, it becomes possible to adapt the stiffness of prosthetic limbs to mimic the natural behaviour of human joints, thereby enhancing the functionality and usability of these devices.

Stiffness estimation is an essential first step for a successful control of the prothesis. The first step of the project was to analyse the various estimation methods available in the literature to identify the most appropriate one for our application.

A literature review was therefore conducted using the PubMed, IEEE Xplore and Scopus database by combining the following keywords and logic operators: "Joint" AND ("Stiffness" OR "Impedance") AND ("Estimation" OR "Assessment"). The following inclusion criteria were applied:

- full-length publication in a peer-reviewed journal;
- only human joint stiffness publications were considered;
- upper/lower limb stiffness article were included.

The search strategy followed the PRISMA (which stands for "Preferred Reporting Items for Systematic Reviews and Meta-Analysis"; Page et al., 2021) guidelines, as illustrated in **Figure 1**. The identified studies were later subjected to a screening process to ascertain adherence to the eligibility criteria.

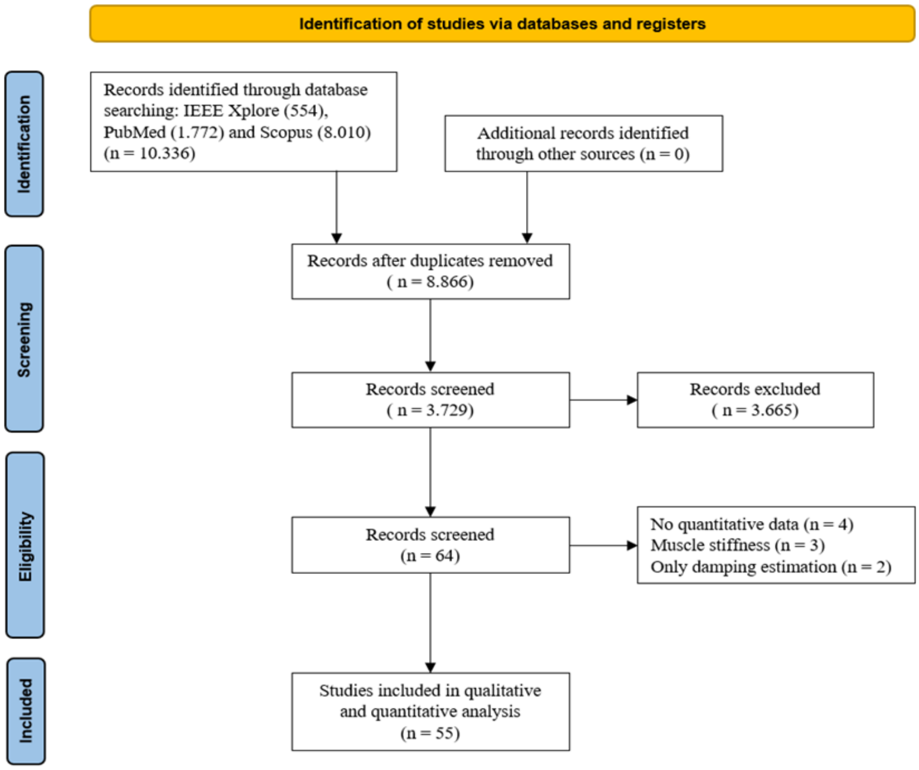


Fig. 1 - PRISMA flowchart of the search and inclusion process.

These studies used different stiffness estimation methods that can be summarised by using the graph reported in **Figure 2**. Stiffness estimation methods can be classified as either indirect or direct. Indirect methods estimate joint rigidity through perturbation applied by an external device (Perreault et al., 2021), whereas direct methods derive joint stiffness from the user's intention retrieved by electromyographic (EMG) signals (Gomi and Kawato, 1997). These two categories can be distinguished based on the type of stiffness under investigation, namely, passive or active. Passive stiffness is assessed when the joint of the individual is relaxed (without muscle contraction; Formica et al., 2012; Kuxhaus et al., 2014; Lee and Ashton-Miller, 2015), while active stiffness is evaluated when the individual voluntarily contracts the muscles (Phan et al., 2020). Indirect active stiffness, on the other hand, involves static or dynamic evaluation, with the former refers to isometric contraction, while the latter involves point-to-point movements. Instead, direct active stiffness can be estimated by using Machine Learning algorithms, such as Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs), or the Hill model algorithm which considers all (OpenSim) or a few (Dynamic Model) of the muscles involved in joint movement.

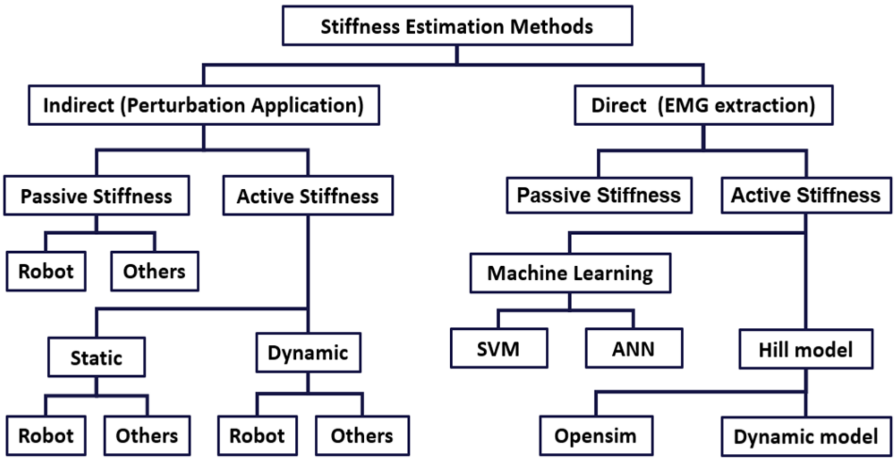


Fig. 2 - Classification of the Stiffness Estimation Method.

Methods based on Machine Learning are used to estimate the force exerted by the muscles involved in joint movements. A dynamic model is then used to calculate the joint stiffness. Bambad et al. (2022) applied this approach to estimate the muscle force of the knee by using a Support Vector Regression (SVR) algorithm. The joint stiffness is estimated by the application of the knee dynamic model. Tests were conducted on the right leg of a healthy individual during isometric contraction and the application of perturbation by a single-axis actuator module. The obtained results showed that the Machine Learning algorithm was able to accurately estimate the knee torque when compared to measurements from a torque sensor.

To estimate human joint stiffness using the Hill model, it is necessary to calibrate the EMG-driven model to find the appropriate Hill parameters for each volunteer. The dynamic model used only a few muscles that contribute to the joint movement, but it is always necessary to find out the Hill model parameters of the involved muscles. Radmilovic et al. (2023) presented a study investigating a general methodology for assessing individual-specific elbow joint stiffness and predicting non-measurable parameters of the elbow antagonist muscles (biceps and triceps). More in detail, a genetic algorithm was used to estimate biceps and triceps model parameters during elbow dynamic movements (that is, the modified Wolf motor function test). The results showed that the estimated Hill parameters of biceps and triceps were different from the ones provided by the literature. Instead, Cop et al. (2022) used an OpenSim model to estimate ankle stiffness during flexion-extension movements and compared the output of the same model but with different types of reference for calibration. More specifically, the first calibration takes as input the ankle torque provided by the individual during the movement, whereas the second calibration uses the torque but also the stiffness of the joint, obtained by means of the perturbation method. Then, the two models were validated by comparing their output to reference data obtained through the perturbation method. The obtained results indicate that the model calibrated with torque-stiffness reference is more accurate than the one using only torque as reference.

The performed analysis will guide the next step of IMPLANT, that is, the implementation of a direct active stiffness method that will take into account the contribution of the upper-limb residual muscles of a transhumeral amputee.

2.1.2.2 Use of neuromodulation during training of prosthetic users

A significant proportion of myoelectric prostheses users, up to 44%, discontinue their use primarily due to socket discomfort, prosthetic weight, and long training protocols (Salminger et al., 2022). In this regard, there are several techniques still under-research in the context of upper limb prosthesis control, and that can be used to address these issues. Particularly, we conducted a literature search aimed at identifying neuromodulation strategies adopted in the context of myoelectric prosthesis use.

