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► **To cite this version:**

Dorian Verdel, Jonathan Eden, Hector Cervantes-Culebro, Carsten Mehring, Mattia Pinaridi, et al.. A predictive coding framework for safe and versatile control of supernumerary robotic limbs. 2024. hal-04830213

HAL Id: hal-04830213

<https://hal.science/hal-04830213v1>

Preprint submitted on 10 Dec 2024

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A predictive coding framework for safe and versatile control of supernumerary robotic limbs

XX
XX(X):1–18
©The Author(s) 2024
DOI: ToBeAssigned
ToBeAssigned
ToBeAssigned

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Abstract

Robotic supernumerary limbs (SLs) can enable humans to perform alone tasks requiring more than two hands. By increasing the number of effective degrees of freedom of the human body, SLs could have a major impact for industrial and medical applications, and profoundly change the way humans interact with their environment. However, the current use of SLs is limited, with applications focused on specific use cases and lacking a comprehensive framework for versatile and ubiquitous use. This limitation stems primarily from the intertwined challenges of ensuring safety and coordination between the natural limbs and SLs. This paper presents a novel control framework for sensorimotor augmentation with SLs based on predictive coding, a process rooted in the hierarchical neural structures that enable the brain to seamlessly manage coordinated and complex actions. Our framework comprises three levels where each level generates predictions for and receives prediction errors from the level below. The α -layer detects the human movement intent and ensures safety through generated constraints. The β -layer controls action and related sensory feedback. For this layer, we propose a novel general voluntary control mechanism that offers a continuum between fully autonomous SLs behaviors and direct control, thereby allowing a user to control SLs in complex tasks with minimal cognitive effort. Finally, the γ -layer executes the SLs control and handles their interaction with the human body and the environment. For each component of our framework, we review the relevant literature and illustrate implementation strategies that can pave the way for safe and versatile SLs control.

Keywords

Sensorimotor augmentation, multilimb coordination, supernumerary robotic limbs, predictive coding, human intent prediction, human-robot interactive control

1 Introduction

Science fiction has long envisioned humans augmented with artificial limbs, such as Spiderman's Dr. Octopus, who can seamlessly control *robotic supernumerary limbs* (SLs) independently of or in coordination with their *natural limbs* (NLs). The potential of SLs is supported by the superior motor capabilities observed in individuals with natural augmentation, such as polydactyly individuals born with more than five fingers by hand (Mehring et al. 2019). In the past two decades, various SL prototypes have emerged (Prattichizzo et al. 2021; Yang et al. 2021), designed to enable users to perform tasks alone that typically require collaboration with others, such as complex and skillful assembly (Parietti and Asada 2016), assistance of individuals with impaired motor function to carry out activities of daily living (Hussain et al. 2016; Wu and Asada 2016), or multi-handed surgery (Huang et al. 2021c) (Fig. 1). However, despite many devices being built, usage has been limited due to issues in interfacing the human and SLs (Eden et al. 2022).

Our goal is to create a safe, versatile, intuitive, and efficient control for SLs, enabling robotic augmentation far beyond the limited abilities of current systems. *Safety* in human-SL-environment interaction has received little attention, resulting in simplistic and overconservative solutions that restrict functionality (Khoramshahi et al.

2023). Regarding *versatility* – the ability to perform a wide range of tasks with the same controller – SL control has primarily relied on direct control supported by visual feedback, or on a restricted set of autonomous behaviors, which may not always align with user intentions. Finally, achieving *intuitive and efficient SL control* requires an augmentation mechanism that seamlessly integrates SLs into the user's natural motion planning, enabling them to function as extensions of the user's body with minimal additional cognitive effort.

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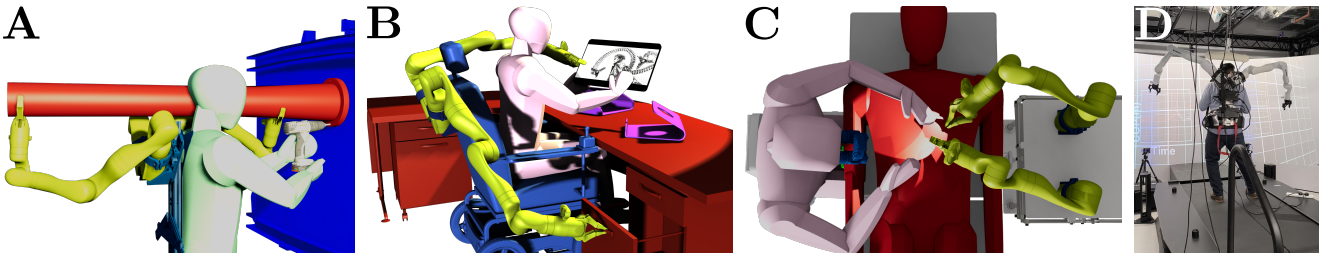


Figure 1. Illustration of possible augmentation with SLs. A. Four-handed assembly task with SLs worn by the user. B. SLs moving with one’s wheelchair to assist in carrying out activities of daily living. C. Solo microsurgery using SLs attached to an independent mechanical structure. D. Example of the **MULTi-limb Virtual Environment (MUVE)** as a possible implementation platform.

How can these challenges be addressed? Considering animal behavior, we observe that many species can seamlessly perform complex tasks requiring high levels of coordination, using sensory inputs affected by large temporal delays and noise. These advanced control abilities are believed to stem from the inherently predictive nature of the perception and control mechanisms employed by the mammal brain (Bar 2011). This idea traces back to Hermann von Helmholtz’s insight that perception functions as a process of unconscious inference (von Helmholtz 1866). Here, it is widely accepted that the animal brain continuously relies on predictions about the evolution of its actions and environment, using statistical regularities in sensory information and minimizing prediction errors by integrating current sensory input.

We argue that, similar to biological systems, a framework enabling safe, intuitive, and versatile control of SLs through rich sensory feedback must incorporate robust predictive capabilities at its core. To this end, we propose a hierarchical control framework inspired by the predictive coding mechanism, wherein the mammalian brain predicts future sensory information and leverages these predictions for control (Huang and Rao 2011; Friston 2018; Millidge et al. 2021; Parr et al. 2022). In our framework, each layer generates predictions and receives error signals from the layer below, mirroring the organization hypothesized in sensory areas of animal brains (Rao and Ballard 1999; Blank and Davis 2016; Marques et al. 2018; Lao-Rodríguez et al. 2023). Specifically, we aim to implement hierarchical control that integrates automatic reflexes — ensuring safety with minimal cognitive effort — with higher-level motor skills under voluntary control. While the conceptual framework proposed by (Seminara et al. 2023) focuses on prosthetics, we extend its scope by considering the implementation of general movement augmentation, and discussing each mechanism from the safety of working with SLs, to their control, and how human users can interact with them.

Developing a predictive coding framework requires a reciprocal understanding between the human and robot, so that the human user is able to decode and predict their SLs’ behavior, and is able to translate their desired control to them. For this purpose it is important to establish reciprocal *legibility* (i.e., the ability to infer the movement goal) and *predictability* (i.e., the ability to anticipate upcoming steps of the movement by observing previous ones) between the SLs and their human user (Dragan and Srinivasa 2014).

For humans to effectively understand the SLs’ action, it is essential to provide feedback about their state

concerning the task at hand and their interactions with the environment. However, experiments in human augmentation have shown that current strategies for encoding artificial sensory feedback related to SLs are not easily interpretable and do not consistently improve control performance (Pino et al. 2014; Pinardi et al. 2021). A critical component of the predictive coding framework is, therefore, the design of sensory feedback that enables the brain to accurately predict task-relevant parameters, allowing the central nervous system (CNS) to establish sensorimotor loops for efficient and intuitive SL control.

To understand human intent effectively, a detailed description of the task and its constraints is crucial for SLs. Over the past decades, optimal control (OC) techniques have been applied to model human motor control (Scott 2012) and design robotic control (Mainprice et al. 2015), incorporating sensory feedback to compute appropriate motor commands. OC offers a practical framework to precisely define task and constraints without imposing a fixed motor plan. To implement OC for SL control, a broader framework is required, that considers the specific sensorimotor interactions with the human user. This can be achieved by leveraging (i) the sensory exchanges observed and modeled between collaborating humans over the last decade (Ganesh et al. 2014; Takagi et al. 2017, 2019; Sebanz and Knoblich 2021; Dockendorff et al. 2023), and (ii) advancements in optimal control for human-robot interaction, using differential game theory as developed in (Jarrassé et al. 2012; Li et al. 2019; Hafs et al. 2024) to specify the roles adopted by the human and robot agents.

