

# A Topology of Shared Control Systems – Finding Common Ground in Diversity

David A. Abbink, *Senior Member, IEEE*, Tom Carlson, *Member, IEEE*, Mark Mulder, Joost C. F. de Winter, Farzad Aminravan, Tricia L. Gibo, and Erwin R. Boer, *Member, IEEE*

**Abstract**— Shared control is an increasingly popular approach to facilitate control and communication between humans and intelligent machines. However, there is little consensus in guidelines for design and evaluation of shared control, or even in a definition of what constitutes shared control. This lack of consensus complicates cross-fertilization of shared control research between different application domains. This paper provides 1) a definition for shared control in context with previous definitions, and 2) a set of general axioms for design and evaluation of shared control solutions. The utility of the definition and axioms are demonstrated by applying them to four application domains: automotive, robot-assisted surgery, brain-machine interfaces and learning. Literature is discussed for each of these four domains in light of the proposed definition and axioms. Finally, to facilitate design choices for other applications, we propose a hierarchical framework for shared control that links the shared control literature to traded control, co-operative control and other human-automation interaction methods. Future work should reveal the generalizability and utility of the proposed shared control framework in designing useful, safe, and comfortable interaction between humans and intelligent machines.

**Index Terms**—shared control, supervisory control, traded control cooperation, human-machine interaction, human-robot interaction, human-automation interaction

## I. INTRODUCTION

Norbert Wiener stated in 1950 “...in the future development of (...) messages and communication facilities, messages between man and machines, between machines and man, and between machine and machine, are destined to play an ever increasing part” [1]. He advocated intuitive human-machine communication, where

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D. A. Abbink, M. Mulder, T. L. Gibo and E. R. Boer are with the Department of Cognitive Robotics and J. C. F. de Winter, is with the Department of Biomechanical Engineering of the Faculty of Mechanical, Maritime & Materials Engineering, Delft University of Technology, Mekelweg 2, 2628 CD Delft, The Netherlands (e-mail: d.a.abbink@tudelft.nl; mark.mulder@tudelft.nl; j.c.f.dewinter@tudelft.nl; t.l.gibo@tudelft.nl; e.r.boer@tudelft.nl).

T. Carlson is with the Aspire Centre for Rehabilitation Engineering and Assistive Technology, University College London, Royal National Orthopaedic Hospital, Stanmore, HA7 4LP (e-mail: t.carlson@ucl.ac.uk).

F. Aminravan is with the Advanced Control and Intelligent Systems Laboratory of the School of Engineering, University of British Columbia, EME 2218, 1137 Alumni Ave, Kelowna, BC V1V 1V7, Canada (email: farzad.aminravan@gmail.com)

communication can be defined as the “...*exchanging of information by speaking, writing, or using some other medium*” [2]. An even broader perspective of communication is suggested by its Latin roots: the Latin verb ‘*communicare*’ means ‘to share’.

Since then, increasing technological sophistication and the availability of inexpensive mechatronics and artificial intelligence (AI) have substantially increased the capabilities of machines. However, the challenge to create effective embodied artificial intelligence–intelligent machines that can physically interact with their environment–remains huge, especially in unstructured environments. To avoid confusion, we will use the single term robot to describe a designed system that has a degree of ‘intelligence’ and ‘autonomy’ (self-directedness), which it uses to interact physically in and with its environment. Robots, therefore, include intelligent vehicles, brain-controlled wheelchairs, exoskeletons, semi-autonomous systems, etc.

The ability for robots to be *fully autonomous always and everywhere* is a myth [3], despite the impressive demonstrations of today’s highly-automated planes and cars, or of the DARPA Robotic Challenges. Full automation can be achieved in environments which can be predicted with high accuracy and where the consequences of failure are acceptable (e.g., a conveyor belt). But in more complex and unpredictable environments, some form of human control is needed to achieve adequate performance in the overall task that the robot is designed for. We will use the term human-robot interaction (HRI) to describe the interaction and communication between human and robot [4], specifically when completing a task in a physical environment; and the term human is hereafter used for the operator, driver, pilot or teammate of the robot. HRI is studied in the field of human factors and ergonomics [5][6][7], and is also addressed as human-computer interaction or human-automation interaction. In these fields, it is recognized that in unpredictable real-world environments, human and robot need to cooperate to robustly keep performing the overall task. Depending on the individual capabilities of robot and human in the specific environment, co-operation can occur at different levels [8]: low-level subtasks (executing physical actions) up to high-level tasks (judging situations, developing plans, making decisions, and implementing actions). Successful cooperation between human and robot at different levels requires effective communication and interaction [9]: the long-standing challenge described by Wiener, pursued already in the 50’s [10] and 60’s [11], is still relevant today [5].

One of the most influential concepts for human-robot interaction was published in a 1967 issue of IEEE Spectrum, in which Ferrell and Sheridan studied control over a remote robot and introduced the concept of *supervisory control*. Supervisory control does not require full robot autonomy, but ‘merely’ the ability to achieve some goals independently, while the human supervisor sets high-level intermediary goals. One of the main issues according to the authors is “...*setting up a method of communication between the operator and the machine*” [12]. In later work on subsea robotics [13], Sheridan and Verplank distinguished two types of control: “*To share control means that both human and computer are active at the same time. To trade control means that at one time the computer is active, at another the human is*”. Traded control became a widespread paradigm for HRI, where trained operators act as a backup system for the robot (i.e., the automation system controlling a plant/vehicle/device). One of the best-known applications of traded control is in aviation, a domain that is exposed to human factors issues arising from limited communication between human and robot [14]. These issues identified decades ago in aviation [15][16] and other domains [17][18] persist today [19], and include problems with: trust [20], switching authority, loss of skills and situation awareness, overreliance, and inaccurate ‘calibration’ with regards to robot reliability [19][21][22][23].

Shared control, on the other hand, has only recently received popularity. A full-text search for “shared control” between 1966–1999 yields only 348 publications on IEEE Explore and 4,300 hits on Google Scholar. The same search between 2000–2016 yields 2,078 publications through IEEE Explore, and over 17,100 hits on Google Scholar. Even accounting for a 5% year-by-year increase in publications in general, this illustrates the recent rapid growth in using the term “shared control”. Shared control has been applied to a wide range of control tasks and a diversity of applications. This diversity is illustrated by the backgrounds of the authors of this paper: each of us has been working to develop shared control solutions in different domains (automotive, brain-machine interfaces, telerobotic surgery and transfer of learning). Intrigued by the similarities and differences across domains, three of the authors founded the IEEE SMC Technical Committee on Shared Control [3] in 2011, with the goal of stimulating cross-fertilization and sharing of design and evaluation methods. In annual workshops, the organizers and participants discussed each other’s work as well as recent and early literature. We encountered much confusion about what constitutes shared control and what does not; which design principles should be followed; where shared control can and cannot be applied; and how shared control systems should be evaluated. In short, we experienced a lack of a coherent design and evaluation framework for shared control.

The goal of this paper is to provide researchers interested in shared control with 1) a common definition for shared control, grounded in previous definitions in the literature, 2) general axioms for design and evaluation, 3) a review of shared control in four contrasting application domains; 4) a hierarchical shared control framework to identify how communication and interaction can aid the human in

remaining aware and able.

In Section II we provide an overview of definitions in the literature, along with a consensus definition of shared control. We include three axioms that reflect our guidelines for design and evaluation of shared control applications. Next, we illustrate domain-specific issues regarding the design and evaluation of shared control technology across four fields: automotive (Section III), robot-assisted surgery (Section IV), brain-machine interfaces (Section V) and learning (Section VI). In Section VII, we propose a framework that structures different types and levels of control into a hierarchical task decomposition, that can guide design considerations about which types of shared control are most suitable for given tasks and conditions (Section VII). The framework constitutes a principled approach to comparing and contrasting the pros and cons of different shared control designs within a specific domain, and exposes possibilities for communication and interaction.