We focused mainly on transcranial electrical stimulation (tES) techniques, such as transcranial direct current stimulation (tDCS), because they have recently gained significant attention in the field of cognitive neuroscience and neurorehabilitation due to its potential to enhance cognitive functions (such as memory; Bjekić et al., 2022) and facilitate learning processes (including skill acquisition and motor learning; Qi et al., 2022). Moreover, they emerged as potential solutions, thanks to their low cost, versatility, and portability (Pan et al., 2015).

tES is a non-invasive brain stimulation technique that involves the application of weak electrical currents to the scalp to modulate brain activity. So far, research suggested that anodal tDCS, that is, delivering of current from the anode to cathode electrode, can enhance motor cortex excitability and improve motor function, mainly in stroke patients and healthy individuals (Hummel et al., 2017). Few studies focused on amputees, proposing that tDCS could potentially “awaken” frozen phantom limb movement representations, accelerate the relearning process, and improve the quality of EMG signals (Pan et al., 2017). This, in turn, could shorten the training phase and reduce its complexity for myoelectric prosthesis control. Specifically, (Pan et al., 2015) adopted an anodal tDCS intervention on the contralateral primary motor cortex with respect to the affected side. This approach significantly enhanced EMG classification performance for the affected side of the amputees. In another work, Pan et al. (2017) tested both user training (UT) and tDCS training independently, and in combination. They concluded that there was no significant difference in the classification performance between the tDCS with UT intervention and the tDCS without UT intervention. However, both interventions showed significantly better classification performance compared to the UT intervention. More recently, Hordacre et al. (2016) highlighted the potential of non-invasive brain stimulation as a tool for improving functional outcomes in lower limb amputees.

To conclude, abovementioned research suggests that cortical reorganization occurring after amputation is associated with functional outcomes in amputees and could be a suitable focus for innovative interventions. Previous studies have demonstrated that non-invasive neuromodulation techniques can be utilized to specifically enhance neuroplasticity in cortical representations related to lower limb function, resulting in improvements in overall functionality (Hordacre et al., 2016). Since tES has also been highlighted as potential shortening the learning period for amputees (Pan et al., 2015), IMPLANT could prove the capability of neuromodulation techniques to enhance functional outcomes in ULP too.

It emerges that, based on the literature, there are two possible spots from where applying neuromodulation:

- primary motor cortex (M1), with the anodal electrode placed over C3 or C4 (international 10/20 EEG system). The other electrode placed over the contralateral supraorbital area, and
- attentive networks.

As for what concern quantitative assessment for evaluating our approach effectiveness, we will measure both cortico-spinal (motor evoked potentials - MEPs), as well as cortical (thanks to EEG) indices.

The first refers to stimulate noninvasively the motor cortex, while the resulting responses (in terms of amplitude) are monitored in peripheral muscle groups (at the stump level), via EMG sensors. In our case, this measure will be recorded both pre and post intervention, and an increase in amplitude is expected, since MEPs have been proven to have excellent sensitivity for monitoring the functional integrity of the corticospinal tract.

As for EEG, we will measure EEG functional connectivity in resting state recordings (RS-EEG), both pre and post training, as a measure of cortical plasticity changes and motor learning.

2.1.2.3 Possible neuromodulation systems

During the first months of IMPLANT, we considered several systems for recording brain signals with EEG and for stimulating the brain cortex. We thus conducted a market search and interviewed several colleagues in our network using such devices to evaluate the best options for our purposes.

We finally selected the mBrainTrain (MBT) system, (device: Smarting PROX 64 channels) for EEG recording and the Soterix System for neuromodulation due to its better balance between cost and performance.

2.1.3 Work in progress

2.1.3.1 Clinical protocol preparation

We submitted a clinical protocol to the ethical committee of Budrio. This protocol foresees the training of 7 prosthetic users with the Hannes hand with 3 degrees of freedom (DoF). During the training, volunteers will undergo a short session of neuromodulation to test: (i) the feasibility of neuromodulation during prosthetic training; (ii) the efficacy of the method in short-term learning; (iii) user acceptance. Before and after the training, volunteers will undergo a short session of EEG recording during resting state. Brain connectivity measures will be extracted and correlated with scores in tests and questionnaires with the aim to extract brain-related metrics of training.

We are preparing another clinical protocol to be submitted at the ethical committee of Regione Liguria. This protocol foresees the collection of several signals (EEG, EMG, kinematics) during reaching and grasping with the upper limb. Both healthy volunteers and amputees will participate to the study. The aim is to extract metrics that can be related to movements performed with the natural or phantom limb and thus to the embodiment process taking place during prosthetic use.

The next phase of IMPLANT will be devoted to performing a biomechanical analysis of the human behaviour during bimanual tasks and ADLs both on healthy volunteers and on above elbow prothesis users to extract performance indicators related to arm kinematic, dynamic, and muscular activity. Furthermore, the stiffness estimation strategy will be developed and tested in simulation and on healthy participants.

Data collection and analysis will be performed to test neuromodulation and the training process.

3 EXODAI4: EXOSKELETON OPTIMIZATION & CONTROL BY DATA & ARTIFICIAL INTELLIGENCE 4.0

This project brings together different research areas, among which medical and wearable robotics, statistics, data science, and medicine stand out. Therefore, it sees involved: Fanny Ficuciello, professor of automation and robotics at the University of Naples Federico II; Roberta Siciliano, professor of statistics at the University of Naples Federico II; Francesco Amato, professor of electronic and computer bioengineering at the University of Naples Federico II; Giovanni Acampora, professor of computer science at the University of Naples Federico II; Michele Staiano, statistics researcher for experimental and technological research at University of Naples Federico II; Nicola Vitiello, professor at the BioRobotics Institute of the Scuola Superiore Sant'Anna where he is Co-PI of the wearable robotics laboratory. The project aims to address neurological impairments by leveraging robotic rehabilitation, particularly through the utilization of exoskeletons, with the overarching goal of improving mobility and enhancing the quality of life for individuals affected by debilitating conditions such as stroke, spinal cord injury, and multiple sclerosis. Despite the potential benefits offered by exoskeletons, several challenges remain prevalent, including issues related to weight, comfort, control systems, safety, and costs. To tackle these challenges, the project focuses on comprehensive approaches encompassing dataset collection, optimization, and control strategies. The initiative kicks off with foundational research delving into the intricacies of exoskeleton structures, intelligent control mechanisms, and human-robot interfaces. A pivotal aspect of this phase involves the gathering of data from both exoskeletons and users, including vital bio signals, which in turn aids in refining technologies and protocols. The project timeline encompasses activities such as the evaluation of sensor and exoskeleton technologies, selection of pertinent bio-signals, development of control strategies, and subsequent testing on both commercial and prototype platforms. Anticipated outcomes include achieving a Technology Readiness Level (TRL) of 3/4, validating experimental proof of concept and efficacy. In parallel, clinical case studies, primarily focusing on patients with Amyotrophic Lateral Sclerosis (ALS), are conducted to evaluate the effectiveness of wearable technology, experimental protocols and control techniques. Additionally, analyses of various technologies help identify exoskeletons best suited for different phenotypes.

In recent decades, in the field of assistance and rehabilitation robotics, new technologies such as exoskeletons have made their debut, the applications of which are constantly growing due to the advantages they bring to patients and users in general, whether they are frail people or workers. Exoskeletons are devices that can enhance or augment human physical capabilities. The industrial sector is the fastest growing in the development of exoskeletons: in this regard, we can consider those wearable devices that support operators in performing physically demanding tasks, such as carrying or lifting heavy weights. Alongside the industrial sector is the biomedical sector, which includes those exoskeletal devices whose purpose is to improve the physical condition of people with temporary or permanent disabilities of the upper and/or lower limbs.

Therefore, exoskeletons can effectively provide a wide range of benefits: in industrial settings, they can reduce workers' risks of injuries and increase their productivity; while in medical applications, they can effectively improve the motor skills of people with physical impairments. However, there are some limitations such as the design that, to provide sufficient power, does not provide enough lightness and comfort to allow long-term wear; they also require complex control systems, to ensure that the movements of the wearer are synchronized with the movements of the exoskeleton; safety and costs are other important limitations.

Despite challenges, this technology is increasing rapidly, and research is mainly focusing on the development of lightweight materials and new control strategies, to make these devices more comfortable and capable to adapt to the wearer's movements, new power sources, and sensors, development of testing and validation protocols to ensure their safety, effectiveness, and usability in real-world applications.

3.1.1 Main goals

The goal of EXODAI4 is the development of innovative control techniques to be implemented in commercial technologies and prototypes for the support and assistance of individuals with varying degrees and severities of motor difficulties. To achieve this final objective, specific activities are in order:

- Literature review on the current state of the art regarding technologies currently available on the market and in use with patients, the types of patients for whom they are intended, and the types of data collected for analysis.
- Selection of bio-signals (that is, EMG, EEG, EOG, ECG, etc.) of greatest interest for synergistic human-machine control, followed by the definition of the most suitable protocols for the detection and interpretation of these signals.
- Selection of the best statistical and artificial intelligence approaches to process and classify the extracted bio-signals. Through these approaches, it will be possible not only to improve the definition of experimental protocols and data acquisition but also to evaluate the results obtained, providing insights into potential system enhancements and the development of new human-in-the-loop control algorithms.
- Clinical evaluation on patients with specific pathologies with motor deficits, to assess the effectiveness and usability of the exoskeletons and control techniques employed.