In this paper to develop the framework’s implementation methods, we review existing movement prediction and control techniques in robotics, human motor control and human-robot interaction. Section 2 describes the novel framework and Section 3 illustrates its potential through representative examples. Section 4 then explains how the framework can enable users to control SLs dynamically and safely, independently of or in coordination with NLs. Finally, Section 5 outlines how flexible action planning and the associated artificial sensory feedback can be implemented.

2 Augmentation concepts and framework

We conceive an augmented human with N SLs as $1 + N$ agents each equipped with sensing, motion planning and motor skills, which communicate with each other to carry out a common task (see Fig. 2). This task will be represented as a set of *goals* $\mathcal{G} \in \mathbb{R}^{6+1}$, that are 6D poses to reach with

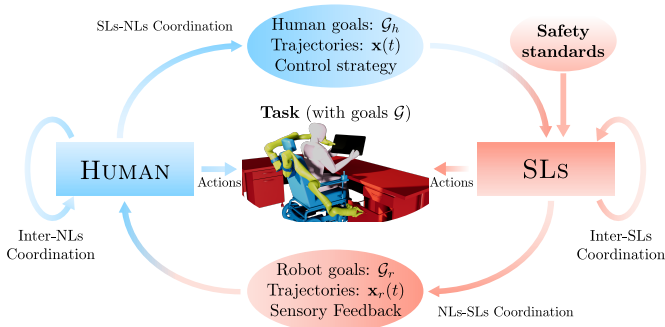


Figure 2. General concept of human-SLs interaction. Each task corresponds to a set of goals \mathcal{G} , which is understood as subtasks corresponding to both the human NLs and the SLs. For instance, if two hands are needed to manipulate an object, we describe the task as comprising two goals. SLs have to comply with the safety standards of robots working closely with humans, as well as to human goals, motions and control strategies to select their goals, and plan and execute associated actions. Conversely, the behaviors of SLs and artificial sensory feedback can impact human behaviors, leading to a co-adaptation process.

the endeffector of a NL or SL in the task space, and one time constraint, as certain goals are necessarily performed before others, e.g. when carrying an object from an initial to a final location. Each of these goals is accomplished by one limb, either a NL or a SL, so that they can be subdivided into human and robots goals as follows: $\mathcal{G} = \mathcal{G}_h \cup \mathcal{G}_r$, $\mathcal{G}_h \cap \mathcal{G}_r = \emptyset$. Note that in this representation, human and SLs goals are necessarily different at a given instant to avoid collisions. However, they are sometimes mechanically coupled such as when collaboratively carrying an object. Finally, each human or SL goal is associated with a subtask, that allows for the generation of goal-directed *limb trajectories*, which we represent by concatenating the evolution of the NLs states $\mathbf{x}_h(t)$ and SLs states $\mathbf{x}_r(t)$ in a single global state $\mathbf{x}(t) \equiv [\mathbf{x}_h(t), \mathbf{x}_r(t)]$. Note that this state variable can be of varying dimensions and contain different information (e.g. limb joints angular positions, speeds, torques) depending on the representation chosen for the control variable of SLs and NLs, $\mathbf{u}(t) \equiv [\mathbf{u}_h(t), \mathbf{u}_r(t)]$. For instance, in a controlled torque change framework, as is often used in human motor control (Burdet et al. 2013), the control variable is $\mathbf{u}(t) \equiv [\dot{\boldsymbol{\tau}}_h(t), \dot{\boldsymbol{\tau}}_r(t)]$, and the state $\mathbf{x}(t)$ will contain information relative to the joints torques of the NLs $\boldsymbol{\tau}_h(t)$ and SLs $\boldsymbol{\tau}_r(t)$.

To illustrate these definitions, let us consider an augmented microsurgical operation as depicted in Fig. 1C. In this scenario, the human’s goals \mathcal{G}_h identified by the SLs agents, using sensing as detailed throughout the paper, can be represented as a set of poses through time required to complete a suture. The robots’ goals \mathcal{G}_r , which typically correspond to tasks that would be carried out by a human assistant, may be a set of poses to suction blood and clear the surgeon’s view, or to hold a retractor steady to prevent soft tissue from interfering with the surgeon’s goals.

Achieving goals requires planning compatible SL and NL trajectories. To fulfill their goals, the augmented human needs appropriate sensory stimulation, usually referred to as *sensory feedback* $\mathbf{y}_r(t)$ conveying information regarding the SLs’ movement, represented by its state evolution $\mathbf{x}_r(t)$.

This sensory feedback enables humans to evaluate the relevance of the chosen NL-SL coordination strategy. The SLs aim to achieve the goals directly or indirectly assigned to them by the human. To do so, they rely on contextual information on the task, the human, the environment, and the assigned control strategy. We note that the SLs are not necessarily under the direct control of the human as they may execute an autonomous behavior.

How to determine the SLs’ control? Over the past three decades, optimal control methods have been developed to model human motor control (Todorov and Jordan 2002; Berret et al. 2021), providing insight into how the CNS may generate motor commands and coordinate limbs and muscles in the redundant musculoskeletal system (Berret et al. 2024). These methods typically use a cost function that captures task constraints and plant dynamics to compute motor commands. Recently, we have leveraged differential game theory (GT), which allows for optimal control in interactions with another agent, to enhance human-robot interaction (Jarrassé et al. 2012; Li et al. 2019; Hafs et al. 2024). By combining optimal control and GT, we can design a novel SL control that coordinates seamlessly with NLs, which we will refer to as *general voluntary control* (GVC), as will be discussed in Section 5.3.

To handle the complex problem of controlling SLs in an efficient and intuitive way, we propose a framework for regulating the information exchange between the human and their SLs inspired by the predictive coding process identified in the animal brain. Our *hierarchical predictive coding framework* comprises three levels as shown in Figure 3. Higher layers in the hierarchy manage broad aspects of the task and the interaction with the environment, while lower layers focus on local control aspects, with the following roles:

- **Coordination α -layer** generates safety constraints in both space and time, encompassing the entire environment, tasks, and predictions about their future evolution. Implementation-wise, this layer should be central, common to all SLs and aggregate all the available information with regard to the environment, SLs and the human user. It is composed of three main blocks to: (i) encode static and normative safety constraints, (ii) infer human intent and trajectories, and (iii) assign (optimal) tasks to each SL and coordinate limbs to avoid inter-SLs collisions and handle balance issues. The α -layer sends to the β -layer predictions of the human goals and trajectories with associated predicted motion constraints due to the human ($\hat{\mathbf{c}}_h(t)$), the environment and safety standards ($\hat{\mathbf{c}}_e(t)$), and the planned behavior of other SLs ($\hat{\mathbf{c}}_c(t)$). It receives prediction errors between the observed and the predicted constraints for high-level safety monitoring ($\delta(t)$) from the β -layer.
- **Action planning β -layer** plans SL motions and artificial sensory feedback based on knowledge at the level of each SL, and applies the most relevant control method. Three of the four blocks are used to control the SLs under different paradigms, continuously regulating the human and robot task contributions. The remaining block computes sensory feedback specific to the control mode in order to provide the user with sensory stimuli conveying information relevant to the interaction. The