## II. WORKING WITH SHARED CONTROL

### A. Shared Control Defined

There is no single definition for shared control that is used across application domains. Often, studies use the term ‘shared control’ without providing a definition, and among studies that do define the term, definitions vary.

One early definition of shared control was provided by Sheridan [17]: shared control is a situation where the human acts “...*as supervisor with respect to control of some variables and direct controller with respect to other variables.*” Exactly what variables this definition refers to remains unclear. Niemeyer et al. [24] stated that we could speak of shared control “*if task execution is shared between direct control and (...) autonomy, or if user feedback is augmented from virtual reality or other automatic aids.*”

More recent definitions introduce a hierarchy of subtasks: in shared control “...*the remote system can exert control over some aspects of the task while the human operator maintains access to low-level forces and motions...*” [25], or “...*the robot can control low-level functions (...) while the human operator maintains high-level control*” [26]. In the field of brain-machine interfaces (BMI), shared control was first applied by Srinivasan’s group [27], who defined continuous shared control as being: “...*continuous because the interaction is immediate and does not have the ‘wait and see’ characteristics of a planner-based approach or the switching characteristic of a traded-control*” and “*shared because it always reflects input of both brain and sensor, as distinguished from traded control where control switches discreetly from direct operator control to the autonomy of the robot depending on task and situation.*”

Another view is put forward by Endsley and Kaber [16], who discussed shared control in the context of levels of automation, where during shared control “...*both the human and the computer generate possible decision options. The human still retains full control over the selection of which option to implement; however, carrying out the actions is*

*shared between the human and the system.*” Here, the essence of sharing control lies in the execution of actions, although ‘monitoring’ and ‘generating’ can also be shared. This emphasis on shared control for ‘low-level’ execution is also central to proposed definitions for the automotive domain. Shared control solutions can be divided into two general methods [28]: input-mixing shared control and haptic shared control. The former approach steers a vehicle using “...*a final steer command which is a blend of a human driver and an optimal controller*” [29]. In haptic shared control, the shared control occurs at the force level: “...*the human utilizes the haptic sensory modality to share control of the machine interface with an automatic controller*” [30][31]. The confusion over what does and does not constitute shared control largely results from a different perspective on what constitutes control. Our position is that sharing of task control between human and robot can occur at different hierarchical levels of control and learning. During shared control, human and robot jointly arrive at a plan, decision, or control action for a system (vehicle/device), each of which can differ from the one that either agent alone would generate. In sum, in this paper we propose the following definition of shared control:

***In shared control, human(s) and robot(s) are interacting congruently in a perception-action cycle to perform a dynamic task, that either the human or the robot could execute individually under ideal circumstances.***

This definition excludes full automation (where there is no human) or manual control (where there is no automation). It also excludes traded control, because in traded control human-machine interaction is not temporally congruent. More specifically, a case where control is traded to the human – who goes out of the loop temporarily to get back into the loop later – would not fall under our shared control definition. Shared control also excludes binary warning systems and decision support systems because these systems only support the perception side of the perception-action cycle. That is, decision support systems or mission planning systems do not close the perception-action cycle by themselves (although they may provide inputs to a shared controller). Our definition furthermore excludes stability control systems (e.g., in high-performance vehicles or aircraft) when these support humans outside their control bandwidth because those tasks could not be performed by the human alone (e.g., when the computer system fails). This definition *does* include robots that support the human beyond physical limitations (e.g., exoskeletons, telemanipulators, robotic prostheses, intelligent wheelchairs).

Our definition is open to many forms of shared control, such as the interaction between multiple humans and one system, or one operator controlling multiple systems. However, this paper focuses on shared control applications where a single human controls a single tool or vehicle.

### *B. General Design Approach for Shared Control*

Sharing of control between human and robot can take place via different modalities and at different task levels. For

example, a driver and an intelligent vehicle may both act haptically on the steering wheel, or a BMI wheelchair user and an intelligent wheelchair may both act on the decisions to initiate a turn at the next suitable location. The key element of shared control is that mechanisms are created to facilitate the communication of some aspect of control (planning, decision-making, action execution), from which the human and robot can understand each other’s activity and intent. **Axiom 1** for shared control design is therefore:

***Shared control should link the actions of the human(s) and the robot(s) by combining their efforts towards a final control action, decision, or plan, such that each agent directly perceives how its intent is shaped by the other agent, without having to wait for controlled system dynamics to reveal the outcome of their joint efforts.***

To encourage cooperation and minimize conflict between human and robot intentions, it may prove beneficial to model robot behavior based on human behavior [28], as advocated by human-centered automation [32]. This leads to the following **human-centered design corollary**:

***In shared control, conflicts between the human and the robot should be minimized, by modeling robot actions based on human behavior; and in case of conflicts, the robot should ensure that the human has the time and ability to influence the robot’s actions.***

For example, during BMI wheelchair control that involves shared control at the decision level, the system has to communicate the chosen maneuvering decisions sufficiently far in advance for the human to be able to overrule or influence that decision.

Thus far, we have mainly discussed limitations on the side of the robot. Humans also have limitations, which is the reason to create robotic systems in the first place. Effective shared control design allows *mutually* guiding and protecting roles for robot and human.

### *C. When to Employ Shared Control?*

Shared control is not necessarily the best choice for every kind of human-robot interaction. Traded control may be perfectly acceptable when control authority can be traded with enough time margins for the human operator to get back in the loop and respond adequately. This offers the benefit that the human operator can safely focus his or her attention elsewhere, in the assurance that all situations where human intervention is required can be identified accurately and communicated timely. However, an essential complication for many HRI scenarios is that robot functionality is not constant, but *situated* [33][34]. That is, the situation or context impacts the functionality, which may shrink or shift outside of the expectations of the operator (whose preferences and abilities are dynamic and situated as well). Although the robot may function as intended *within* the boundaries of certain situations and conditions, it requires the human operator *outside* of them. Unexpectedly and rapidly changing boundaries complicate

exactly *when* and *how* to trade control between robot and human [35][36]. Situated robot abilities and the accompanying human factors issues also limit the utility of conventional binary warning systems and adaptive automation [37].

As long as a human operator is needed for system integrity, then he or she also needs to be supported in maintaining appropriate situation awareness and understanding the robot's situated limitations: that is, the human must develop mental models of situated robot functioning and utility. This is in line with Billings' concept of human-centered automation [32]. We hypothesize that shared control is especially useful to foster awareness of the robot's control activities, intent, and capabilities, especially when the robot reaches its functional limits, or when the situation changes so that the robot shows degraded performance.

**Axiom 2** for shared control design in terms of safety and performance is therefore:

*Shared control finds its highest safety utility in circumstances where situations and conditions can rapidly change beyond the envisioned design boundaries of the robot, and where rapid adaptation in human involvement is needed to maintain system integrity.*

*Shared control finds its highest performance utility in circumstances where a human's situated control, perception, or cognitive ability is the main limiting factor for the combined performance, and where the robot complements these human abilities.*

The accompanying **design corollary** is:

*For humans to understand the utility of a robot under realistic conditions, task domains and system design limitations need to be made explicit and used to shape the communication between human and robot.*

#### D. Shared Control Evaluation

Conventionally, shared control designs have been evaluated to show their advantages compared to manual control. Many researchers concerned with shared control, including ourselves, have the vision that shared control has the potential to mitigate many of the known issues of traded control. However, solid evidence for this statement is lacking due to the manner in which we have been evaluating shared control systems [38].