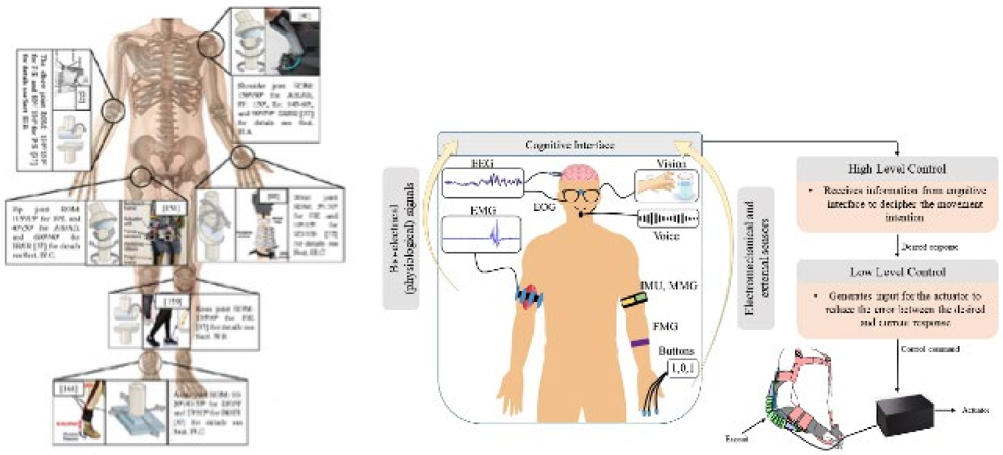


Fig. 3 - Categorization according to the intended assisted joint (on the left) and overview of a cognitive interface and framework (on the right).

3.1.2 Literature analysis

The analysis of the state of the art regarding the design and control techniques in the field of soft wearable systems for assistance and rehabilitation has been submitted for publication.

The first submission focuses on the two main components of a soft exoskeleton: the actuation mechanisms for generating forces and torques, and the physical interfaces that anchor the robot to the user's body. The submission analyses the progress made in these two areas, categorizing systems based on which joint is assisted (**Figure 4.**), the number of active degrees of freedom (DOFs), and the type of device. The objective of this work is to establish concepts for developing an assistive system capable of supporting multiple anatomical joints while maintaining a compact form factor, a simple and intuitive interface, and user comfort.

The second submission, on the other hand, focuses on the two main aspects of the human-robot cognitive interface (**Figure 3** on the right): how to detect the user's intentions and how to plan movement and control based on this detection. The classification is made based on high and low-level controls, with a further sub-classification based on the cognitive interface. The future aim of this work is to develop a control system based on intention and context detection to manage various degrees of freedom simultaneously and continuously.

Additionally, two more papers are under development aimied at covering specific aspects. In particular, the first will focus on the use of bio-signals in rehabilitation and tele-rehabilitation systems, while the latter on the use of artificial intelligence for the analysis and interpretation of bio-signals.

3.1.3 Work in progress

3.1.3.1 Data collection

In this context, collecting data is fundamental, not only to understand devices' effectiveness and to improve the technology but also to improve application protocols and to understand which technology best face a particular category of people. These data can be collected using appropriate sensing devices, either directly from the exoskeletons or the users, and by the development of dedicated protocols. Data from users allow us to assess important aspects such as the level of stress during usage, the muscles fatigue, and the actual improvements in terms of performance.

EXODAI4 aims to collect data from the exoskeletons and biosignals from users using ad hoc protocols. The collected data can be then processed and used for various purposes such as technology assessment, protocol assessment, development of innovative control algorithms with the human in the loop. The studies will be initially conducted on devices for commercial use, but the possibility of collecting data on research devices is not excluded.

The goal is the generation of a large dataset, whose public disclosure would be one of our further objectives. This last aspect is key to encourage and increase collaboration, reproducibility, accessibility, and transparency among different research institutions. Specific technical solutions, as eg. data lake platforms, will be considered.

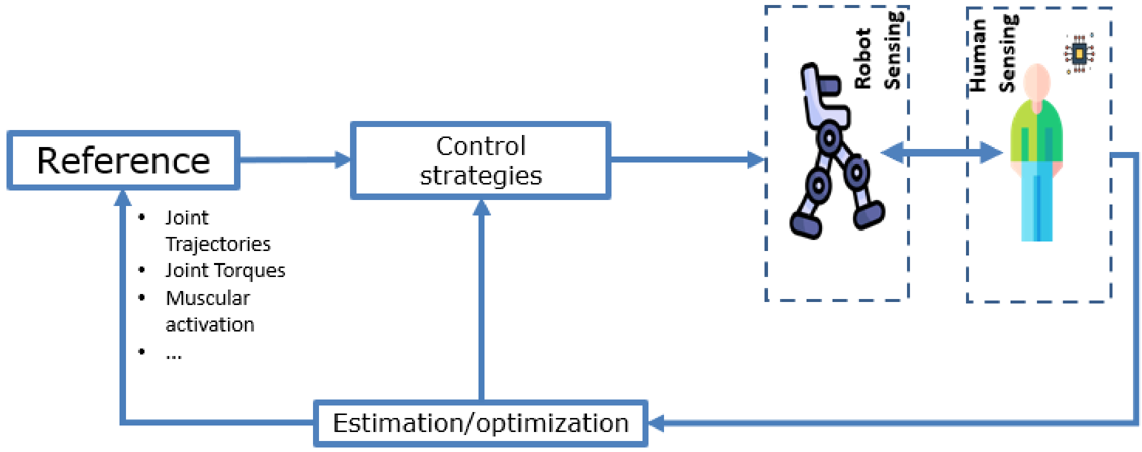


Fig. 4 - Control scheme.

3.1.3.2 Optimisation and control aspects

To fit exoskeletons (commercial ones as well as prototypes under study) to the specific needs of a patient for rehabilitation or empowerment, statistical learning and computational intelligence competencies will synergize toward a meta-control strategy. The approach to the development of such a strategy is based on three steps:

1. develop specific solutions for understanding what the human needs/desires;
2. capturing and representing how the coupled system (human/exoskeleton) works and the two components interact, as well as identifying the dynamic models and parameters of both the exoskeleton and the user using the captured dataset (it is necessary to accurately capture and represent the complex interaction of the coupled human-robot system);
3. developing a master controller, capable of supplying the onboard exoskeleton control with optimal parameters, tuned on the patient (inter-patient optimization) and timely recalibrated with respect to their current condition (intra-patient optimization); physicians, patients, caregivers can interact with the meta-control system via computing-with-words, that is, "I want a *smoother* movement", "a *lighter* workout routine", etc.

The specific methodologies to develop the system include:

- statistical and discourse analysis of medical condition and responses to interviews administered to physicians, patients, and caregivers, also by means of factorial analysis to identify the relevant variables and their relationships, as well as clustering techniques to characterize groups of similar individuals;
- training of a suitable Machine Learning models related to the coupled system that will function as a specialized digital twin of the human/exoskeleton;
- development of an optimal control strategy for the system based on fuzzy logic, so that it will be possible to boost the structuring of suitable control rules based on the computing-with-words paradigm and integrating it in a wider AI-based framework for further enhancements; furthermore, the development of a multi-modal shared control approach based on an optimal and adaptive control strategy that incorporates fuzzy logic for optimal parameter tuning and implements a model-based approach to human-robot interaction; the control goals are defined by an AI framework that supports high-level interactions, that is, the computing-with-words paradigm.

The goal of optimization and control is not only the tailoring of the exoskeleton to a patient/user but also making the system adaptive to the specific context and situation they are facing (***Figure 4***). Toward this end the integration within an Internet of Things ecosystem can enable an augmented degree of adaptiveness of the exoskeleton, that is, by a connected onboard control system we can make it possible that the meta-control strategy deployed in cloud will provide on-the-fly recalibration of the exoskeleton parameters with a certain degree of situational awareness (for example, thanks to a smartphone app recognizing the activity ongoing and the level of fatigue of the individual via smart sensors, or even a more widespread set of connected domotic devices when in indoor) upon direct request by the human and remote control by caregivers.

Fig. 5 - Example of assisted walking for a volunteer affected by FL since 2 years (on the top), and examples of two volunteers affected by FA (since 6 years on the bottom left, and 2 years on the bottom right).