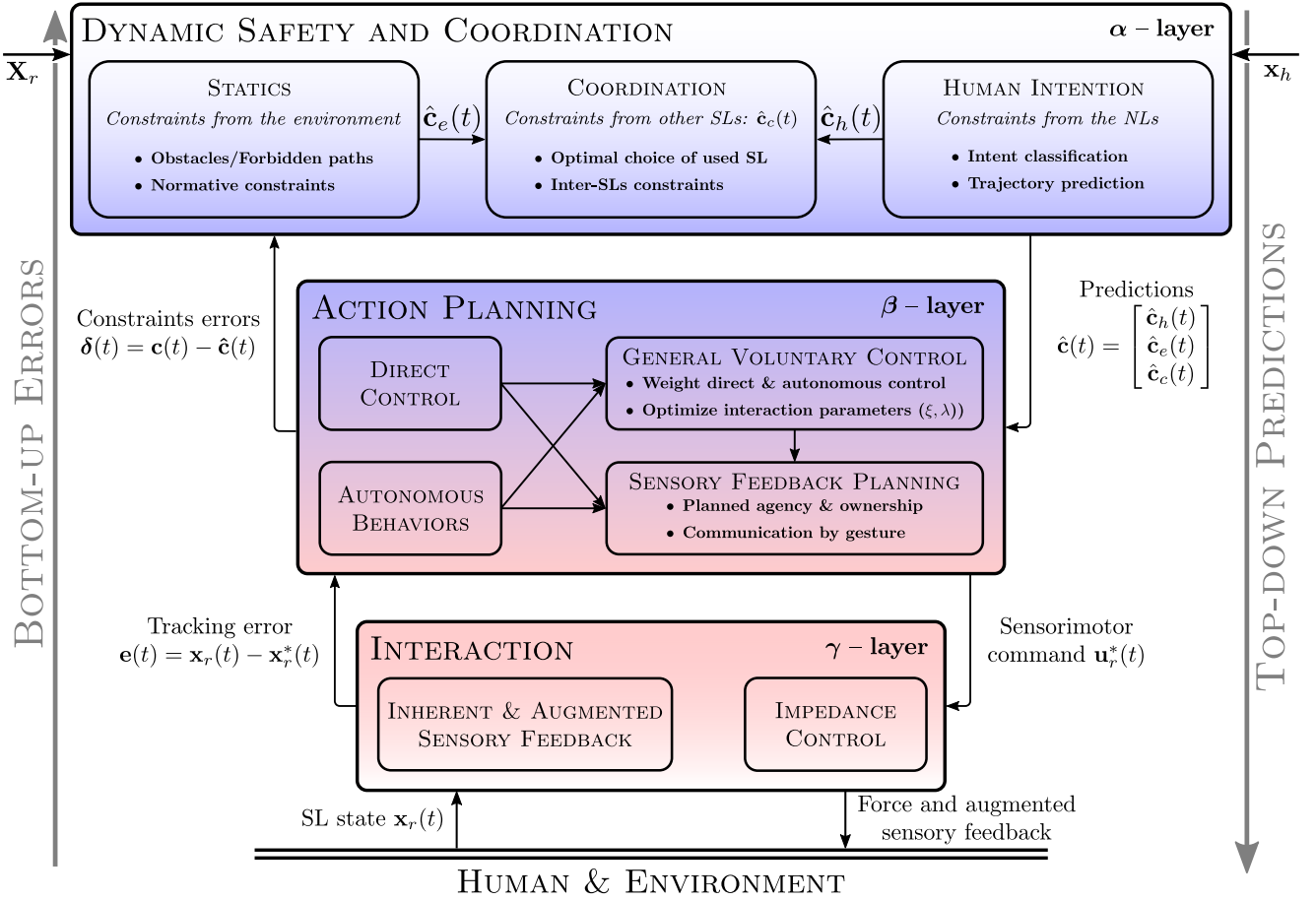


Figure 3. Proposed hierarchical framework controlling one SL, composed of three layers that generate descending predictions and ascending errors. In the common highest layer, the framework receives information describing the human state \mathbf{x}_h and the other SLs states \mathbf{X}_r .

planned SL control and associated sensory feedback are concatenated in a planned sensorimotor command $\mathbf{u}_r^*(t)$, corresponding to a planned state trajectory $\mathbf{x}_r^*(t)$, which is sent to the γ -layer. In parallel, the β -layer receives the tracking error ($\mathbf{e}(t)$) between the SL state and the planned trajectory for possible motion re-planning. One can also envision the β -layer as receiving measures of expected error in the human brain to detect discrepancies between the observed SL behavior and the expected SL behavior encoded in their internal model, which would allow optimizing both trajectories and sensory feedback strategies.

- **Interaction γ -layer** executes the planned SL motion and delivers sensory feedback according to a selected strategy, using local knowledge of the SLs and real-time sensor signals. This layer is composed of (i) a trajectory tracking block enabling the SLs to accurately follow planned motions and to modulate impedance, for instance to maximize safety during physical interaction, and (ii) a sensory feedback execution block, conveying the planned sensory stimulation to the human. The resulting motor and sensory feedback commands are sent by the γ -layer to each SL and relevant sensory feedback devices are activated. Finally, the γ -layer receives the current measures from each SL and feedback device under the form of a current general state ($\mathbf{x}_r(t)$).

This framework contains two important features by design. First, the α -layer is designed to ensure that the human-SLs-environment interaction is safe and free from harmful collisions. These functions, which are mainly produced by unconscious processes in human motor control (Blakemore et al. 2002), are incorporated as constraints in the α -layer. To illustrate such processes, consider the stabilization of a human-SL system. When performing a task, humans naturally and automatically adjust their posture and muscle activity to ensure balance. For SLs, such an automatic adjustment would prevent the destabilization of the human stance and can be implemented as a minimization of gravity related torques which results in a SL being used as a counterweight (see Section 4.3 and Fig. 4A).

The second feature is that the β -layer enables the generation of a variety of SL behaviors by implementing three main types of SLs control: *direct control*, *autonomous behavior*, and a novel *general voluntary control* to combine them. This can significantly enhance the versatility of SLs and their adaptive capacity compared to current uni-modal approaches. Simultaneously, planning the sensory feedback conveyed to the user over the movement duration allows for implementing optimized strategies that convey predictive information with regard to the task at hand, such as the future grip strength of the SL. This could significantly improve the predictability and legibility of SL behaviors

compared to simple mappings between SLs state and the sensory feedback currently implemented.

3 Use cases

To illustrate the framework's function and versatility, we describe how it can be used to implement the three use cases of Fig. 1. Here we illustrate the different control strategies rather than listing all possible strategies for each case.

Industrial assembly. A large number of common assembly tasks, such as fixing a tube to a structure as illustrated in Fig. 1A, usually requires two people, one holding the tube while the other assembles it. However, this may be impractical in narrow spaces and the collaboration may lead to a number of misunderstandings and errors. Ideally, this type of four-handed task could be performed alone with worn SLs that would understand their user's intent and adopt a complementary (e.g. follower) role, which defines the sequence of subtasks it has to perform and avoid errors. The SLs would provide sensory feedback of the interaction with the body and the environment.

The main challenges of this task are in accurate positioning and the stabilization of the tube during assembly. In our framework, the α -layer, based on human intent classification (see Section 4.2), detects the role of the SLs and the associated subtasks and goals. A possible output sequence may consist of: (i) grabbing the tube, (ii) co-manipulating it to position it for assembly, (iii) stabilizing it while the human grabs tools and performs the assembly, and (iv) moving back to a home position for the next task. Then, human motion prediction could be used to flexibly adjust the goals and assist the user during each subtask. Subtask (ii) may be completed using GVC (see Section 5.3) to optimally assist the user during tube positioning, while all other subtasks may use autonomous behaviors (see Section 5.2.2). During these different phases, sensory feedback would first include haptic feedback at the body-SL interface from the interaction force with the environment, as well as feedback at the interaction of the hands with the tube. Artificial sensory feedback could provide functional information such as SL-tube interaction forces.

Carrying out daily living activities from a wheelchair In this use case illustrated in Fig. 1B, SLs are fixed on a wheelchair, allowing them to extend the user's workspace, augment their manipulation capabilities to multimanual operations, and assist an impaired NL. As in the previous use case, intention detection is critical to estimate the human user's targets and to constrain SL behaviors. Moreover, the different control modes available are used for different situations ranging from co-manipulation to collaborative pick-and-place. In this case ensuring the balance of the human-wheelchair-SLs system is easier than with worn SLs, although it is still critical to avoid destabilizing the wheelchair as the user may be unable to compensate for instability. Additionally, natural feedback of the interaction force with the environment is strongly reduced as the SLs are not in direct contact with the body, which could be even more pronounced for users with sensory impairments. Therefore, artificial sensory feedback becomes necessary for successful object manipulation.

Micro-surgery assistance. SLs fixed to an independent platform can be used for instance to augment the abilities of a microsurgeon as illustrated in Fig. 1C. In this case, the SLs complement the surgeon for tasks that today would be carried out by a human assistant. The SLs coordinate with the NLs, for instance to safely grab tools and manipulate fragile biological tissues to perform interventions in a manner that may be different from the typical human surgeon-assistant collaboration. The vessel suturing operation may be broken down in (Villavisanis et al. 2023) (i) vessel visualization, (ii) vessel stabilization, i.e. moving to and grabbing the vessel, (iii) holding the suture that may require minor position adjustments based on surgeon behavior, (iv) cutting the suture, (v) irrigating, and (vi) back wall suturing. In this scheme, the α -layer would detect the ongoing sub-task and the role taken by the surgeon, thus determining appropriate sub-tasks for the SLs to plan their movements accordingly. Specifically, (i) could be performed entirely by the surgeon, (ii) in direct control, (iii) with GVC to optimally adapt to the surgeon's movements, (iv) and (v) could be carried out autonomously, and (vi) using GVC. In this case, ensuring the wearer's balance is no longer necessary, and as for the previous example, there is no inherent haptic feedback, which requires developing artificial sensory feedback.