We have often followed the same, rather self-confirming approach observed in other groups: evaluating the human-robot system within the task domain for which the robot (support system) was specifically designed, effectively ensuring that human-robot system limitations are not exposed during evaluation. Only quite recently have several studies specifically addressed the evaluation of shared control outside of design boundaries [39][40][41][42]. As argued above, the true quality of human-robot interaction emerges when crossing robot limitations, either by conditions in the environment or

by the human operator who may try to 'push' the robot boundaries. Obviously, it is impossible to evaluate utility and satisfaction for human-robot interaction for every conceivable situation, but we advocate purposeful evaluation of situations and conditions for which the robot was not specifically designed. **Axiom 3** is therefore that:

*To evaluate a human-robot system it is necessary to evaluate within and beyond the boundaries of the task domain for which the robot was designed, as well as within and beyond the boundaries of the robot limitations imposed by hardware, cost or policy—insofar as necessary to meet the full spectrum of realistic situations and conditions where humans may use the robot.*

The accompanying **evaluation corollary** is that:

*To fairly compare different robot designs and human-robot interaction philosophies, it is necessary that the experimental conditions include static and dynamic conditions that fall within and beyond the boundaries of the task domain (design scope), within which each agent yields maximal independence (autonomy) and thus performance.*

The key of Axiom 3 and its corollary is that, if applied to shared control, it tests Axiom 2 and its corresponding corollary at a task level above the common task-level. Hence, it allows for comparisons of shared control designs across tasks.

The three axioms will serve as a focus in sections III-VI, which provide a shared control literature review for four application domains: automotive, robot-assisted surgery, brain-machine interfaces, and skill transfer.

### III. THE AUTOMOTIVE DOMAIN

Driving is a partially self-paced hierarchical task, based on (sampled) visual information from the road and other road users, although drivers also receive valuable auditory, haptic and vestibular cues. An insightful perspective on this hierarchical driving task is tolerance management: minimizing the risk of reaching spatiotemporal constraints such as lane boundaries or other road users. Because tolerances on these constraints are not rigid, but instead depend both on the driver as well as on the situation (Axiom 2), a large variety of different driving strategies exist that depend on driver ability (e.g., skill, insight, physiology, age) and preferences or needs (comfort, speed, safety). The demands of the driving situation sometimes exceed the ability of the driver, resulting in dangerous conditions or even accidents. Hence, the automotive industry has a long history of driver support systems [43] and steps towards self-driving cars [44]. In the last decade the abilities of advanced driver support systems (ADAS) have increased so much that intelligent vehicles are sometimes called 'self-driving' in the media, although in reality the cars employ traded control: they need to be

supervised by a driver to whom control will be traded back when the ADAS boundaries are reached in real-world scenario's (Axiom 3) or in case of conflicts (Axiom 1).

#### A. Task of Support Systems

The variety of driving tasks that ADAS can support can be hierarchically classified [45][46] using three levels:

- i) Strategic Level: planning and task set adaptation, e.g., recognizing that an intersection is approaching and that stopping and turning are new tasks to “load” into the tactical level.
- ii) Tactical Level: decision making and task management such as initiating a lane change or changing the following distance
- iii) Operational Level: continuous control and discrete maneuvers such as lane keeping, car following

These levels correspond to aviation's navigation, guidance, and control [47]. A fourth level is sometimes included as well: an Execution Level that captures the neuromuscular control loops, ensuring the execution of Operational Level commands. Most ADAS are not based on shared control, but either on warning signals (such as auditory parking assistance and lane-departure warning systems) or traded control of longitudinal control tasks (e.g., cruise control, adaptive cruise control) and lateral control tasks [48].

#### B. Design of Driver Support Systems

The need to think about shared control design between the driver and an ADAS that can individually perform (part of) the hierarchical driving task can be well illustrated by considering the example of one of the most widely available ADAS: adaptive cruise control (ACC). This ADAS can follow a lead vehicle: it automates the driver task of car-following at the *operational level*, leaving the driver free to remove the foot from the gas pedal and communicate the tactical choice of the desired following distance by pressing a button. However, ACC has dynamic, situated limitations: bad weather conditions degrade lead vehicle tracking; sharp bends and roundabouts lead to sudden loss of the lead vehicle; the capabilities and authority to accelerate and decelerate are limited. As a result, the ACC capabilities may shrink as a result of changes in the system (degraded sensors) or changes in the environment (changing weather conditions, sharp curves). The situated task for the combined human-robot system may shift according to traffic density, the chosen speed, or following distance. Such shifts are an example of Axiom 2, and call for continuous and intuitive communication and interaction between human and robot.

To communicate with the driver, the ACC can give warning signals ‘upwards’ to the driver when it realizes that functional limitations of its operational task are approached. The driver can communicate ‘downwards’ to provide set-points or switch the ACC on or off. Comparatively few attempts have been made to make this communication system and driver more continuous, such as a visual interface to display ACC behavior [49], intended to “...*promote appropriate reliance and support effective transitions between manual and ACC control.*” This

work recognized the need for *continuous* communication of ADAS limitations. The results showed that drivers responded properly to system failures when braking limits were exceeded.

Shared control offers an alternative approach: employing the same sensor suite of ACC but translating separation states continuously to forces on a haptic gas pedal [50], instead of feeding to direct control inputs to the vehicle. This approach is called haptic shared control [28] and essentially physically couples the driver's operational control actions to the operational control actions of the robot (ADAS). The action-perception coupling persistently links the communication between the system and driver to the concurrent situation, allowing mutual awareness of conflicts and immediate resolution (Axiom 1). The continuous nature of the communication and interaction keeps drivers comfortably in the loop, and enhances situation awareness also outside system boundaries (Axiom 3). Haptic shared control has demonstrated to be an effective way to not only improve driver performance but also to reduce risk [51]. The haptic gas pedal can also communicate legal speed limits [52] and be useful for eco-driving [53].

Haptic shared control for lateral tasks require a haptic steering wheel, and has been explored for lane keeping and curve negotiation [54][55]), but also for discrete maneuvers, such as evasive maneuvers [56], lane changing [57], and merging/cut-in [58]. Flemisch and colleagues [59] proposed the “H(orse)-Metaphor” as a design metaphor for the communication and interaction with a highly automated vehicle. Later they developed the concept of ‘cooperative guidance and control’ [40][60][61], linking support at the operational (=‘control’) and tactical (=‘guidance’) levels. Recent literature [62] proposed to unify ‘cooperative guidance and control’ with ‘shared control’ by treating ‘shared control’ as a subset for the encompassing ‘cooperative guidance and control’, which may include both shared and traded control solutions in a cooperative manner. Regardless, a design metaphor (such as the horse metaphor [59][60]) is useful to guide shared control design as well as to communicate the concept to users.

Two of the main design challenges for shared control for steering include 1) designing the underlying controllers that calculate steering inputs from the sensed environment 2) deciding what control inputs to share with the human, and how to weigh them. The first design challenge is essentially that of designing the controllers that can autonomously steer the vehicle within the design boundaries. Based on Axiom 2, the underlying controllers should be human-centered (and possibly even individualized) to increase comfort and predictability of the actions of the intelligent vehicle. In some cases it may even be necessary to base robot behavior on the individual operator's behavior [63][64], or to adapt continuously to the adapting human as situations and conditions change [65]. The second design challenge strongly depends on the choice for either sharing control at the level of generated *steering angles* (i.e., input-mixing shared control [29] [66], or the related ‘indirect haptic aiding’ [67]) or at the

level of generated *steering torques* that will jointly realize the steering angle input to the vehicle (i.e., haptic shared control [28] [30][50][55][60] [68]).

Input-mixing shared control inherently assigns the final steering authority to the robot [28], which conflicts with Axiom 2. This version of shared control may work well in situations where the automation is always reliable and the driver is unlikely to make responsible steering movements, but may pose problems when the driver wishes to overrule the automation's actions [69]. The sharing of control depends on design choices concerning the (static or dynamic) contribution of each steering input to the vehicle [66]. Note that input-mixing masks the controller's activity unless feedback is provided [67], and variably changing the ratio of steering wheel angle to tire angle may result in a significant period of motor adaptation [70].