3.1.3.3 Clinical case studies

Cardiovascular and neurodegenerative diseases such as heart attacks, Multiple Sclerosis (MS), and Amyotrophic Lateral Sclerosis (ALS) are among the leading causes of severe neurological damage to millions of people each year, resulting in motor and cognitive limitations for years.

In the perspective of evaluating the control and analysis techniques that will be developed, a clinical protocol has been drafted, in collaboration with Dr. Raffaele Dubbioso from the Department of Neuroscience at the Federico II University Hospital, for submission to an ethics committee. This protocol is intended for experimentation using exoskeletons on patients with the specific phenotypes of ALS, treated by Dr. Dubbioso's team.

ALS is a neurodegenerative disease characterized by progressive muscle paralysis that reflects the degeneration of motor neurons in the primary corticospinal cortex, brainstem, and spinal cord. Globally, the disease has an estimated annual incidence of 1.68 new cases per 100,000 people (data updated to 2022; Feldman et al., 2022). Approximately two-thirds of ALS patients present with a spinal form of the disease, developing symptoms related to muscle weakness and atrophy, either distally or proximally, in the upper or lower limbs. Weakened and atrophic limbs can develop spasticity, affecting dexterity and mobility (Wijesekera and Nigel Leigh, 2009). The onset of ALS can occur in various forms, including the 'flail arm' (FA) and 'flail leg' (FL) subtypes, contributing to an average of 13% and 5.5% of cases, respectively. It affects both sexes, with a slight male predominance and an increased likelihood with age (Feldman et al., 2022). The FA phenotype (known as scapulohumeral form) generally presents with progressive weakness and atrophy of the upper limbs, usually symmetric and proximal, without significant functional involvement of the lower limb muscles (Wijesekera et al, 2009). The FL phenotype (known as pseudopolineuritic form) indicates a syndrome of weakening and loss of motor abilities in the lower limbs, often with asymmetric onset, absence of tendon reflexes in the lower limbs, slow progression, but without significant involvement of motor abilities in the upper limbs (Wijesekera et al, 2009).

The collaboration aims to acquire various types of signals (biological and biomechanical) from individuals affected by these two phenotypes with and without the use of exoskeletons. This is done to determine any potential positive effects and simultaneously define a comprehensive dataset of information to enhance the implemented control techniques.

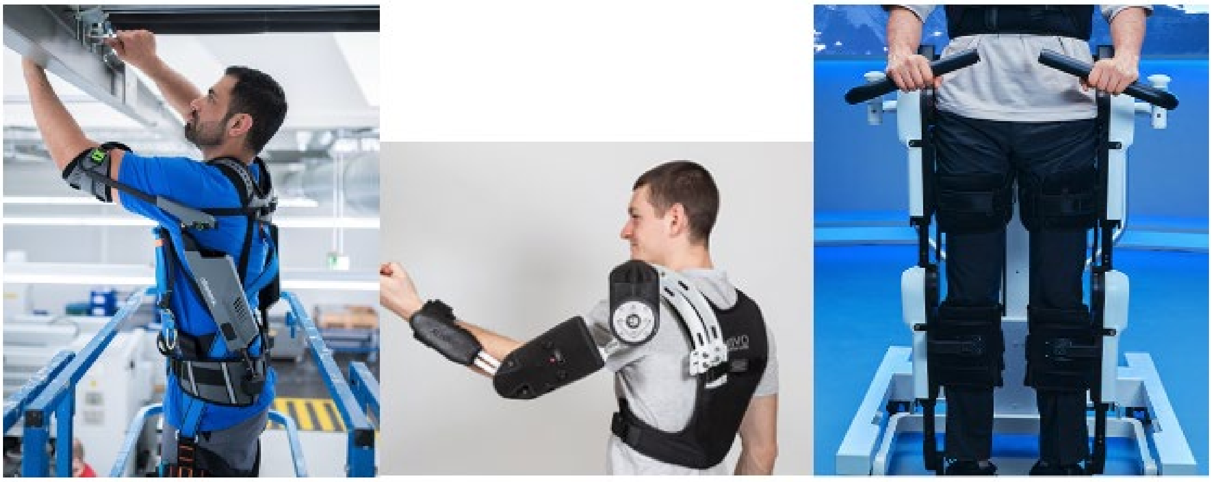


Fig. 6 - Images of the three exoskeletons selected for this study (from left to right): Ottobock Shoulder by SuitX, EduExo Pro by Auxivo, and ExoMotus M4 by Fourier Intelligence.

3.1.3.4 Technological aspects

As part of this experimentation, several commercial wearable devices have been identified for purchase to intervene with these patients. For patients with the FA phenotype, two possible assistive approaches have been considered based on the severity of motor deficits due to the condition. For patients with a wide range of residual movement but a rapid and high onset of fatigue (**Figure 5** on the bottom right), weakness, and muscle pain, a passive support system has been chosen, specifically the Ottobock Shoulder from SuitX (**Figure 6** on the left). This exoskeleton reduces fatigue in the shoulder muscles due to its lightweight design and wide industrial use. In cases of patients with severe limitations in independent range of motion (**Figure 5** on the bottom left), an active, open-source, fully programmable exoskeleton has been selected. It offers active support for 3 degrees of freedom, adaptable sizing, and a mechanical spring that constantly supports the shoulder joint, that is, the EduExo Pro from Auxivo (**Figure 6** in the center). On the other hand, for patients with the FL phenotype (**Figure 5** on the top), the idea of a passive exoskeleton approach has been considered less effective, as these patients quickly lose the ability to stand without support. Therefore, an open-source lower-limb exoskeleton with two degrees of freedom for each leg, an integrated seating system, ankle and foot support, and inertial and torque sensors has been chosen, that is, the ExoMotus M4 from Fourier Intelligence (**Figure 5** on the right).

4 DUAL-CEREB-CONTROL

Humans demonstrate a remarkable ability to generate accurate and appropriate motor behaviour under many different and often uncertain environmental conditions (Wolpert and Kawato, 1998). Robotics offers a potential complementary modelling platform, with advantages such as embodiment and physical environmental interaction yet with easily monitored and adjustable parameters (Pronin et al., 2021). Indeed, roboticists and neuroscientists are interested in understanding and reproducing the neural and cognitive mechanisms behind the human ability to interact with unknown and changing environments as well as to learn and execute fine movements. In particular, the focus is on the system-level neurocomputational models of human motor system: biomimetic models simulating the functional activity of the cerebellum, the basal ganglia, the motor cortex, and the spinal cord, which are the main central nervous system areas involved in the learning, execution, and control of movements. From the beginning of 1970, when the first cerebellar model was realized, up to nowadays, when the embodiment of these models into robots that act in the real world and into software agents acting in a virtual environment has become of paramount importance to close the action-perception-cognition loops. Neurocomputational models have contributed to the comprehension and reproduction of neural mechanisms underlying reaching movements, but much remains to be done because a whole model of the central nervous system controlling musculoskeletal robots is still missing.

The approach of embodiment in neurorobotics derives from the general concept that “Brain is embodied, and the body is embedded in the environment” (Seth et al., 2005; McKinstry et al., 2006). Embodiment of computational neural models in a robot allows for direct sensory-action closed-loop interactions with a real environment as well as with environmental noise, improving the generalizability of experiments to real world scenarios. This can be advantageous for both understanding human cognition and neurological or psychiatric disorders, particularly because the latter are often characterized by behaviour and interaction. It allows precise implementation of theoretical models and consequential controlled manipulation (to investigate disorders implicitly) that is not possible in animal models because of ethical reasons or limited methodology. Robot models increase the replicability of experiments and avoid the issues of individual fatigue.

4.1.1 Main goals

The project DUAL-CEREB-CONTROL aims at developing an efficient neuro-inspired controller for sensorimotor learning and control, based on specific brain neural structures and their dynamics. We will focus on a computational architecture employing a tandem configuration of forward and inverse internal models. It has been shown that patients with cerebellar degenerative diseases show behavioural impairment consistent with tandemly arranged internal models (Honda et al., 2018). These findings validate computational tandemization of internal models in motor control and its potential uses in more complex forms of learning and cognition. The brain represents future states consistent with a class of planning algorithms, and it is a foundation of the coupling between neuroscience and Artificial Intelligence (Mattar et al., 2022).

We will design a physiologically plausible control scheme that embeds a realistic spiking model of the cerebellum into a network of interconnected functional blocks. Each block is associated to a functionally related brain area, and the connections can be validated using the Allen brain connectivity atlas. Specifically, two cerebellar modules will define a forward and an inverse model. The forward model receives an efference copy of the motor commands through the mossy fibers and predicts their sensory consequences (Shadmehr and Krakauer, 2008). Learning is guided by the error in predicting the sensory information, which is fed to the cerebellum through the inferior olives. The inverse model receives the desired motor plan via the mossy fibers and computes the corresponding motor commands in a feedforward fashion [8]. As such, this mechanism allows to adjust the motor commands computed by the motor cortices even before obtaining the sensory information. Learning is therefore driven by the error in executing the desired plan, fed into the cerebellar microcircuit via the inferior olives. The cerebellar models will be endowed with advanced physiologically inspired plasticity rules.