4 Dynamic safety and coordination

The α -layer ensures dynamic safety and coordination in human-SL interactions by extracting predictive, time-dependent motion constraints to guide SL behaviors. A similar approach has been developed for controlling humanoid robots (Mainprice and Berenson 2013; Mainprice et al. 2015), but the multilimb control of SLs in contact with the user's body imposes significantly more stringent safety and coordination requirements.

4.1 Static constraints

The α -layer should first implement normative constraints to mitigate the risks of workspace sharing between humans and SLs. In particular, Annex 1 of the *Machinery Directive 2006/42/EC* incorporates standards *ISO 10218-1:2011 & -2:2011* and *ISO 13849-1:2015*, and describes the basic safety measures that should be implemented in robots including those working alongside humans. These safety standards necessitate the automatic stopping of the system if communication is defective. Furthermore, the *ISO 12100:2010* and *ISO 13855:2010* standards mandate safeguard positioning and speed limits based on the part of the human body being approached, the robot's power limits, maximum velocity, distance to the human user, and the energy exchanged during contact. Such information may be estimated using anthropometric models of the user Winter (1990), proximity detection skins (e.g. inductance skins), body and limbs states estimated using inertial measurement units (IMUs), or a combination of all to mitigate their respective limits, e.g. the drift due to integration in IMU-based estimation.

A basic implementation of these safety standards can be achieved using hardware and software limits to saturate velocity and power. Further basic requirements include (i)

Table 1. Summary of non-invasive human intent classification techniques. Neurophysiological signals used for human intent decoding are classified into proactive (PA) or reactive (RA) depending on whether they are available before or after movement onset. The success rates ranges correspond to the lower and higher performances reported in the referenced papers.

	Signal type	Sensors	Classifier / algorithm used	Performance
Proactive (PA)	Brain activity / Error potential	Electroencephalographic (EEG)	Shrinkage linear discriminant analysis Blankertz et al. (2011) ; Multivariate statistics Bai et al. (2007) Wang and Makeig (2009) ; Lew et al. (2012) ; Wavelet signal decomposition Kevric and Subasi (2017) ;	Success 70%–90% Low frequency ($< 10\text{Hz}$)
			Artificial neural networks (ANN) Bai et al. (2007) Maksimenko et al. (2018) ; Huang et al. (2021a) ; Sparse logistic regression Ganesh et al. (2018) ; Cross-association / Coherence Kim et al. (2017)	
	Eye kinematics	Eye tracker	Deep learning Festor et al. (2022) ; Nearest neighborhood Jang et al. (2014) Support vector machine (SVM) Jang et al. (2014) Huang and Mutlu (2016) ; Markov processes Javdani et al. (2015) ; Direct modeling Chadalavada et al. (2020) Krausz et al. (2020)	Success 70%–95% Low frequency ($< 10\text{Hz}$)
	Muscle activity	Electromyographic (EMG) / Mechanomyographic (MMG)	Deep learning Yang et al. (2023) ; SVM Krausz et al. (2020) ; Extreme learning machine Cene and Balbinot (2020) ; Markov processes Trigili et al. (2019) ; ANN Lin and Lukodono (2021) ; Yang et al. (2023) ; Hodges detector Balasubramanian et al. (2018) ; Cross-association / Coherence Kim et al. (2017)	Success 70%–99% Real-time
Reactive (RA)	Limbs kinematics	Motion capture (markers) / Cameras (markerless)	Classification and regression tree Cavallo et al. (2016) ; SVM and others Hemeren et al. (2021) ; Deep learning Yu and Lee (2015) ; Vondrick et al. (2016) Jain et al. (2016) ; Kong et al. (2017) ; ANN Fermüller et al. (2017) ; Subject-adversarial Zunino et al. (2019) Probabilistic suffix tree Li et al. (2012)	Success 65%–95% Real-time
			Interaction forces	Force-torque sensors

the implementation of static constraints to prevent SLs from entering certain zones ([Khoramshahi et al. 2023](#)); and (ii) the avoidance of self-collisions along a path, which can be guaranteed using general path validation algorithms ([Bury et al. 2023](#); [Wen and Pagilla 2023](#)). Note that in the case of multiple SLs, self-collision avoidance should also be implemented as multilimb coordination (see Section 4.3). More advanced strategies that have been employed include collision detection and classification to limit the exchanged energy in case of contact with a human or with the environment ([Haddadin et al. 2009](#); [Lippi and Marino 2020](#)), and using passivity theory and energy budgets to ensure stable and efficient performance depending on the task at hand ([Lachner et al. 2021](#); [Michel et al. 2024](#)).

The implementation of these standards and collision avoidance and detection algorithms is a necessary step for all human-SL interaction scenarios, whether the SLs are worn or fixed to an external support.

4.2 Detection of human intention

Efficient algorithms are needed to (i) identify the planned human task, intent, and role (corresponding to legibility from the SLs perspective) and (ii) predict the NLs trajectories (i.e., predictability), as described in the next two sections. These areas, which have been extensively studied in recent years, still pose numerous implementation challenges due to the complexities of neurophysiological signals recording and analysis, as well as fundamental limitations in understanding human user behavior.

4.2.1 Intent identification The robot's objective is to infer the human legible goals i.e. (i) the general task at hand and associated sequence of sub-tasks, and (ii) the current goal and role of the human in the task. Such information is usually extracted by using classifiers based on statistical and machine-learning techniques and trained on human physiological recordings during specific tasks. General considerations can be found in survey papers ([Losey et al. 2018](#); [Luo et al. 2024](#)), including kinematics- and interaction effort-based classification.

Table 2. Summary of human trajectory prediction techniques. Neurophysiological signals used to predict trajectories are classified into proactive (PA) and reactive (RA) depending on whether they are available before or after movement onset.

Signal type		Sensors	Prediction method
PA	Muscle activity	Electromyographic (EMG) / Mechanomyographic (MMG)	Learning from demonstration Siu et al. (2018) ; Artificial neural networks (ANN) Siu et al. (2020) ; Direct modeling Quesada et al. (2024b,a)
	Limbs kinematics	Motion capture (markers) / Cameras (markerless) / Robotic interfaces	Learning from demonstration Burdet et al. (2000) ; Calinon et al. (2010a,b) Mainprice and Berenson (2013) ; Ijspeert et al. (2013) ; Luo et al. (2017) Jamsek et al. (2021) ; Davchev et al. (2022) Saveriano et al. (2023) ; Orhan et al. (2024) ; Optimal control Mainprice et al. (2015)
RA	Interaction forces	Force-torque sensors	Interaction primitives Medina et al. (2015) ; ANN Li and Ge (2014) ; Yu et al. (2020) ; Gaussian mixtures Johannsmeier and Haddadin (2017) ; Optimal control Noohi et al. (2016) ; Kalman filtering Takagi et al. (2017, 2018, 2019, 2021)

Neurophysiological signals exploited to classify human intent include muscle activity ([Ahsan et al. 2009](#); [Nazmi et al. 2016](#); [Mohd Khairuddin et al. 2021](#)), eye gaze ([Belardinelli 2023](#)), and brain activity ([Shakeel et al. 2015](#)), which can provide information prior to the motion onset ([Wong et al. 2014](#)) thereby allowing proactive control of SLs. The extracted information can be an actual goal as previously defined or other information, depending on the signal used. For instance, brain activity can be used to extract movement intention such as moving left or right ([Ganesh et al. 2018](#)), muscle activity can provide the upcoming movement direction of a limb ([Trigili et al. 2019](#)), and eye gaze can be used to determine a goal in a scene ([Admoni and Srinivasa 2016](#)).