In contrast, for haptic shared control, the sharing occurs at torque level, thereby including the fast and highly adaptive neuromuscular system of the driver [71] to communicate and interact with the automation. Here, the sharing of control depends on the magnitude of the forces [68] [72] and the level of haptic authority [28] (i.e., stiffness [73] around the controller's optimal steering angle). The tuning of the magnitude of the shared control forces can be formalized when based on measured neuromuscular behavior [74].

### C. Evaluation of Shared Control Solutions

Shared control solutions are usually evaluated safely within intended system boundaries, and not compared to traded control ADAS. An interesting exception is a study that compared a haptic gas pedal and an adaptive cruise control on the expressways around Minneapolis-Saint Paul in high traffic density conditions. Drivers had to engage and disengage ACC each time the speed dropped below 40 mph ACC and had to press the brake when a deceleration greater than  $2.5 \text{ m/s}^2$  was needed. Under these conditions, drivers preferred the shared control provided by the haptic gas pedal over the traded control of the ACC and over manual driving, mainly due to annoyance with repeated disengaging and engaging of the ACC due to the traffic. In more recent studies of steering support in highly automated vehicles [75], different shared control design options for shared control were evaluated [40] [41] within and beyond the design boundaries (Axiom 3).

## IV. ROBOT-ASSISTED SURGERY

Surgery is a domain that continues to be enhanced by the addition of supporting technology into the operating room, both assisting existing surgical procedures and enabling new techniques that were not previously possible. Surgical procedures demand both dexterous motor and cognitive skills, which can pose challenges to even the most experienced surgeons. While the accuracy and precision of robotic devices offer a promising approach to provide assistance in the operating room, full automation is often not possible due to the high level of risk involved in surgical procedures [76]. In contrast to the previously discussed automotive domain, surgery encompasses a large range of operations that are

performed with a variety of tools by highly trained specialists, who often have high expectations for support system transparency and low acceptance of systems that they feel will hinder their work [77].

### A. Task of surgical robotic support systems

A variety of computer-assisted support systems have been considered to enhance a range of procedures, from orthopedics to percutaneous therapies to laparoscopic surgery. Support systems have been designed to assist during different phases of these surgical operations, both with preoperative planning, intraoperative procedures, and postoperative verification. In this paper, we limit the discussion to robotic support systems that have been designed to aid and improve the intraoperative phase. The unique surgical environment presents a handful of additional constraints that challenge the surgeon's sensorimotor and spatial reasoning skills: delicate surrounding tissues to avoid damaging, intricate anatomical structures around which to maneuver, and complex mappings and kinematics of robotic instruments. The assisted intraoperative subtasks vary greatly with different surgical procedures, ranging from tissue manipulation to needle driving, from suturing to navigation. Despite this subtask variability, support systems can be considered to assist the surgeon in the following types of tasks:

- i. Extension of sensing/motor capabilities: The limits of the human sensorimotor system, which are often approached due to the scale of some procedures, can be enhanced to help the surgeon operate within the environment constraints (e.g., small anatomical structures, delicate tissues, low interaction forces).
- ii. Information integration: Incorporating different sources of information (e.g., patient-specific anatomy from different imaging modalities) in a seamless manner can aid the surgeon in efficiently determining and executing a desired plan.

### B. Design of surgical robotic support systems

Surgical robotic support systems, both in the clinical and experimental stage, have been designed with varying levels of automation [78]. While it is usually desirable to keep the surgeon in-the-loop, the complexity of the procedure and the dynamics of the environment affect the acceptable level of automation.

Autonomous robotic systems that replace specific subtasks of the surgeon have been used in some clinical applications, particularly orthopedics and neurosurgery. These particular applications allow for accurate registration of the surgical tools to rigid bony structures, with little deformation to the targeted anatomy. One of the first clinical systems was the ROBODOC Surgical System (Curexo Technology Corp., USA), designed to improve the precision of manual joint replacement surgery [79]. Prior to the operation, the surgeon selects the appropriate implant based on preoperative computed tomography (CT) images and determines the desired placement. The ROBODOC system autonomously

mills the desired shape for the selected implant, while the surgeon serves a supervisory role with the ability to monitor and abort the process. Other clinical robotic systems have been developed to support the surgeon by automating such subtasks as positioning a mechanical guide for the manual insertion of a tool (e.g., NeuroMate for neurosurgery, Reinshaw, UK). Experimental systems are also being developed to automate subtasks in less predictable situations or deformable environments, such as suturing (EndoBot, [80]).

Automation of surgical procedures is limited, however, because “...situations and conditions can rapidly change beyond the envisioned boundaries” (Axiom 2). It comes as no surprise then that many surgical robotic devices have been designed to share control with surgeons, improving their performance rather than autonomously executing tasks. These systems use the principles of either teleoperation (master-slave system) or cooperative manipulation (surgeon and robot both hold the tool). Since the surgeon and robotic system are continuously in physical interaction, this presents the possibility for synergistic shared control. The da Vinci Surgical System (Intuitive Surgical, USA), one of the most successful commercial teleoperation surgical systems, currently features tremor filtering and motion scaling but does not include haptic feedback [81].

Researchers have considered a form of shared control to compensate for physiological motion, due to respiration or heartbeat. During teleoperated cardiac surgery, robotic technologies have been investigated to eliminate the need for constraining the heart with mechanical or vacuum stabilizers. If the slave device tracks and moves with the physiological motion, the surgeon can operate on a static image of the heart. This approach is a form of “input-mixing” shared control [28], since the automatic controller and surgeon control the robotic system concurrently, but the activity of the automatic controller is not continuously communicated to the operator.

Other clinical and experimental surgical robotic systems have implemented haptic shared control, enabling the surgeon and an intelligent controller to communicate their respective actions to one another directly, without inducing sensory overload via additional sounds or lights in an already hectic operating room environment. Virtual fixtures have been widely investigated to support an operator, either preventing the incursion of designated forbidden regions (passive assistance) or providing guidance along desired paths (active assistance) [82]. By integrating patient-specific anatomical information (e.g., CT or MR images), the intelligent controller can help the surgeon stay at the surface of an organ or avoid puncture of delicate structures. In contrast to the autonomous ROBODOC, the RIO Robotic Arm Interactive Orthopedic System (MAKO Surgical Corp., USA) allows the surgeon to stay involved in the milling process, providing support via virtual fixtures [83]. The surgeon manually moves the robotic arm to guide the cutting process and only feels resisting forces if the tool begins to move outside the predetermined surgical plan.

Virtual fixtures for haptic shared control have been investigated to tackle these issues for a variety of other

surgical procedures, although they remain in the experimental stage [84][85][86]. Park et al. used forbidden region virtual fixtures to prevent excursions from the area of interest in a blunt dissection task with the application of cardiac surgery [84]. For the application of ophthalmic microsurgery, Becker et al. generated real-time virtual fixtures from microscope video to prevent over-penetration of the retinal membrane [86]. Virtual fixtures have also been explored to provide guidance by imposing motion constraints during various endoscopic procedures and tasks, including the insertion of tools during sinus surgery [87], steering of flexible endoscopes [88], and suturing [89].

The design of a surgical support system that is accepted with confidence for use in clinical stage remains a challenge. The design challenges for shared control are driven by high surgical accuracy, on-demand maneuvers, and anatomical considerations in different surgical procedures. Operator proficiency issues and variability in the surgical subtasks can severely impact the ability of surgeons supported by surgical robot systems to achieve optimal performance and safety in the shared (sub)tasks [78]. These challenges demand improved design and evaluation methods to communicate and process critical information at different levels of intraoperative subtasks.