Predicted and actual sensory signals are integrated by the state estimator (presumably located in somatosensory cortices). Using a process of Bayesian integration, the state estimator computes a weighted average of these two sensory signals based on their reliability.

This computational architecture will be embodied into a human-like robotic platform, focusing on specific degrees of freedom depending on the tasks to be performed.

The system controller will be used to explore pathological states in patients with movement disorders involving the cerebellar tandem loops, monitoring both internal parameters and external behaviour with the environment. These models can be potentially used to guide therapeutics and rehabilitation.

Another potential fall-out is to create a patient-specific digital brain twin, through a mapping process on brain atlases. This could pave the way to define a solid infrastructure and tools as the bases for digital clinical trials, to test in-silico interventions (such as neuromodulation techniques) on patient's brain with focus on the motor control system.

The foreseen timeline is:

- Months 1-12: design of the computational architecture and tuning of the cerebellar modules and their plasticity rules.
    - Deliverables: report of the design.
- Months 12-24: embodiment, tests with simple arm-reaching tasks and design of more complex tasks with perturbations.
    - Deliverables: results of task performance.
- Months 24-36: test of pathological states involving the cerebellar tandem loops.
    - Deliverables: use cases on patients with movement disorders.

4.1.2 Work in progress

In these first months of the project:

- We have completed the recruitment: 1 PhD Emiliano Buttarazzi, with a strong background in bioengineering, within the "dottorato nazionale in intelligenza artificiale", starting 1st November 2023.
- We have started the design of the computational architecture.

Figure 7 shows the scheme of the computational architecture, with a "BRAIN" side and a "BODY" side. The brain controller is made up of blocks, working with spiking signals. This brain-like system exploits the neural simulator NEST. The cerebellar networks (inverse and forward models) are generated by a realistic reconstruction workflow able to reproduce its intricate topology (Brain Scaffold Builder; https://www.ebrains.eu/tools/bsb) (De Shepper et al., 2022). Specifically, the cerebellar models will be endowed with long-term plasticity rules to simulate motor learning. The plasticity rules and the single-point neurons representing the different cerebellar neural populations will be tuned starting from previous works on eye-blink classical conditioning driven by spiking cerebellar networks (Geminiani et al., 2022).

The body and environment will be modelled exploiting Python libraries such as pyBullet. Communication between physics engine and brain-like system exploits MUSIC; MUSIC libraries are used to interface the two sides, allowing synchronisation among asynchronous processes.

We are defining descending signals as forces or torques, acting on simple rotational joint(s) (rigid rod connected to mechanical ground, single or double pendula), signals fed back may include joint angle and angle velocity.

We are focusing on a simple task: arm reaching. This way, we tackle the open issue about the deep understanding of upper-limb movements via neurocomputational models of sensorimotor system and neurorobotics.

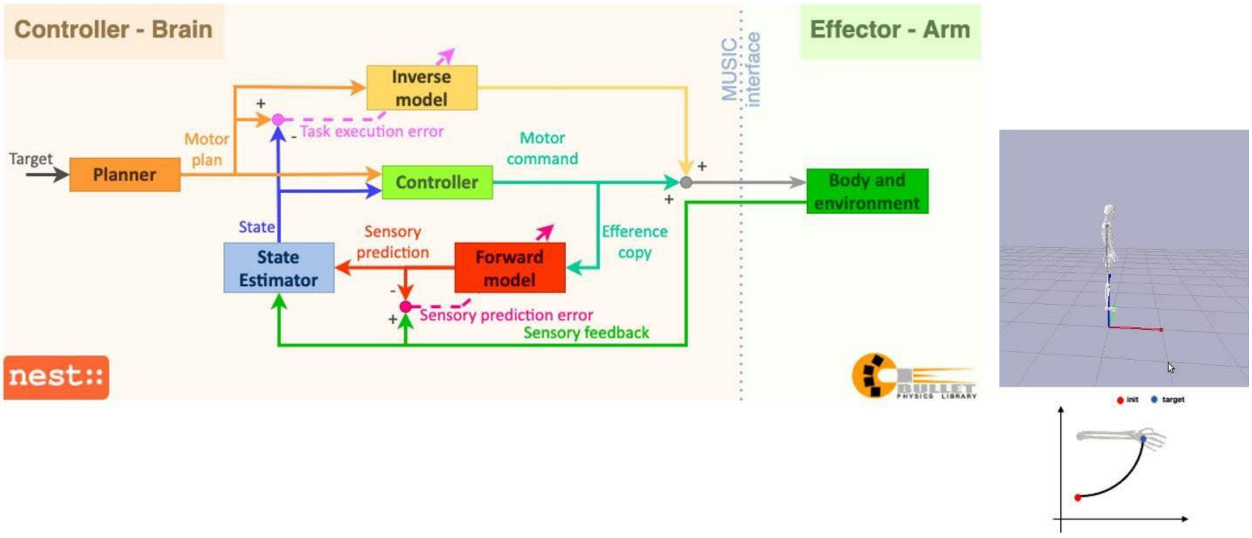


Fig. 7 - Scheme of the computational architecture. The brain blocks and the body blocks. Concerning the "state estimator" block, a spiking Bayesian network has been developed by our group.

We associate each block to a functionally related brain area and validate the proposed connections using the Allen brain connectivity atlas (**Figure 8**).

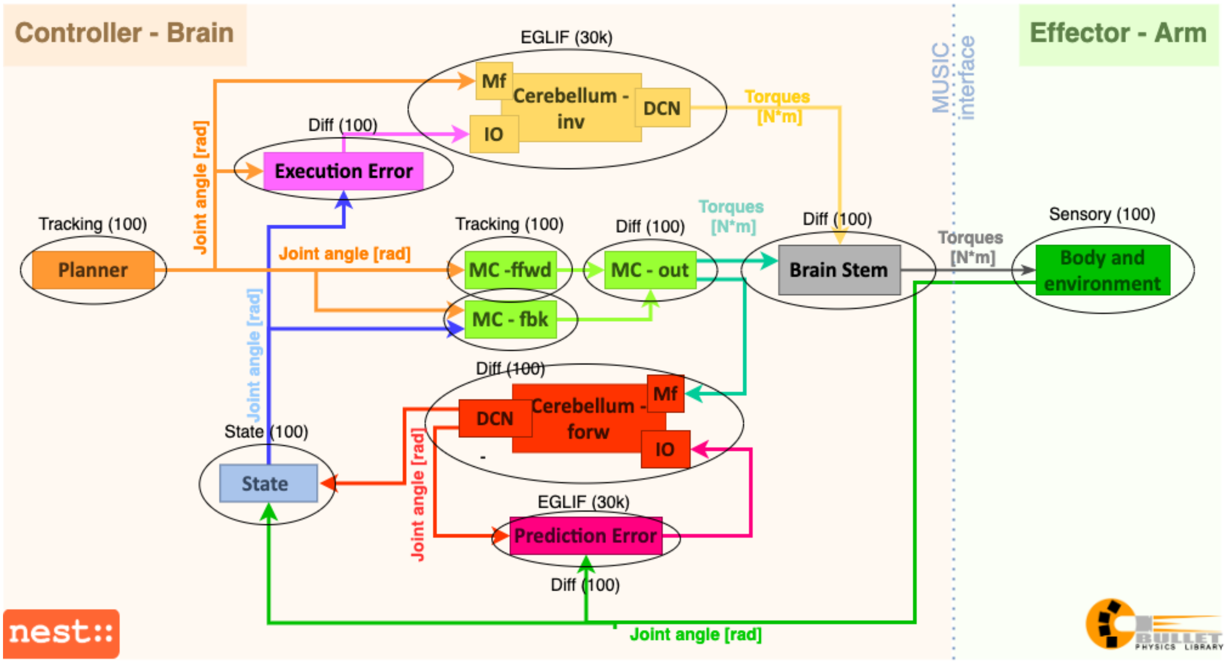


Fig. 8 - Details about each block in terms of neural populations of specific brain regions. A possible design about the signals traveling across these regions are indicated on the arrows. The connections are educated by using Allen connectivity atlas.