Limb kinematics and the interaction force for contacts provide information after movement onset, which can be used for reactive SL control and the correction of outputs from the previous proactive classifiers. Table 1 provides a summary of usual proactive and reactive signals and classification techniques. In the case of our framework, outputs obtained with classifiers using both information prior to and during movement would facilitate prediction error correction, mitigate the risk of inappropriate decision for SLs roles, and enable the extraction of human goals through multimodal classification (i.e. with multiple input signals). Note that the displayed performances are averaged across populations of participants and thus do not account for inter-individual variability. Furthermore, the accuracy of these classification techniques is highly impacted by the task at hand, which means that one cannot extrapolate easily on their potential performance during human-SLs interaction. Consequently, multimodal recordings and the validation of the exposed classification techniques during varied NLs-SLs coordination scenarios will be a critical step towards their effective integration in SLs control.

4.2.2 Trajectory prediction The other aim of the intention component of the α -layer is to predict the human limb's trajectory over a horizon, extending to the next goal or sequence of goals represented as a series of poses over time, forming the predictable human trajectory. This process does not necessarily have to be informed about the motion goal, however when available it can be used for conditioning for the prediction, which strongly increase its robustness

by limiting the possible outcomes. Kinematic and force data, along with muscle activity, are typically employed for this purpose. Time-dependent volumetric constraints are then computed and used to plan SL motion based on this prediction. These constraints are time-dependent in two ways: explicitly, as the predicted trajectories are time series; and implicitly, as predictions are iteratively updated and corrected at a specified frequency based on errors arising from the β -layer. The constraints are volumetric to reflect the volume occupied by the human user's NLs over time, serving to restrict SL motion planning. Table 2 summarizes common techniques to predict human movement.

4.3 Limb coordination

Ensuring dynamic safety requires enforcing further constraints, some specific to the type of human-SL interfacing. In all cases, it is necessary to complete the human-SLs collision avoidance system described in Sections 4.1 and using predictions from Section 4.2 by ensuring that SLs do not collide with each other. A possible solution to guarantee this is to consider a generalized state accounting for multiple SLs and employing the same tools as for avoiding self-collisions mentioned in Section 4.1, see ([Bury et al. 2023](#); [Wen and Pagilla 2023](#)). It is also possible to consider simple solutions like completely separating the workspaces of the two robots using task-based constraints, which can be implemented for instance using bounding boxes ([Khoramshahi et al. 2023](#)).

Furthermore, for all types of human-SLs interfacing, we can specify the choice of tasks to perform by each SL through using strategies found in human motor control. For instance, when multiple SLs are available, the one closer to the target can be used to reach it, as humans do with their NLs ([Bryden et al. 2000](#)), or predefined working areas could be defined, as humans tend to assign to directly controlled SLs ([Huang et al. 2022](#)). To reduce possible ambiguities, the user can further define a dominant SL.

Importantly, for wearable or co-moving SLs, it is necessary to guarantee the balance of the augmented human with SLs as exemplified in Fig. 4A,B. For instance, using multiple SLs for tasks in the same region of space could jeopardize balance. Several strategies have been tested to balance a human with worn SLs, and dedicated

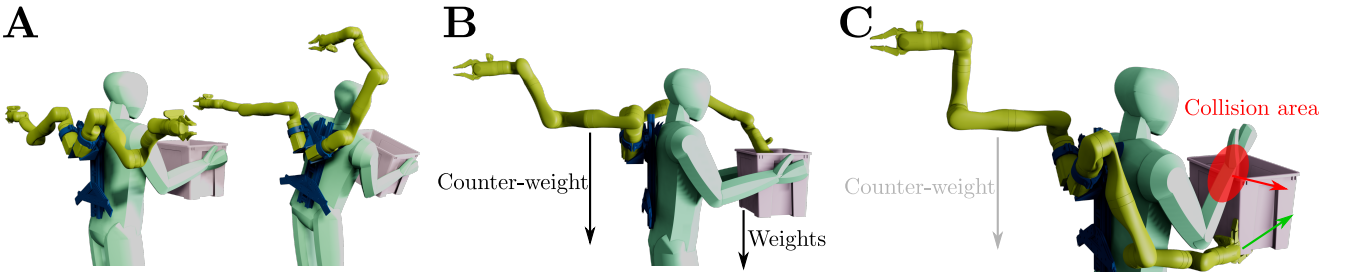


Figure 4. Coordination behaviors between SLs. **A.** Balance augmentation with SLs, also demonstrated in this [simulation video](#) and in this [illustration video](#). The left panel illustrates lateral stabilization by increasing inertia in the frontal plane. The right panel shows compensatory movements provided by the SL when the human loses balance. **B.** Stabilization of the human-SL system during a collaborative task. One SL retrieves an item from the box while the other acts as a counterweight. **C.** If the human collides with the box (indicated by the red arrow), the right SL can counteract this disturbance (indicated by the green arrow). The GVC (described in Section 5.3) would interpret such a change in interaction effort as volitional and filter it out until the collision ceases.

SLs have been developed to improve balance. Pioneering works used two 3-DoFs SLs as anchors to keep balance in industrial environments, e.g. during aircraft assembly (Parietti and Asada 2014; Parietti et al. 2015; Parietti and Asada 2016). It has been recently proposed to equip humans with a tail that reduces the risk of falls by actively compensating for the loss of balance in the sagittal plane (Abeywardena and Farkhatdinov 2023; Abeywardena et al. 2023). Another approach to enhancing human balance is to use supernumerary legs (Gonzalez and Asada 2019; Hao et al. 2020; Khazoom et al. 2020). Moreover, balance improvement can also be achieved using devices that work alongside supernumerary legs, such as a stabilizing backpack with rotating elements that utilize Coriolis forces (Romtrairat et al. 2019; Lemus et al. 2020).

In contrast to these specific developments, we would like to have a general method for balance augmentation, based on the use of multiple SLs. For this purpose, we propose to minimize the center of mass (CoM) shift using the following cost function under other constraints from the α -layer

$$\begin{aligned} \begin{bmatrix} \mathbf{q}_1 \\ \vdots \\ \mathbf{q}_N \end{bmatrix} = \underset{\mathbf{q}_1, \dots, \mathbf{q}_N}{arg \min} & \left\{ \underbrace{\int_{t_0}^{t_f} \left(\sum_{i=1}^N \tau_{g,i}(\mathbf{q}_i(t)) \right)^2 dt}_{\text{CoM shift}} \right. \\ & \left. + \underbrace{\sum_{i=1}^N \|\mathbf{g}_i(\mathbf{q}_i(t_f)) - \mathbf{g}_i(\mathbf{q}_i(t_0))\|^2}_{\text{start-end distance (solve redundancy)}} \right\} \quad (1) \end{aligned}$$

where $t_f = \max\{t_{f,1} \dots t_{f,N}\}$ is the final time of the working SLs trajectory, $[\mathbf{q}'_1, \dots, \mathbf{q}'_N]'$ is the vector of planned joints positions of the SL_i , $i \in \{1, \dots, N\}$, $\tau_{g,i}$ the torque due to gravity imposed by the planned joints positions \mathbf{q}_i of the SL_i , computed at the human-SLs interface, and \mathbf{g}_i the position of the CoM of the SL_i . This solution is sufficient for co-moving SLs as sketched in Fig. 1B and demonstrated in this [simulation video](#) and in this [illustration video](#). For wearable SLs the cost function has to integrate the NLs, as illustrated in Fig. 4A. As the balance problem has in general multiple solutions, we suggest including an optimization criterion minimizing the SLs intervention used the sum of the squared norms of the total displacement of the center of

mass of each SL. Other solutions include using a dynamic cost instead of the geometric proposed here.

This optimal motion planning problem should be solved under the safety constraints imposed by the human movement prediction and the environment, and the task constraints. Under this criterion, the different solutions presented above, such as using the environment or adjusting the pose of the SLs, can be envisioned and the most appropriate selected for each task as illustrated in Fig. 4.

5 Flexible action planning

5.1 Predictive sensory feedback to human user

Human motor control exploits instantaneous multisensory feedback which monitors the current state of the motor system, and predicted sensory feedback to anticipate the result of an action and compensate for delays in feedback control. For the NLs, this incorporates a multitude of sensors distributed across the skin and muscles that provide touch and proprioceptive inputs. In contrast, current SLs are typically monitored only through natural visual and auditory feedback. The resulting audio-visual multisensory integration requires constant monitoring of the SL activity, mainly through vision, which can result in large cognitive load and fatigue. Furthermore, both sensory modalities can be obstructed by environmental factors.