While current clinical robotic systems mainly serve to extend the surgeon’s eyes and hands, the implementations of haptic shared control discussed above supplement the surgeon with additional guidance at the Operational Level (see Section III.A). Further developments in advanced visualization and recognition algorithms, informatics, and machine learning will enable future systems to provide not only increased dexterity and precision but also knowledge, thereby supporting decisions at the Strategic and Tactical Levels.

### C. Evaluation of surgical support systems

Due to the high concern for patient safety in surgery, it is of utmost importance to also evaluate shared control for robotic systems outside of conditions for which it was originally designed [90] (Axiom 3). It is imperative to understand the effects of system malfunctions and conflicts (Axiom 1) between the intentions of the surgeon and intelligent controller on the surgeon’s behavior and the overall objectives of the surgical procedure.

For image-guided navigation, one method for displaying the system’s uncertainty of tool or anatomy position is to show an ellipse representing registration imprecision [77]. Analogous methods need to be implemented to inform the surgeon of the limitations of the haptic shared controller. Conversely, methods to improve the controller’s awareness of the surgeon’s limitations, such as hand tremor or insufficient dexterity, can be implemented. There has been some work on varying the guidance gains (level of haptic authority) and adapting assistance based on user intent using continuous hidden Markov models [91]; however, these adaptive methods require further attention in terms of design and evaluation. In addition, due to the specific targeted population for surgical support systems, these systems should be evaluated in the

appropriate context. Evaluation with and feedback from surgeons can produce different results from testing the system with laypersons or tests on virtual surgery simulators. It is also important to assess how well the support system integrates into the overall flow of the surgical environment. And lastly, while improvements in performance metrics (e.g., accuracy and precision) are often emphasized, the effect on clinical outcome must be prioritized.

## V. BRAIN-MACHINE INTERFACES

In the previous two sections on vehicle control and robot-assisted surgery, we have seen how haptic shared control provides an effective methodology for blending human input with robot precision at the level of physical interaction, while maintaining the user's authority. However, some applications render it impractical or impossible to physically interact with a control interface, especially in the domain of assistive technology for people with severe motor impairments, where the end-user often has weak or no voluntary muscular activity. This means that activities of daily living, such as locomotion, reaching and grasping are extremely limited or impossible to achieve independently. One possible solution that has been gaining increasing attention over recent years is to use brain signals directly to control robot-assistive technologies, thus bypassing the usually peripheral motor-output pathways.

### A. Task of Brain-Machine Interfaces

Brain-Machine Interfaces (BMIs) aim to empower people with severe motor impairments to get on with (some) of their activities of daily living, by using thoughts alone to control assistive robotic devices [92][93]. Typical activities include operating self-feeding systems, environmental control units, prosthetic devices, text-entry systems and wheelchairs. BMIs monitor the user's brain activity, most often through non-invasive electroencephalography (EEG) and translate his or her intentions into commands, which can be sent to external devices, computer programs [94], or physical devices such as the wheelchair that we will use as a case study in this section [95].

The primary aims of a brain-machine interface are to:

- Monitor the user's brain signals
- Recognize the correlates of a predetermined set of mental activities or processes in real-time
- Map these correlates to control actions
- Provide feedback to the user about his or her perceived mental state and the corresponding selected control actions.

### B. Design of Brain-Machine Interfaces

Many BMI implementations rely upon the subject attending to visual or auditory stimuli, which are synchronously presented by the system [96]. This leads to a duality between control and feedback: is the robot or the user initiating the control? Conversely, our philosophy is to keep as much authority with the users as possible, such that the user should be able to spontaneously and asynchronously control the wheelchair, for example by performing a motor imagery task

[95]. Since this does not rely upon visual stimuli, it does not interfere with the visual task of navigation. Furthermore, when dealing with motor-impaired patients, it makes sense to use motor imagery, since this involves a part of the cortex, which may have become redundant; that is, the task does not interfere with the residual capabilities of the patient.

As we have previously seen, in haptic interfaces, the system provides a force, which the user can yield to, or override. In BMI, the system (robot) can either initiate an action or give an indication that it will initiate an action, having detected a particular pattern of brain signals (Axiom 1). If the robot executes or proposes an action, which the human deems to be incorrect, it is possible to detect a so-called error-related potential (ErrP) in the human EEG signal [97]. Such "cognitive states" can be used as feedback to the system, to correct mistakes or inform the refinement of a learned control policy [98].

This framework, however, poses several challenges in determining the human's intention from such uncertain channels and consequently generating the most appropriate control signals. These challenges are associated with relatively low accuracies; low temporal precision; and low information transfer rates in the human control input signals. Furthermore, uncertainty in the system, such as the human's internal state (attention, workload, fatigue, etc.); the non-stationary nature of brain signals; and the variation of the class-discriminative information, both within and between users, exacerbate the challenge [96]. Shared control seems like a reasonable approach to compensate for these inherent ambiguities associated with BMIs.

### C. Input-Mixing Shared Control for BMIs

In contrast with Sections II and III, to support humans in performing tasks with BMIs, we propose to share control at the higher tactical level by using an input-mixing shared control system. The human input is interpreted given contextual information (e.g., the environment surrounding an assistive robotic device) to determine the resultant control signals that should be sent to the robot (e.g., wheelchair), to achieve acceptable performance and maintain safety (Axiom 2). Under such a scheme, the user is provided with feedback through alternative modalities, such as visual, auditory, vibrotactile, electrotactile, etc.

There are some critical issues to be considered when designing shared control systems for BMI applications. Commands from the BMI and the contextual information need to be fused to determine the final command that should be delivered to the device, but this can be done in many different ways, using approaches such as gating, fusion or regulation [99]. Gating (in the automotive domain often called "transition of control") means that one signal from the user or the device enables the other party to take control. However, this approach does not fit with our definition of shared control since it violates Axiom 1. Instead, this approach would be categorized under the broader term co-operative control [62]. Conversely, fusion is an excellent example of shared control, since it means that both the user input and the information from the



device contribute directly to the final control command, through rules including competitive methods, weighted sums, and probabilistic reasoning. Alternatively, the notion of regulation fits nicely with Axiom 2, since it means that one or more of the signals can be used to adjust the parameters of the shared control system, resulting in changes in the level of assistance that the robot provides to the human. For example, a dynamic Bayesian network (DBN) has been used to track the human's intended actions or goal destinations [98]. Finally, the gating, fusion and regulation approaches can be cascaded to create more complex or flexible behaviors [99].

Another important aspect to consider in the design is the level of assistance (or automation) that is provided by the robot to the human. End-users of such devices often prefer to have authority over the device rather than to be controlled by it, but at the same time, safety should take precedence. In other words, the system should provide a transparent assistance for the human and allow the assistance to be overridden in non-safety critical situations [96][100].

Most shared control systems tend to have predefined settings based on the task and the environment in which the task is performed. Additionally, the provided level of assistance is usually constant for each user. However, to have an effective interaction, shared control assistance should be well-matched to each user and should adapt to complement their dynamic and evolving capabilities [65].

Finally, hybrid control techniques can be used to take control of additional degrees of freedom or combat the fatigue associated with a particular control channel. This allows the users to take more or less low-level (operational level) control and switch between different modalities when they want or need to do so [95][96][101].

#### *D. Evaluation of BMIs with Shared Control*

Many shared control implementations are still evaluated with respect to the global system or specific task performance. The use of shared control systems, in which both human and robot contribute to the control process have been shown to be beneficial [27][102]. Operating devices with a BMI combined with shared control techniques result in better performance, higher speed and safety while reducing the required effort compared with not having the additional support, as we would expect from Axiom 2 [96][103]. Expert users aside, such metrics will often lead to a fully automated controller outperforming any other control approach, especially if the validation task is relatively trivial.