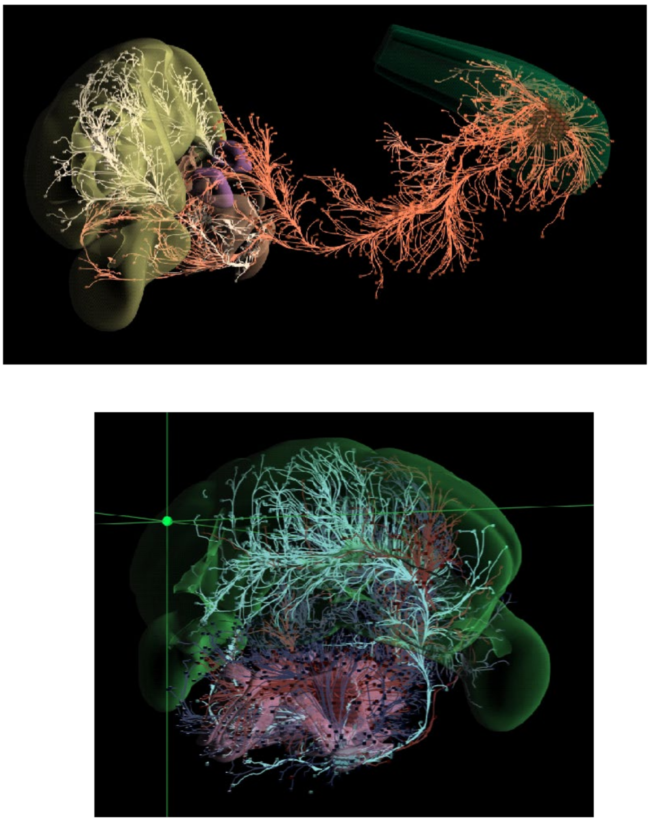


Fig. 9 - Allen connectivity atlas. An example about the main connection pathways involving the cerebellum.

The entire system will allow to tackle issues like neural coding (Shadmehr, 2020) and the interaction between multiple cerebellar modules during learning. The hypothesis is that the cerebellum may decipher cause-and-effect relationships through time-dependent generalisation mechanisms (Calame et al., 2023). Moreover, it will be used to explore pathological states in patients with movement disorders involving the cerebellar tandem loops.

5 COGBMI-XR: COGNITIVE BRAIN-MACHINE INTERFACES WITH THE AID OF XR

COGBMI-XR originates from the merge of two previous subprojects, namely:

- COGBMI: cognitive brain-machine interfaces, originally proposed by Università di Genova (UniGe), Istituto Italiano di Tecnologia (IIT), and Università Campus Biomedico (UCBM).
- ISOTONIC: XR for BCI-based human-robot interaction in healthcare, proposed by Università di Napoli Federico II.

The original goals of COGBMI were:

1. designing an action-oriented, semantic, and cognitive layer to the non-linear control space from body signals to assistive devices;
2. designing techniques for modulating control actions based on principles related to physical and cognitive ergonomics;
3. performing tests on scenarios involving the feedback-based tele-operation of mobile manipulators provided with sensate dexterous hands to execute a few tasks involving navigation, reaching, grasping, and manipulation.

Conversely, the original goals of ISOTONIC were:

1. designing an innovative hardware and software platform based on XR technology to ground human-robot interaction;
2. integrating brain-computer interfaces with XR technology to control and operate a wide range of robots, with major focus on (a) minimally invasive surgical robot, and (b) rehabilitation tasks using collaborative robots;
3. developing state of the art techniques to measure the stress level of a person, with the aim of modulating their interaction with robots.

The two projects, even if very different in many aspects, shared some common ground and philosophy, in the sense that they both focused on different but complementary aspects of the human/machine interaction. This consideration prompted the idea to merge the two projects, with the main intent to foster cross-fertilization of ideas, and to fuel collaborations between different groups working on parallel lines of research.

5.1.1 Main goals

During the first period of the project, we worked to integrate the two original projects and to synthesize their goals, as well as distributing them into corresponding Work Packages (WPs). Therefore, the integrated goals of COGBMI-XR are:

1. designing an innovative hardware and software platform based on XR technology to ground human-robot interaction using body-machine and/or brain-computer interfaces;
2. designing techniques for modulating control actions leveraging principles related to physical and cognitive ergonomics, which are informed by state-of-the-art techniques to measure the stress level of the person controlling the robot, with the aim of modulating the interaction at the control level;
3. develop robot-agnostic control techniques, involving (a) the feedback-based teleoperation of mobile manipulators provided with sensate dexterous hands to execute rehabilitation tasks involving navigation, reaching, grasping, and manipulation, and (b) robots for minimally invasive surgery, for example to support the pre- and intra-operative surgical phases.

Goal 1 is mapped to WP 1, from Month 1 to Month 24, goal 2 is mapped to WP 2, from Month 18 to Month 40, and goal 3 is mapped to WP 3, from Month 18 to Month 40. Therefore, all the activities described here are related to WP1.

It can be observed that, as far as this first period is concerned, IIT and UniNa focused on initial human-human and human-robot studies, UCBM on shared robot control, and UniGe on XR technologies for intention recognition as well as on control aspects.

5.1.2 Work in progress

5.1.2.1 Neuroscientific methods to evaluate user's experience when performing actions through artificial effectors

The research unit at IIT specializes in using cognitive neuroscience methods in human-robot interaction. For COGBMI-XR project, the unit focuses on the evaluation of the user's sense of agency over the actions generated through artificial effectors.

Our objective is to design experimental protocols and establish objective measures for user's experience when performing actions through artificial effectors. We focus specifically on the Sense of Agency (SoA). SoA is the experience of being in control over one's own actions and their sensory outcomes. This is one of the most crucial and fundamental mechanism for proper functioning in the environment. In case of patients with physical impairments, where they are performing actions with the use of artificial limbs, it is not guaranteed that SoA will emerge over the actions produced by means of the artificial limbs to the same extent is it does in cases when natural limbs are being used. Based on our experience (Ciardo et al., 2020; Hinz et al., 2021; Roselli et al., 2021; 2022), we are developing the most reliable and objective measures of SoA experienced by patients. Instead of using questionnaires and surveys that are often prone to various biases and are not always reliable, we are using cognitive neuroscience methods to quantify SoA.

Our activities related to this theme have been centred around designing new experimental paradigms and identifying neural markers of SoA in teleoperation of a robot. So far, we have focused on lab studies and healthy adult participants. One we will have identified the exact neural markers, we will translate the lab experiments into clinical setting involving patients with impairments.

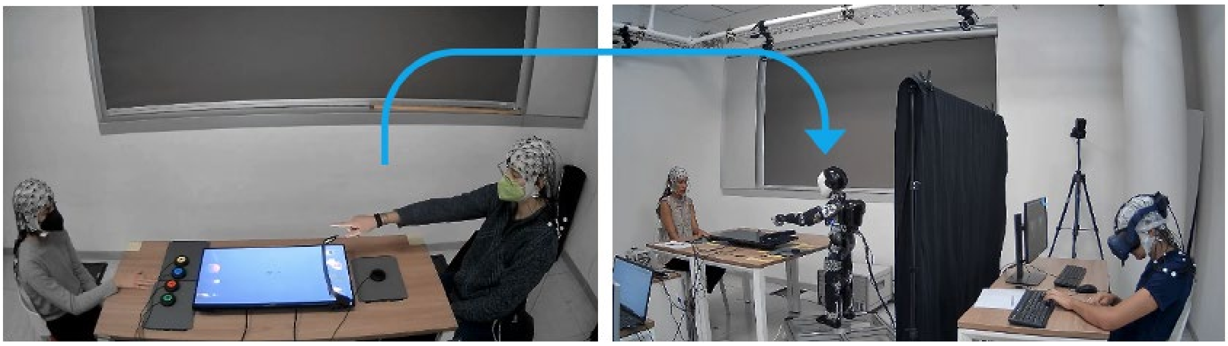


Fig. 10 - A representation of Experiment #1.

In our first preliminary study, we asked participants to perform a human-human (HH) collaboration task (Experiment 1) where dyads of participants were "constructing" an object together. In Experiment 2, one of the partners was replaced by a humanoid robot (HRH) which was teleoperated by another human (behind an occluding curtain).
We measured EEG on both participants in the HH condition and the HRH condition (robot-mediated). The idea was to use inter-brain synchronization as an objective measure of quality of the teleoperation system. An ideal system should allow for the same degree of inter-brain synchronization as in the direct HH case. Our results showed a difference in EEG activity for the condition when participants were involved in HRH, compared to the HH condition. We are still working on ways to quantify inter-brain synchronization. In addition, this paradigm allowed us to also address the SoA of the operator and compare it also to the condition of HH where each participant has direct access to the task space. Time-frequency analyses focusing on the SoA are currently underway.
In another study, we designed a similar experimental setup, but in this study, we utilized an experimental protocol that has been designed specifically to test SoA, namely temporal interval estimate protocol. It is a well-established phenomenon that for voluntarily produced actions, temporal estimates of the duration between the action event and its sensory outcome are compressed, compared to control conditions (involuntary actions or externally generated sensory events). This measure can therefore be used as an implicit measure of SoA. We used this measure in a study in which dyads were performing a joint task in a direct HH interaction condition, or in a condition in which one member of the dyad was performing the task with a robot teleoperated by the other member of the dyad. We

again measured EEG on both participants, and we measured SoA through temporal interval estimates. Analyses are underway.