SL feedback is critically lacking the contribution of the somatosensory modality (i.e., touch and proprioception), which is known to impact motor control and outperform other modalities (Crevecoeur et al. 2016) while being unobtrusive and discreet. Drawing from the neurophysiological mechanisms underpinning NL control, we propose that a supplementary afferent stream that exploits somatosensory afferent pathways should be introduced for SL users to (i) convey current SL state and task-related information that cannot be easily assessed with vision or hearing (e.g., grip force or distance to a target), and (ii) provide predicted sensory feedback (e.g., targets or required interaction types) to support human predictive coding behaviors. Both of these developments aim at improving the SLs' *agency*, the awareness of controlling them, and their *ownership*, the perception of them as ones' own limbs (Blanke et al. 2015).

Any provided supplemental feedback should convey the necessary information with which to understand the task as well as the SL's behavior, which might imply

the need of a dynamic feedback signal, that changes in content, encoding algorithm and possibly modality, as the goal and behavior of the SL change. This requires that the SL's goal is legible and its trajectory predictable. Relying on visual feedback, predictable trajectories can be computed by using human motor control models to generate human-like behaviors, from which legibility can then be enhanced through gradient descent methods to maximize a predefined legibility score (Dragan and Srinivasa 2014). Such techniques can also be applied to feedback related to SLs in our framework (Fig. 3), to extend (Dragan and Srinivasa 2014) from audio-visual integration to multisensory integration that includes the somatosensory modality. For instance, using vibrotactile devices, one could augment current state feedback with a mapping between the frequency and amplitude of vibrations and the planned states of the SLs. This would likely require a method to distinguish actual feedback from predictive feedback, potentially using different encoding strategies – for example, conveying the actual state via vibrotactile feedback and the planned state via electro-tactile feedback.

Decoding supplementary feedback can impose a significant cognitive load. In human-SL interaction, the CNS is challenged with processing sensory streams for both NLs and SLs, creating a risk of information overload (Dominijanni et al. 2021). Therefore, artificial sensory feedback must be carefully optimized to convey only essential instantaneous, functional, and predictive information with a minimal number of modalities or actuators. This requires selecting the most effective stimulation patterns and body locations. To date, there has been limited systematic research into identifying optimal sensory feedback strategies and developing models for their interpretation by users (Pinardi et al. 2023a). However, recent studies have started to address these issues. For instance, it has been found that providing SL end-effector Cartesian position information is more effective early in the learning process, while joint-related information (e.g., joint angles) may become more beneficial over time (Pinardi et al. 2021, 2023b).

5.2 Control modes

5.2.1 Direct control. Most augmentation applications to date have relied on direct control of SLs (Eden et al. 2022), using some of the physiological signals listed in Table 1. Movements of limbs or motor functions not used in a task, such as feet movement for a seated surgeon, or ear movements (Schmalfuss et al. 2018), can be picked up by a suitable *body interface* and exploited to control SLs. This *augmentation by transfer* (Eden et al. 2022) based on natural sensorimotor functions enables successful SL operations, such as controlling a soft endoscope via a foot-controlled robotic interface (Huang et al. 2021c).

Efforts to create more flexible solutions include utilizing the tasks' nullspace with kinematic or muscle activation signals (Salviotti et al. 2016; Gurgone et al. 2022; Lisini Baldi et al. 2024), although the number of degrees-of-freedom (DoF) gained this way may be limited (Kutch and Valero-Cuevas 2011; Lee et al. 2024) and will vary with the task. In general, direct and continuous control, using neural, muscle (Gurgone et al. 2022; Farina et al. 2023) and body (Koike

et al. 2016; Huang et al. 2021b; Kieliba et al. 2021; Huang et al. 2022; Dominijanni et al. 2023) interfaces, is cognitively costly, and constrained by the control limits of the human brain (Dominijanni et al. (2021); Eden et al. (2022); Makin et al. (2022) and answer to Penalzo and Nishio (2018)), peripheral neural signals (Bräcklein et al. 2022), and body coordination (Huang et al. 2023).

On the other hand, studies using invasive (Bashford et al. 2018) and non-invasive (Ibáñez et al. 2024; Ofner et al. 2024) neural signals suggest the potential for *augmentation by extension* (Eden et al. 2022), providing extra DoF without interfering with other sensorimotor functions. However, these initial works lack associated proprioceptive feedback and have demonstrated augmentation with only a limited number of DoF, very far from matching the natural augmentation observed in polydactyly individuals (Mehring et al. 2019). Furthermore, to our knowledge no non-invasive augmentation by extension has yet been demonstrated, which prevents their practical use in able body humans. This is partly due to challenges in decoding intent and reliably predicting desired SL trajectories in real time using physiological signals (see Tables 1 and 2).

5.2.2 Autonomous behaviors Fewer works have used autonomous behaviors for SLs (Bonilla and Asada 2014) than direct control. Autonomous behaviors could minimize the mental and physical effort required for control and improve performance by avoiding sensorimotor noise injected through direct control. They can be defined either in the world frame, for instance to stabilize an object at a given position while the human may be moving, or in the human frame, e.g. to stabilize objects relative to the human user. Hence in the example of Fig. 1A it is necessary to hold the tube part steady relative to the wall for assembly by the human. Conversely, in Fig. 1B, feeding, moving and holding digital tablets must be performed relative to the human user.

Basic autonomous behaviors applicable across many tasks include force control, such as applying constant pressure or maintaining tension on a membrane during surgery in the example of Fig. 1C. Additional fundamental behaviors, like autonomous grasping and grip strength adjustment, allow objects to be safely grasped by adapting for fragility and friction, which is essential in various applications. Techniques developed for these tasks include computer vision methods (Du et al. 2021), deep-learning approaches for grasp planning (Newbury et al. 2023), learning-from-demonstration methods (Filippidis et al. 2012), and analytical solutions (Ciocarlie and Allen 2009).

Furthermore, application-specific skills may be either designed based on task requirements, or learned from data extracted from expert behavior, such as using data from surgeons and human assistants to create a robotic surgical assistant for four-handed surgery (Leblanc et al. 2024). Autonomous behaviors can also be designed to align with NLs' movement characteristics, for example, by matching motion timing with features of the user's movements, like vigor (Shadmehr and Ahmed 2020; Verdel et al. 2023), which could enhance SL-NL coordination and improve movement legibility and predictability.

Overall, autonomous SLs behaviors remain underexplored compared to direct control methods (as has also been

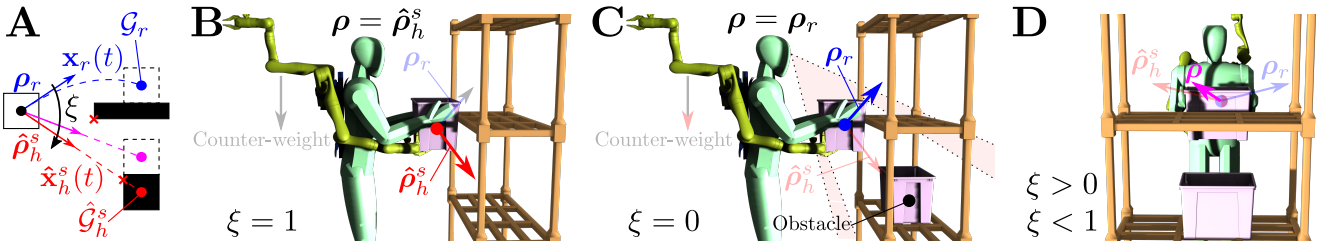


Figure 5. Illustration of ξ modulation during mechanically coupled interaction. **A.** Effect of ξ on the selected target when moving an object to a location. The curved black arrow shows the transition of the target from $\hat{\rho}_h^s$ to ρ_r as ξ increases, with red crosses illustrate potential collisions. **B.** Discrepancy between task-based ρ_r and the human target $\hat{\rho}_h^s$ estimated by the robot. When both agents have similar information $\xi = 1$ can be set. **C.** Same scenario as B, but with an information discrepancy due to a visual occlusion (shaded area). Here, if the obstacle is known only to the robot, then $\xi = 0$. **D.** Target redundancy scenario where both targets and any intermediary target are acceptable based on the available information. In this case, $0 < \xi < 1$ can be chosen based on additional factors such as the human’s expertise level.

observed in human-computer interfaces (Jain et al. 2020)). This may be due to concerns over potential safety risks associated with automatic behaviors, as well as a common overestimation of human voluntary control capacity and underestimation of the role of reflexive and automatic behaviors (Morsella and Poehlman 2013; Hommel 2017).