Although these traditional metrics (like speed and efficiency) are important, the ultimate goal is that the user is able to complete tasks voluntarily when they want. Therefore evaluations should additionally place great emphasis on a human factors analysis [65]. As an example, we can employ standardized validated questionnaires, such as the NASA-TLX [104], which also take into account subjective measures such as the user's frustration.

There still exists much work to be done in particular in investigating *adaptive* shared control for brain-machine interfaces. It will be particularly challenging to decide exactly

how to evaluate such systems. Nevertheless, they could have a high impact in related fields, such as neuro-rehabilitation, where for example the level of assistance is usually decreased over time as motor skills are re-learned. Moreover, we have not yet found any examples of BMI systems being evaluated on or beyond the boundaries of the task domain (Axiom 3), which is necessary if we are to see them used more widely outside of the lab.

## VI. LEARNING

Cognitive psychologists have stated that it takes 10,000 hours of deliberate practice to become an expert at a complex task [105]. However, not everybody gets to be an expert performer, because of lack of talent, or physical or mental limitations such as aging factors [106]. Can shared control be used for accelerating the learning process?

In this paper, we adopt the following definition: "*learning is a relatively permanent change in knowledge that occurs as a result of experience*" [107]. Learning is crucial for survival, as the knowledge acquired through learning allows us to anticipate the future from past experiences and to control an ever-changing environment [108]. When a person is new to a task, he or she tends to apply knowledge-based behavior, meaning that information processing is relatively slow and sequential. When learning, knowledge becomes implicit, and information processing becomes fast and parallel, that is, the person applies skill-based behavior [124].

Technology may facilitate learning by providing the learner with computer-stored knowledge in appropriate doses and at appropriate moments, either in the form of error feedback and guidance at the operational level, or in the form tactical feedback of strategic advice. Shared control appears to be an effective medium for communicating knowledge between human and machine (Axiom 1), and so could be valuable in learning. In particular, feedback from a haptic display is in agreement with the proximity compatibility principle [109] if the haptic feedback is applied directly at the control interface. For example, whereas visual feedback (e.g., a warning light indicating to the learner that he/she makes an error) needs to be attended to and interpreted before implementing a decision, haptic feedback (e.g., force feedback at a joystick) can support the learner directly and reflexively.

Haptic shared control for learning (usually called haptic guidance) has mostly been studied for tasks at the operational level, such as in the learning of tracking tasks [110][111]. However, in complex tasks, having excellent skills at the operational level does not suffice for safety. A classic illustration is provided by Williams and O'Neill [112]. These authors showed that nationally licensed race drivers (who can be assumed to have excellent vehicle handling skills) were involved in more police-registered accidents than a comparison group of similar age, race, and sex. Motivations to drive are higher-order determinants that place demands on the operational level, which is situated lower in the hierarchy. That is, accidents cannot be prevented by only perfecting skills at the operational level; training interventions should also tackle risk-taking at the strategic level [113]–[115].

Haptic shared control may be a promising means for acquiring knowledge at the strategic level. However, participants get annoyed when they have to resist forces contrary to their intentions. Applying extreme pressures on the human skin may result in discomfort, arousal, and even pain. Interestingly, frustration and emotionally arousing events facilitate the formation of long-term memory structures [116] and may promote self-reflection. But we aim for a different learning method: inspired by the “horse metaphor” [59][60] haptic shared control and cooperative guidance and control may facilitate mutual trust and social bonding between human and robot.

#### A. Open issues in the use of shared control for learning

Schmidt and Bjork [117] argued that the goal of training is to be able to apply knowledge in the long term and novel circumstances (Axiom 3). Although augmented feedback may temporality boost human knowledge, in some cases feedback may hamper long-term retention and the ability to complete the task independently from the computer aid. Hancock and Hancock [3], for example, stated: “...it is (...) common for many individuals today to have problems performing even basic mathematical additions when the computer is ‘down’. The problem here is that the balance of some forms of expertise has shifted over toward the computer side and suddenly we have purportedly ‘smart’ machines being operated by sadly ‘dumb’ humans.”

Similarly, humans may become overly dependent on guidance from haptic shared control, and as pointed out by [111], non-adaptive (fixed-gain) haptic guidance protocols may even be detrimental to motor learning, since “...such schemes actively interfere with the coupled system dynamics and cause participants to experience task dynamics that are altered from those of the real task.” [118]. If inappropriately implemented, shared or traded control may, in fact, de-skill operators [14][18][19], which – rather than empowering operators – gradually disables them as they become increasingly reliant upon the robot.

Semantically rich messages for effective learning at the strategic level [39] are usually communicated through visual or auditory means, and it is still unknown how to haptically convey such messages. Presumably, low-dimensional channels such as pedals, steering wheels, and joysticks will be insufficient, and richer multidimensional interfaces (e.g., pressure seats) will have to be developed to communicate goals and intent of human and robot. The degree to which the human should be required to learn a task (i.e., to store knowledge in the brain), versus the degree to which knowledge should be accessible via a computerized aid, is an ongoing source of debate (cf., [119]). Technological potential, such as computational speed of chips and hard disk storage capacity, grow at an exponential rate [120]. Accordingly, knowledge is now often retained in computerized support systems, and as pointed out by Hancock and Hancock “...crucial knowledge and thus one aspect of ‘expertise’ does not necessarily need to be resident in the head of the operator” [3]. Computers surpass humans at computational

speed, and memorizing fact and procedures [10][118]. It would therefore be useful to delegate this type of knowledge to machines, unless, of course, the machine’s computing abilities are statistically unreliable or temporarily unavailable (cf. [121]).

On the other hand, humans still surpass artificial intelligence during physical movement and manipulation in situations that require quick adaptation and generalization. Therefore, in the foreseeable future, this type of knowledge will have to either rest with the human, be taught by humans to robots (e.g., by means of learning-from-demonstration techniques), or be efficiently shared with robots.

## VII. TOWARDS A SHARED CONTROL FRAMEWORK

In Section II we proposed a definition of shared control that captures multiple levels of control, and gave three axioms for design and evaluation of shared control. We then provided a review of shared control implementations for four domains: automotive applications (Section III), robotic surgery (Section IV), BMI wheelchair control (Section V), and learning (section VI). In each of these four application areas, we argued that shared control is beneficial to enhance communication between human and robot (Axiom 1) at different hierarchical levels of control, especially where changing conditions require human interventions (Axiom 2). The presented shared control designs resulted from highly domain-specific design approaches, and in almost all cases the evaluation approaches do not explore behavior outside the design boundaries (Axiom 3). Even *within* a specific domain widely different design and evaluation approaches exist, which complicates between-study comparisons of similar support systems (see for example [122][123]) and therefore hinders cross-fertilization.

The above illustrates the need for a shared control framework that facilitates interdisciplinary collaboration and accelerates the development of shared control systems. We here aim to establish a shared control framework that addresses the need to design, understand and evaluate the communication and interaction between a human and a robot. We link multiple frameworks and concepts from diverse disciplines so that our shared control framework can:

1. Capture human and robot control at different task levels, ranging from high-level planning to low-level execution.
2. Capture different behaviors of human information processing ranging from cognitive deliberation to sensory signal processing.
3. Capture interaction between a human and a robot within and between each task level.
4. Comply with shared control Axioms 1, 2, and 3
5. Capture shared control solutions from Sections III-VI and can be extended

The envisioned shared control framework should also facilitate comparisons between alternative human-automation interaction methods (such as traded control and binary warnings) or interface designs (haptic, tactile, visual, auditory, or multimodal).