Taken together, with developing experimental paradigms involving teleoperation, we aim to establish the most reliable metrics of SoA experienced when one's intended actions are performed through a robot effector.

5.1.2.2 Innovative approaches in caregiver-patient dynamics: stress quantification and BCI-XR integration

The research unit at UniNa is pursuing a dual objective in COGBMI-XR. Firstly, the focus lies on advancing cutting-edge methodologies for quantifying the level of stress induced in caregiver-patient dynamics during specific activities (Apicella et al., 2022). This serves the purpose of autonomously identifying situations necessitating intervention, thereby mitigating potential risks or situations where suspending therapeutic treatment is advisable.

Secondly, the unit is exploring the utilization of BCI-XR systems in the domain of rehabilitation. These systems offer the capability to govern the actions of collaborative robots (Apicella et al., 2023), leading to more immersive and engaging rehabilitation regimens for patients. The integration of BCI for controlling robot actions in an XR environment enables patients to partake in interactive and practical rehabilitation exercises, consequently fostering heightened motivation and expediting recovery.

The ongoing efforts have predominantly been directed towards the first objective, focusing on caregivers. The study's focal point has been neurosurgeons, and two initial studies have been conducted.

In the first study (Arpaia et al., 2023a), the effectiveness of neurofeedback (NF) in regulating emotions among neurosurgeons was investigated, employing a combination of EEG and Heart Rate Variability (HRV). Numerous studies have demonstrated the potential impact of stress, apprehension, and fear of failure on surgical performance. For instance, acute stress induced by a patient's severe bleeding can detrimentally affect a neurosurgeon's psychomotor proficiency (Bajunaid et al., 2017). Additionally, heightened anxiety levels can lead to a decline in overall performance (Hanrahan et al., 2018). A neurofeedback-assisted training was devised to empower neurosurgeons to manage their emotions. EEG signals and heart rates were recorded from five neurosurgeons across four sessions while engaging in NF-based emotion regulation (ER). The individuals endeavoured to counteract anxious and stressful states through NF, specifically by reducing beta band power in the midline scalp regions. The evaluation of neurofeedback effectiveness relied on the concurrent use of HRV in conjunction with EEG. The EEG data were leveraged in real-time to guide the feedback, and post-processed along with HRV to assess the overall training efficacy. The results pertaining to the EEG signals demonstrated a consistent decrease in beta band power within each session as the ER proficiency improved, aligning with existing literature. Conversely, HRV did not exhibit the anticipated upward trend within individual trials. However, when considering the entire session and computing HRV over a broader time frame, HRV during NF training consistently surpassed HRV levels during rest and negative baseline phases.

In the second preliminary study (Arpaia et al., 2023b), a hybrid statistical and machine learning methodology is introduced to select the most informative EEG features for detecting cognitive load associated with fine motor activities, particularly during the Purdue Pegboard Test (PPT). This approach is validated through an experimental case study involving neurosurgeons monitored using a wearable EEG system during PPT execution at four escalating levels of complexity. EEG features linked to cognitive workload during fine motor tasks are identified through Spearman rank correlation analysis and Friedman tests. The selected EEG features are then input into machine learning algorithms, with classification accuracy serving as the validation metric. Among the classifiers tested, the k-Nearest Neighbor achieved an average accuracy of 53.3% ± 4.5% in detecting the four levels of cognitive load.

5.1.2.3 XR approaches for human-robot interaction, and design of novel robot control techniques

The two research units at UniGe focused on two related aspects, namely the development of technologies for XR able to support the goals of COGBMI-XR, as well as the design and development of robot control techniques for people with severe physical impairments.

The first research unit decided to leverage the guidelines of Industry 4.0 to envision a human-centric paradigm for the design of a new generation of robots capable of seamlessly interacting with humans. These are enabled by technological advances in multi-modal perception, reasoning, control, and actuation (Ruffaldi et al., 2016). To achieve an adequate level of collaboration, an effective communication is of the utmost importance. Communication involving humans is intrinsically multi-modal, and results from the interplay of explicit and implicit communication channels, or media. In human-human interaction processes, the involved individuals are typically able to infer each other's intentions through different channels, which involve explicit signals, e.g., speech, and implicit cues, such as gaze, posture, and gestures (Klein et al., 2005; Mutlu et al., 2009; Calisgan et al., 2012), just to name a few.

A promising direction to convey such level of communication is represented by Mixed or eXtended Reality (MR, XR) (Milgram and Kishino, 1994), i.e., an hybrid communicative medium resulting from the combination of real physical environment and virtual holographic objects. Unlike Augmented Reality (AR), which is limited to the overlay of digital visual content onto the observed scene, MR creates immersive experiences by bringing interactive and spatially contextualized holograms into the real world. Traditionally, MR interfaces in human-robot interaction are achieved in combination with handheld tablets to show 3D holograms superimposed to the camera's feed, or projectors mounted above the shared workspace to display, for instance, 2D safety boundaries for humans. The introduction of commercial MR head mounted displays such as the Microsoft HoloLens, enables researchers to exploit the MR medium in human-robot interaction scenarios, providing humans with the possibility of perceiving the holographic representation from a first-person perspective.

One important aspect to consider is how to render robot motions for an intuitive interaction. Some studies suggested to use MR to display a static representation of robot's future movements to anticipate whether a particular trajectory is collision free (Rosen et al., 2019; Gruenefeld et al., 2020). These approaches show how using MR to represent future robot motions improve the overall interaction efficiency and fluency.

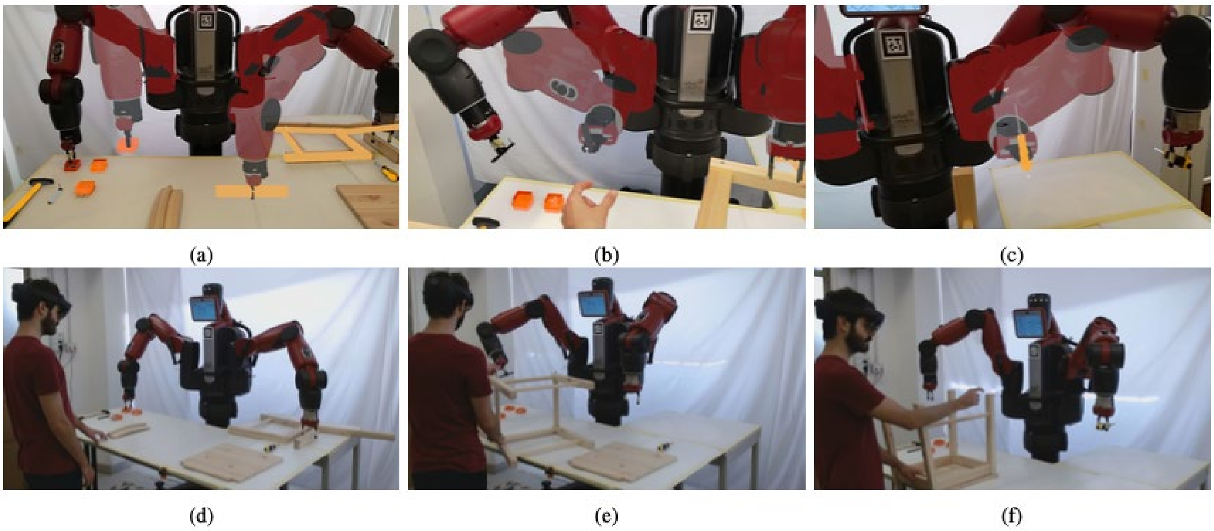


Fig. 11 - A human-robot interaction process from two perspectives: top images (a)-(c) show the first person view with an anticipatory hologram, whereas bottom images (d)-(e) depict the same instants from an external point of view.

In this first part of the COGBMI-XR project, the first research unit at UniGe worked on a model as well as software architecture to show anticipatory motions using MR. The assumption is that conveying dynamic information about upcoming robot motions may be a possible step towards a more fluent interaction. A simple user study has been carried out to assess whether a complex communicative act from the robot to the human, which results from the combination of normal robot motions and anticipatory robot motions conveyed via the holographic representation could effectively improve the interaction process.