5.3 General voluntary control

The effectiveness of automatic behaviors suggests that they should be used for SL control. However, the safety and comfort of the SL user requires a mechanism for modifying or overriding autonomous actions when they deviate from desired performance. We therefore introduce a *general voluntary control* (GVC) that combines the benefits of autonomous control – such as reduced effort and optimized performance – with the safety and responsiveness of voluntary, direct control. To our knowledge the combination of direct control and autonomous behaviors has been considered only by Song and Asada (2021); Amanhoud et al. (2021) who proposed a task specific method, but no general method is available.

Our GVC (i) infers and accounts for the (potentially conflicting) goals and trajectories of both the SLs and the human user, and (ii) allocates effort through a homotopy between direct human control and autonomous robot behavior. It is formulated as a differential game between the SLs and the human user, building on the works of Jarrassé et al. (2012) and Li et al. (2019). The GVC considers each SL as an agent with actuation, sensing, intelligence, and a set of learned task goals \mathcal{G}_r interacting with the NLs to manipulate a common object based on a strategy defined as a cost function.

The SL first estimates the user’s target for it at the center of mass of the manipulated object $\hat{\rho}_h^s$ from sensory information on the NLs during the action*. The SL then combines $\hat{\rho}_h^s$ with its own target ρ_r arising from the task definition and incoming sensory information according to:

$$\rho = \xi \hat{\rho}_h^s + (1 - \xi) \rho_r, \quad 0 \leq \xi \leq 1, \quad (2)$$

where the parameter ξ represents the SL’s *trust* in the estimated human plan (Fig. 5A). $\xi = 1$ denotes full confidence so that the SL can follow the human user’s plan unconditionally, while $\xi = 0$ lets the SL disregard human intent, for instance to avoid an obstacle invisible to them.

The human target for an SL $\hat{\rho}_h^s$ can be estimated from the interaction force (Medina et al. 2015; Takagi et al. 2021) or the estimated trajectory of the NLs $\hat{x}_h(t)$ (Mainprice et al. 2015). ξ can also be used to combine the targets in a stochastically optimal way (similar to what was found in the interaction between humans collaborating on a common task (Takagi et al. 2017)).

Fig. 5 illustrates possibilities offered by the combination of the human and robot targets in Eq. 2. In general, the setting of ξ depends on inputs from the α -layer, considering both the task requirements and predictions of the human state. In the cases illustrated in Fig. 5B,C, choosing ξ is straightforward – either to maximize flexibility or because only one option ensures safe task completion. When ξ can be selected freely, as in the redundant target scenario of Fig. 5D, other criteria must be considered. This redundancy can be used to translate an expectation regarding the task. It may for instance be advantageous to adjust the human target to simplify future subtasks with $\xi < 1$, or to follow human inputs due to the potential for unpredictable future actions with $\xi = 1$.

Once the SL target ρ is determined, the GVC can compute the motor commands to the SLs. Assuming that the NLs and SLs manipulate a common object, GVC allocates the task effort, under the coupled dynamics of human-SL interaction, by minimizing (the integral of) the cost function

$$V(\mathbf{u}_h, \mathbf{u}_1, \dots, \mathbf{u}_N) = (\mathbf{x} - \rho)' \mathcal{Q}_r (\mathbf{x} - \rho) + \lambda \mathbf{u}_h' \mathbf{u}_h + (1 - \lambda) \sum_{i=1}^N \mathbf{u}_i' \mathbf{u}_i, \quad 0 < \lambda < 1, \quad (3)$$

where \mathbf{x} is the state vector of the center of mass of the manipulated object, and $\mathbf{u}_h, \{\mathbf{u}_i\}$ represent the motor commands of the human and the SLs, respectively. The parameter λ governs the *trade-off between the user’s and SL’s effort*. For instance $\lambda \rightarrow 1$ places maximum effort on the SL, $\lambda = 1/2$ is to share the effort with the NLs, and $\lambda \rightarrow 0$ to minimize the SL effort. When collaboratively manipulating a rigid object with pose \mathbf{x} , target ρ , the robot state and the NLs state are related through Euclidean transformations. For a soft object, the model must account

*Variables representing the SL’s estimation of the human are denoted as \bullet_h^s , estimates of human intent for the NLs are denoted as \bullet_n , and the learned task variables for the SL are represented as \bullet_r .

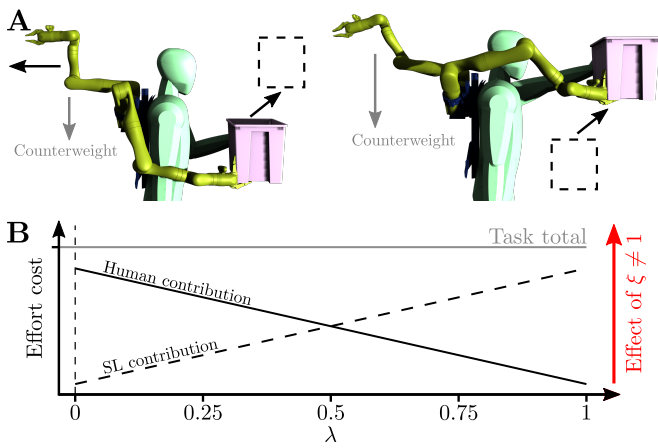


Figure 6. Anticipated effect of λ on effort sharing during a collaborative box-lifting task. **A.** Collaborative lifting task, with black arrows indicating the SLs’ movement directions for automatic counterbalancing and collaboration with the NLs. **B.** Contributions of the human and SLs as a function of λ . As $\lambda \rightarrow 0$, the most of the load is imposed on the human, whereas as $\lambda \rightarrow 1$, the SL is prepared to expend a large amount of energy to reduce human effort. When $\xi \neq 1$, a discrepancy between human and SL targets may increase contributions from both the SL and NL as they use interaction forces to negotiate the target.

for viscoelastic deformation, which also affects human-SL haptic communication (Takagi et al. 2018).

To formulate the multi-agent problem, a cost function for the human must also be considered (Li et al. 2019) such as

$$V_h(\mathbf{u}_h) = (\mathbf{x} - \boldsymbol{\rho})' \mathcal{Q}_h (\mathbf{x} - \boldsymbol{\rho}) + \mathbf{u}_h' \mathbf{u}_h. \quad (4)$$

The simultaneous optimization of Eqs. 3,4 can then be carried out by first identifying the human cost function (i.e. the \mathcal{Q}_h matrix), which can be done using inverse optimal control method (Li et al. 2022), and then a set of Riccati equations as described in (Hafs et al. 2024).

The modulation of effort sharing between agents has not yet been systematically investigated, either to assess the effects of varying λ on human motor behavior and learning or to develop an online method to optimize this parameter. We propose that λ could be adapted based on physiological and ergonomic factors, such as muscle fatigue estimated from EMG signals (Cifrek et al. 2009), ergonomic assessments using scales like RULA or REBA (McAtamney and Corlett 1993; Hignett and McAtamney 2000), or cognitive indicators like pupil dilation and microsaccades (Krejtz et al. 2018). For instance, in a task requiring the storage of boxes at various heights (see Fig. 5), locations above shoulder height that require uncomfortable postures may demand a high λ . In practice, for a given value of λ throughout a task – such as collaboratively lifting a box – the respective contributions of the human and SL can evolve through λ parameter as shown in Fig. 6. Note that the contribution of the robot agent when $\lambda \rightarrow 0$ is not null because the SL still has to correct for human errors with respect to predicted trajectories, which are unavoidable. Conversely, when $\lambda \rightarrow 1$, the human may still try to participate in the task as humans tend to dislike inactivity when interacting with robots, in particular in case of not perfectly aligned timings or trajectories (Verdel et al.

2023). Therefore, the contribution of an agent will likely never be null in GVC, as illustrated in Fig. 6B.

When some SLs are mechanically independent – such as in a collaborative pick-and-place task where each agent manipulates a separate object – the effort cannot be shared as the human’s actions do not directly affect the power provided by the SLs, thus $\lambda \equiv 0$ in Eq. 3. The SL movements can then be determined independently. However, setting their timing to match the human’s vigor (Shadmehr and Ahmed 2020) may facilitate coordination with the NL movements.

The implementation scheme for GVC is described in Fig. 7A, detailing the cases of mechanically coupled and uncoupled limbs. As previously mentioned, even for a mechanically uncoupled limb, human inputs can still influence the target as illustrated in Fig. 7C. Note that in Eq. 2, $\boldsymbol{\rho}$ are local mechanical targets in the case of mechanically coupled interactions (see Fig. 7B). In the case of uncoupled interactions the targets $\boldsymbol{\rho}$ are similar to the goals defined in Section 2 and Fig. 2, and the whole movement of the SL can be planned at once, with inputs from the human triggering a re-planning (see Fig. 7C).