### A. Relevant Hierarchical Frameworks

In the 1970s, Sheridan and Verplank [13] proposed a conceptual framework for a hierarchical division of “computer-aided manipulation” into goals, strategies, tactics, and action, linking this division to the type of commands needed for communication. In the same period, the intelligent control community [126][127][128][129][131][130] focused on developing computational frameworks that could be used to control robots for performing complex tasks that include planning, decision making, and control. Such frameworks have been applied to driving a car [44] and are still used today in the control of automated vehicles. It also inspired the ClaraTY framework [132], a computational framework used for space robotics that stresses the distinction between three layers (strategic layer, decision, functional).

Concerning more human-centered frameworks, a useful approach for decomposing information processing in human-machine systems is Rasmussen’s distinction between knowledge, rules, and skills, (KRS) and the accompanying symbols, signs, and signals needed to communicate at different task levels [124]. With experience or training, tasks can move from the knowledge-based level to skill-based level, requiring less cognitive control. An accompanying design framework for support systems is Ecological Interface Design (EID) [125], an approach that makes complex relationships in the dynamic work environment perceptually evident.

A third research area that generated relevant frameworks is the field of human-machine cooperation. According to [133], cooperation implies “...several agents pursuing interfering goals and trying to manage this interference to facilitate their tasks.” They state that interference management can take place at three hierarchical levels: action level, planning level, and meta-cooperation level. Flemisch *et al.* [60] provided an ‘onion-layered’ framework for cooperative automation, where both human and robot (‘automation’) control a vehicle based on perception and situation-assessment that feed into hierarchical control levels (navigation, maneuvering, short-term planning, control). They aimed to capture shared and traded control at different levels in a framework referred to as ‘shared and cooperative control’[61]. Recent work in conceptual modeling [134][135] has linked a hierarchical dimension of control (operational, tactical and planning levels) to a ‘horizontal’ extension in terms of information gathering, analysis, decision-making, and execution.

The above frameworks explain how human and robot cooperate but do not explicitly incorporate the vital fact that human and robot can perform tasks at different levels at a skill, rule or knowledge-based level, and that these control behaviors require different interface designs to facilitate communication and interaction.

### B. Proposed Design and Evaluation Framework

Why add another framework to describe hierarchical control? The main reason is that no known framework captures the possibilities that shared control offers for human-robot interaction within and between hierarchical control levels, where the robot can also *learn* from a human (and vice

versa) through communication and interaction within and between these levels. An attractive perspective for a comprehensive shared control framework is a combination of vertical *task levels* (i.e., strategic, tactical, operational, executional STOE) and horizontal knowledge-, rule-, and skill-based (KRS) *behaviors* within each level. Such a topology illustrates what can be communicated within and between levels, what needs to be learned at each task level, and accordingly what should be supported at each task level. At each STOE level, control can be performed independently by human or robot, traded between them, or shared. By assigning control within and between each level plus detailing what types of transitions in control are expected (Axiom 1, 2, 3), the required communication opportunities (e.g., visual, auditory or haptic) become apparent, and the most suitable form of interaction can be designed (shared or traded).

The proposed shared control design and evaluation framework is shown in Figure 1. Vertically, it shows the strategic, tactical, operational and executional *task levels*. Within each level, the human and potentially the robot can independently exhibit skill-, rule-, or skill-based behavior. For example, strategic choices and decisions initially require abstract thinking (knowledge-based behavior) but with experience are made quickly and effectively. This process is well established within the naturalistic decision-making field [136]. Similarly, before a high level of skill is achieved in motor control, much practice is needed to build the right situated internal models; a process well established within the motor control community [137]. This framework illustrates that individual human or robot learning is integrated as a progression from knowledge-based interaction at a particular task level to rule-based and finally skill-based interaction.

The framework shows all communication and interaction possibilities between and within STOE levels, under the assumption that the robot and human can individually perform tasks at each task STOE level without the other. In real-life applications, robot capabilities may well be limited to the execution or operational level (e.g., adaptive cruise control). Conversely, the human may also be limited at the execution or operational level (e.g., patients with impaired motor control). The framework illustrates that two types of interfaces can be designed for communication and interaction: within task-level and between task-level.

At each task level, communication and interaction between human and robot may be designed to support knowledge-based behavior (symbols), rule-based behavior (signs) or skill-based behavior (signals). For example, the BMI wheelchair from Section V supports the human at the tactical decision level, to enable the operator to learn intuitive tactical control over the robotic wheelchair; and giving the tactical commands eventually become second nature (i.e., using intuitive skill-based behavior as opposed to the initially rule-based behavior). When the robot is always present, humans will simply learn to operate in the new robot-enhanced environment, whereas in other cases the robot may accelerate learning of a task that normally does not offer such support (Section VI). The framework captures the possibility that

human and robot can mutually teach, show or guide each other through interaction, as well as learn from the other through observation or collaboration, thereby progressing in the KRS behaviors within an STOE level. This duality, as well as the symbiotic relationship between human and robot, is novel in this framework.

Between STOE task levels, the actions of a higher level enter the layer “Goal Sharing / Multi-modal Communication Interface,” to be passed, shared or traded into goals for lower-level control of human or robot. When control is traded to the robot, the robot needs to take control over lower levels - including the communication and interaction required for the human to monitor its performance and influence its goals.

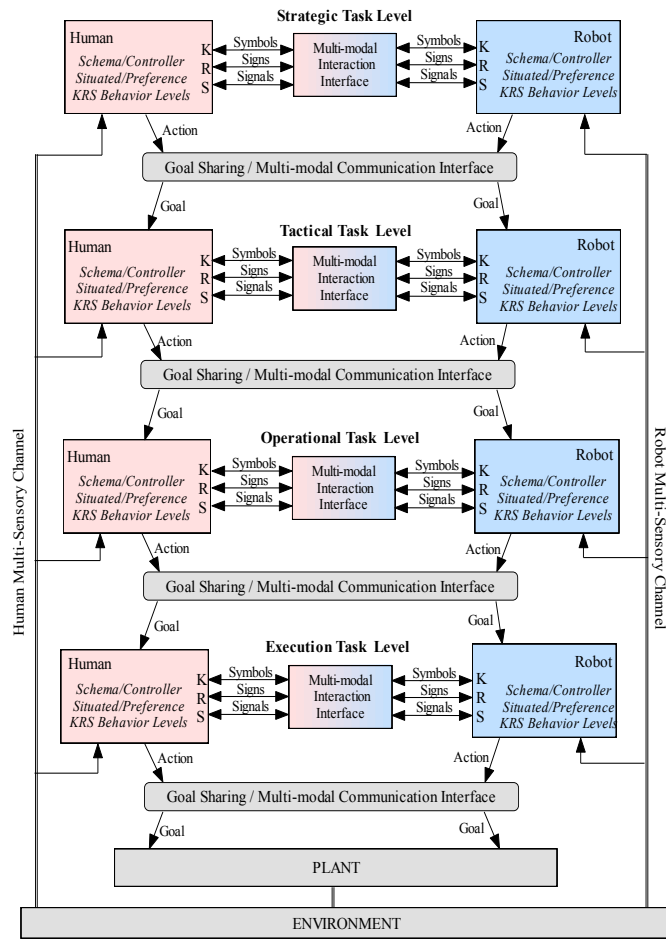


Figure 1. Hierarchical Framework for Shared Control between human/operator (left) and robot/intelligent agent (right), controlling a plant/vehicle within a task-environment. The vertical task decomposition for both human and robot is along the STOE levels. Within each level, humans and robots can learn (KRS behaviors) and through multi-modal interfaces interact to provide, receive or share information in the form of knowledge-based symbols, rule-based signs, or skill based signals. The robot is shown here with the full learning and interactive capabilities of a human, which is a utopia for now.