The second research unit at UniGe focused on the development of an intuitive and easy to use technology, namely a Body-Machine Interface (BoMI), for the control of a computer or a robot allowing people with severe motor disability to control an external device that could help them in their daily living tasks. Specifically, the research unit developed and tested different body-signals and different control modalities for BoMI.

The first one is a video-based BoMI that, using marker-less techniques, allows for a more natural user-friendly interaction with an external device, as it is less invasive and cheaper than a sensor-based one. Specifically, this novel video-based marker-less BoMI empowers individuals to independently control a computer and cursor or an external device (e.g., a Tiago bimanual manipulator) via shoulders and/or head movements without the needs of any sensors other than the computer webcam. Our procedure is composed of different steps (see also **Figure 12**): (1) automatic acquisition of images of the user from a computer webcam; (2) detection of landmark points (e.g., eyes, nose and shoulders) in the image plane using Mediapipe; (3) encoding of the extracted signals to a lower dimensional (control) space via application of a dimensionality reduction (DR) algorithm; (4) handling of the graphic for providing BoMI users with visual feedback of the cursor via a computer monitor.

Fig. 12 - Summary of the video-based BoMI pipeline. The image acquired by the computer webcam is fed through the trained network to detect the body landmarks. Then, a dimensionality reduction (DR) algorithm is applied to the landmarks' signal to obtain.

The DR algorithms explored so far are Principal component analysis (PCA) and non-linear 2D variational Autoencoder (VAE). These allows the creation of the BoMI forward map to obtain the (x, y) coordinates of the computer cursor or signal to control the position of Tiago in the space. Since the movements of the nose and the eyes are extremely correlated, we decide to exclude the latter. Thus, the 2D coordinates of shoulders and nose are organized as a 6D vector (q). The BoMI forward map is obtained by asking a volunteer to freely move his head and shoulders for 30 seconds. Then, the MediaPipe model is applied to the video to extract the vector of body landmarks q for each frame. As a result, a matrix Q containing the estimated coordinates of the landmark points for every frame is obtained. Next, we applied the DR algorithms to obtain a control signal for train a VAE on Q to derive the 2D latent space in which the greatest amount of the body movements variance during calibration is explained. We choose a VAE among the possible methods for dimensionality reduction (e.g., linear AE or vanilla AE) due to its ability to enforce a Gaussian distribution within its latent space. This would ensure a more uniform coverage of the 2D workspace with respect to that obtained training other DR models. The control of an external robot like Tiago would require controlling the position of different parts namely its base and its arm. Therefore, to allow the switch between the two we implemented an eyes-closed switch. Every time the individual was closing the eyes for two seconds then the control would move from the base of Tiago to the arm or vice versa. Future work will focus on more advanced control solutions for piloting simultaneously base and arm of the robot, integrating also shared control with the robot and testing such algorithms on unimpaired people and people with sever motor disabilities.

The second BoMI developed and tested is based on EMG signals and devoted to the control of a computer with also a rehabilitative goal, see **Figure 13**.

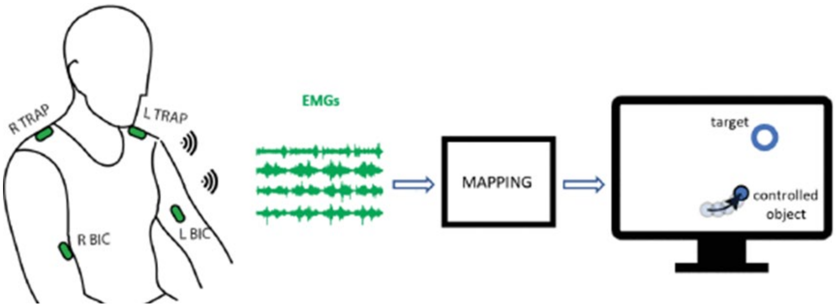


Fig. 13 - Cursor movement controlled by biceps muscles.

Biceps muscles were controlling the cursor movement along the horizontal axis while trapezius muscles the movements along the vertical axis and the goal of the first performed study was to investigate the effect of two weeks of training with a myoelectric computer interface (MCI) on motor functions in younger and older adults. As the population worldwide ages, there is a growing need for assistive technology and effective human-machine interfaces to address the wider range of motor disabilities that older adults may experience. Preliminary findings on the tested population (20 younger and 20 older adults) suggest that the proposed MCI training can be a powerful tool in the framework of assistive technologies for both younger and older adults. Further research is needed to determine the optimal duration and intensity of MCI training for different age groups and to investigate long-term effects of training on physical and cognitive function.

5.1.2.4 Shared human-machine control, and estimation motion intentions from biomechanical information

Research into shared human-machine control and methods for estimating motion intention from biomechanical information are rapidly evolving, as they address industrial contexts (Berg and Lu, 2020; Ajoudani et al., 2018) as well as in clinical settings (Mohebbi, 20220).

Shared human-machine control represents a distinctive category of interaction, where humans and machines collaborate to achieve common objectives. In these systems, a fundamental requirement is the ability to comprehend and interpret user intentions and respond accordingly. Human-computer interfaces empower technology users, including individuals with motor disabilities, to control electronic devices and robots through the analysis of diverse user parameters. Various methodologies and advanced technologies can be harnessed for motion intention analysis. For instance, they include acquiring signals through wearable devices to capture electromyographic activity (EMG), tracking joint kinematics through M-IMU inertial magnetic sensors, and utilizing cutting-edge vision systems for the three-dimensional reconstruction of the user's posture in a contactless manner, using RGB or RGB-D cameras. Additionally, the detection of vital parameters such as heart rate and respiration rate, along with non-vital physiological indicators, such as galvanic skin response, can be combined with facial image analysis from RGB cameras to enable stress and emotional assessment. The development of user state estimation algorithms plays a pivotal role in generating input for tailored shared control algorithms that realize semi-autonomous behaviour based on the estimated state of the person. The measurement of physiological responses provides profound insights into the user's perception of the interface, enabling the characterization of stress levels and the naturalness of use (Szczurek et al., 2023). Simultaneously, combining information on movement intention with the estimated state of the user empowers the control of complex machine behaviour, allowing the machine to react and adapt to the user's preferences, style, and state (Hopko et al., 2022).

Recent works from UCBM investigated new approaches for the fusion of biomechanical and physiological information in human-machine interfaces (Tamantini et al., 2023a; Tamantini at al., 2023b). Specifically, kinematic data related to movement smoothness and motion accuracy serve as a primary driver for generating assistive machine behaviours. These behaviours may include adjusting the stiffness of the interaction or establishing a natural dialogue between the patient and the robot to enhance task performance. Furthermore, physiological signals are exploited by the proposed control strategies to tailor the robot's intervention much more specifically. **Figure 14** reports the experimental setups of the two presented case studies.

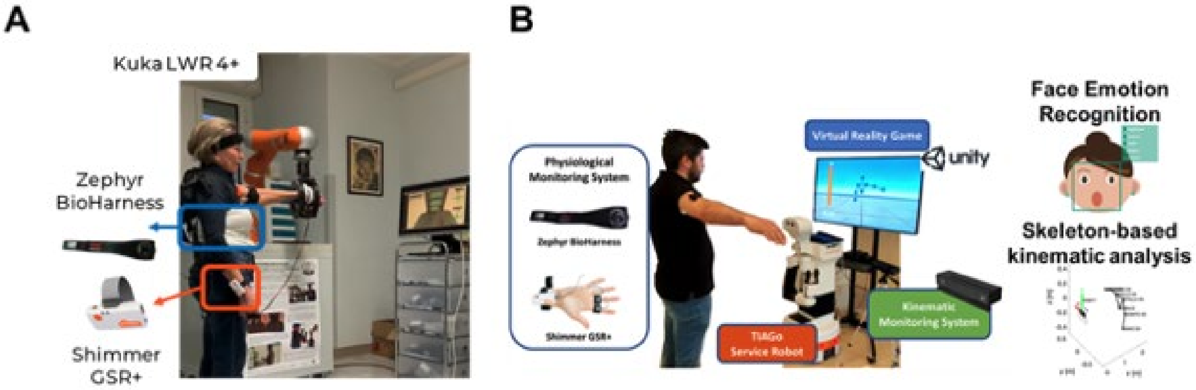


Fig. 14 - Experimental setups developed to test advanced interaction control strategies integrating multi-modal monitoring and (A) Kuka LWR 4+ or (B) the service robot Tiago.

the context of COGBMI-XR, UCBM will leverage the competencies it has developed in this domain to seamlessly integrate the selected sensory systems for the use cases identified in the project. Moreover, shared control strategies to produce semi-autonomous robot behaviour according to the user biomechanical and physiological condition will be developed and tested.

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