6 Discussion

Movement augmentation with robotic supernumerary limbs could profoundly impact industrial and medical applications and change how humans interact with their environment. However, this transformation requires overcoming significant safety and control challenges. To address these challenges, this paper introduced a hierarchical control framework that leverages predictive signals in perception and control, enabling each layer to generate predictions and exchange error feedback with adjacent layers. By integrating human intent decoding, trajectory prediction, and safety constraints in the environment and across limbs, our framework produces reactive behaviors and ensures dynamic stability. Additionally, it supports varied applications through direct and autonomous control, as well as their seamless integration with novel general voluntary control.

Traditionally, in redundant robotic systems, constraints are hierarchically enforced based on condition priority, with each successive constraint applied within the null space of the preceding one (Khatib et al. 2004). While effective for complex systems like humanoid robots, this approach can be computationally intensive, and imposes a strict hierarchy. In contrast, human actions often require flexible prioritization, such as when adapting arm movements to accommodate multiple environmental constraints (Kühn et al. 2021). The optimization-based approach used in our framework offers greater flexibility by balancing multiple constraints simultaneously through cost functions, while still allowing the implementation of hard constraints through workspace limitation for safety as in (Khoramshahi et al. 2023).

To create an intuitive and efficient control, the framework integrates recent insights in sensory augmentation during human collaboration (Takagi et al. 2017) and optimal human-robot interaction (Li et al. 2019). By embedding sensory augmentation within the multi-agent paradigm of Jarrassé et al. (2012), GVC provides a tool to extend SLs control beyond its current task-specific specification.

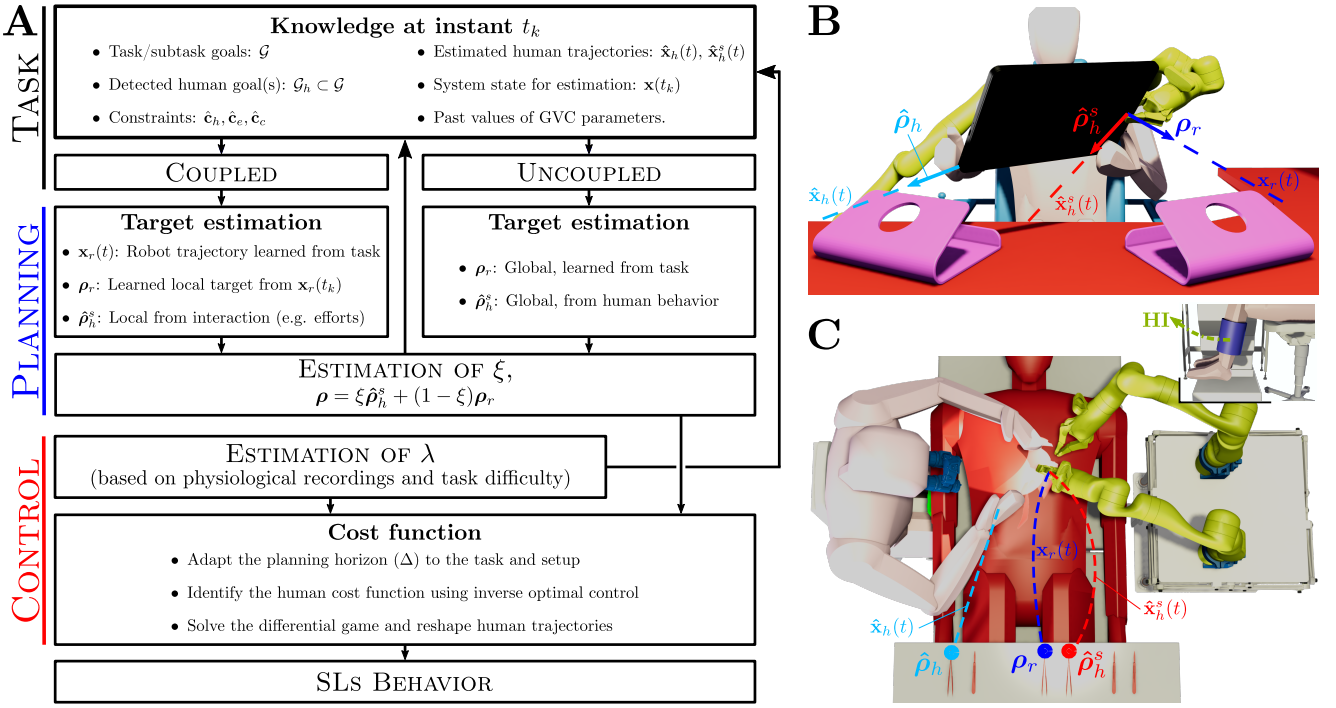


Figure 7. GVC implementation and examples. **A.** GVC involves a planning and a control processes, where the planning is different for mechanically coupled and uncoupled SLs. The planning determines the SL target based on real-time (i.e. at instant t_k) task knowledge and estimation of the human movement. Control shares the effort between SLs and NLs according to the assigned roles. **B.** Example of target handling during mechanically coupled interaction with $\xi = 1$. The task is to place the tablet in one of the two pink supports, and there is a conflict between the goal learned by the robot and the human goal. The desired human target for SLs $\hat{\rho}_h^s$ can be estimated from the interaction force to move the tablet to the position desired by the human. **C.** Example of target handling during mechanically uncoupled interaction with $\xi = 1$. The human and robot must each grasp a tool for a surgical task, with the human preferring the robot to grasp the tool at a greater distance. SL trajectories are curved to improve legibility compared to an optimal straight move. The inset displays human input (HI) via a leg interface equipped with IMUs, enabling adjustments to SL trajectories and target repositioning.

This is achieved via the real-time adjustment of two meta-parameters: trust (ξ) in human motion intent estimation and the distribution of task-related effort (λ). However, a systematic method for determining these parameters and understanding their influence on augmentation behavior is still needed.

How should these parameters be defined? One possibility is to derive them from collaborative behaviors observed between humans or multiple limbs (Rozo et al. 2013; Mainprice et al. 2015; Noohi et al. 2016; Maroger et al. 2022; Peña-Pérez et al. 2023). While previous studies on haptic (Ganesh et al. 2014; Takagi et al. 2017, 2019) and non-haptic (Sebanz and Knoblich 2021) human-human interactions have used simple tasks, more complex, multi-dimensional tasks are necessary to develop robust, data-driven methods across various applications. Alternatively, these parameters can be learned from tasks performed by a human operator in direct control. This could enable a gradual transition to GVC while minimizing the cognitive load in complex operations.

It is unclear how augmentation impacts human sensorimotor control and how the human user and their SLs may co-adapt over time (Eden et al. 2022). Understanding the effects of our approach, including different methods to modulate the meta-parameters (ξ, λ), on haptic and non-haptic human-robot interactions requires experiments with different paradigms and robotic devices. In parallel to these technical developments, human augmentation has to be considered from an ethical perspective. Ethical issues for

the integration of robots with humans include personal responsibility (Oertelt et al. 2017), potential risks of loss of autonomy (Dubljević 2019), as well as social issues such as discrimination (Bloomfield and Dale 2015; Hossain and Ahmed 2021). These issues, as well as associated legal considerations, need to be evaluated in parallel to future SL studies to ensure safe and ethical practice.

Finally, we note that the predictive coding framework and the GVC introduced in this paper can be used with various collaborative robots including rehabilitation robots, industrial cobots, sensor-equipped vehicles with shared driving, teleoperation systems, and surgical robots (Hu et al. 2024). This offers novel opportunities for the development of safe, intuitive, and efficient augmentation through robots.

Author contributions

- Conceptualization – all authors
- Funding acquisition – EB, CM
- Investigation – DV, HC, EB
- Methodology – DV, EB
- Project administration – EB
- Resources – EB
- Supervision – EB
- Visualization – DV
- Writing, original draft – DV
- Writing, review and editing – all authors

Acknowledgements

We thank D. Farina for his help in the funding of this study.

Statements and Declarations

Ethical considerations

Ethical approval was not required for this study.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Declaration of conflicting interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding statement

This study was funded by the H2020 NIMA (FETOPEN 899626), and by the ERC Synergy Natural BionicS (810346).

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