Haptic shared control allows human and robot to communicate and interact at the operational level, through forces on a control interface: signals, denoting skill-based behavior. The human and robot both directly feel each other’s forces and can use stiffness to protect their respective actions against

available safety margins. Together they shape the action that gets passed to the execution level. However, the framework points to other design possibilities for haptic interaction, at all STOE task levels. For example, in driving one could use a joystick interface to select between a number of route alternatives strategically. The force needed to select one of them could be low for those that satisfy many of the driver’s needs and high for those that are less satisfactory. Similarly, regarding the tactical level, stiffness on the turn signal could be used to inform at a skill-based level that the tactical decision to change lanes is wrong (high stiffness) or right (low stiffness). This communication could be augmented (through visual or auditory feedback) to elucidate the motivation for a low or high stiffness, the presence of other cars in adjacent lanes, or the fact that the target lane may be closed soon.

The framework allows exploration of many more such design options. In general, three forms of interaction between robot and human are possible: (1) shared control between task levels (i.e., both handing down goals to the same lower level such that they get mixed or fused by the communication interface), (2) traded control between task levels (e.g., the human hands goals to the robot who performs lower level tasks, or vice versa), and (3) shared control within a task level through mutual sharing and receiving of information (knowledge), demonstration (rules), and action (skill) so that a symbiotic relationship is established. To the best of our knowledge, these three forms of human-robot interaction are for the first time captured within a single framework.

Although useful as a conceptual framework, its structure is meant to house computational frameworks for describing human control, robot control, and human-robot interaction interfaces. Demonstration of this utility of the framework requires more detail in what takes place *within* a task level and what gets communicated *between* task levels.

At each task level, the *goal* from a higher-level controller is transformed into a *controller output action* that constitutes the goal for a specific lower-level controller as illustrated in Figure 3. Some tasks, including driving, involve multiple tasks at the same STOE task level that need to be performed simultaneously. In those cases, goals of multiple lower-level controllers need to be coordinated. Therefore we detail the control framework based on intelligent control concepts of dispatchers and controllers/coordinators [127]. The goal of the task level is targeted through a learned *schema* that implements a *procedure*. The procedure constitutes the dispatching of a series of subtasks to a coordinator that keeps track of what subtask should be implemented next. It does so by communicating with lower level controllers and feeding them each a particular goal while monitoring their progress for timing (as well as for adaptation and learning). The specific inputs, processes and outputs at each of the task levels are shown in Table I with examples for driving.

The downward flow is thus one of the commands to lower levels. The upward stream is sensory information from the environment (impacted by the plant’s state) and lower-level controllers. Sensory information is used for three purposes: i) sensory feedback to assess the situation, in order to select the right mental and internal models employed within each task level, and refine them ii) within-level performance feedback to assess if the task level goal was met, and iii) between-level

performance feedback for the coordinator to keep track of the progress of each of the lower level controllers it manages. Performance feedback is used to learn and shape both the mental models employed by the schema-dispatcher within each task level and the internal models used by the controller-coordinator. Note that the framework explicitly uses processed

sensory feedback to self-evaluate performance and progress. Also note that, to evaluate human-robot systems, it would be beneficial to adopt the same performance metrics that the human also employs; in other words: metrics that capture what matters to the human.

TABLE I.  
DECOMPOSITION OF HIERARCHICAL TASK EXECUTION ALONG THE FOUR STOE TASK LEVELS, SPECIFIED FOR DRIVING. AT EACH TASK LEVEL, A GOAL IS EXECUTED BY A SCHEMA WHOSE TASK IS TO DISPATCH A SEQUENCE TO A (WITHIN-LEVEL) CONTROLLER. THE CONTROLLER OUTPUTS THE ACTIONS THAT SERVE AS GOALS FOR THE LOWER TASK LEVEL.

Task Level (STOE)	Schema Input (= Goal from Higher Level Controller)	Schema Task (to dispatch a Sequence of Tasks with target States)	Schema Output (= Controller Input)	Controller Task – Coordinate what Lower Level Controllers needs to reach what Goal	Controller Output Action (= Goal for Specific Lower Level Controller)
Strategic	Destination	<u>Dispatch</u> - a route that transitions along a number of goal locations; - the sequence of targets to the controller	Sequence of target maneuvers or task (e.g., stop at next intersection or merge at next junction).	<u>Coordinate</u> when what maneuver(s) to select and how to shape them to reach the next target (e.g., stop at stop line or change lane to achieve higher speed).	Specific vehicle maneuver (e.g., merge).
Tactical	Specific vehicle maneuver (e.g., merge)	<u>Dispatch a sequence of</u> goal behavioral stages that achieve the maneuver	Sequence of target behavioral states (e.g., check emptiness of adjacent lane, match speed to an adjacent lane, decide to make a lane change, etc.).	<u>Coordinate</u> what target steady state vehicle states to adopt (e.g., match speed to adjacent traffic).	Specific steady state target vehicle state or specific safety margin to maintain (e.g., reach a speed of adjacent traffic or maintain a certain distance to lead vehicle).
Operational	Specific steady state target vehicle state or specific safety margin to maintain (e.g., reach a speed of adjacent traffic or maintain a certain distance to lead vehicle).	<u>Dispatch a sequence of</u> goal vehicle states that achieve the target environmental state	Sequence of dynamic vehicle states with constraints that need to be satisfied (e.g., maintain distance but do not allow for the gap to grow beyond or below a particular time).	<u>Coordinate</u> what manipulator control needs to be applied or what dynamic vehicle states need to be traversed (e.g., certain deceleration rate).	Specific dynamic target manipulator state (e.g., associated with reaching yaw rate, deceleration rate).
Execution	Specific dynamic target manipulator state (e.g., associated with reaching yaw rate, deceleration rate).	<u>Dispatch a sequence of</u> low-level control actions that achieve the target manipulator state	Sequence of electrical signal adjustments.	Coordinate what low-level signals to send to the actuators (incl. muscles). IM of actuator logic or more precisely neural/electrical mechanisms.	Specific neural signal or voltage or current.

*C. How to use the Proposed Framework for Shared Control for novel studies*

Shared control design is an interplay between creative and engineering processes. The proposed framework can guide and constrain these processes, offering a ‘saliency map’ that draws attention to various opportunities for designing the interface across which information and control are shared between human and robot. The proposed STOE-KRS framework illustrates the types of information that are needed at each task level as well as the information that flows between task levels. Because of its computational nature, it also embodies what needs to be learned at each ‘node’ in the hierarchical intelligent control model and what type of feedback is necessary to facilitate knowledge acquisition and

usage. The framework exposes possible weaknesses in the control of the system when information at the ‘touch points’ between human, robot and controlled system is noisy, limited, or missing. Because the framework proposes an interface that supports interaction at all task levels and across all knowledge levels it promotes a transparency between the controlled system, robot and human that should be implemented, by exposing both the limitations of sensing as well as the knowledge relied upon. The KRS aspect of the framework assures that even when the human is supported to control a particular task level in a skill-based fashion, the domain within which this skill-based support is warranted is exposed through a set of constraints or rules and is further explained in the form of knowledge that exposes the reason for such restrictions. This type of informed transparency enables the human to

know when to rely on the skill-based support or similarly rely on the robot to perform the task reliably. Because the boundaries of robust or reliable support are explicitly exposed in the interface, the human can quickly determine who has control and what level of vigilance is needed under what situational conditions.

The proposed STOE-KRS framework shows the many possibilities to share control between a human and a robot. The shared control community has only scratched the surface of understanding the pros and cons that each constellation of human-robot task sharing holds, especially in the context of real-world support limitations. However, by exploring the different interaction constellations across disciplines and evaluating them against real-world limitations, we hope that a set of design and evaluation ‘best practices’ emerges that can accelerate the informed release of shared control interfaces into unpredictable human-inhabited environments. The STOE-KRS framework captures the efforts representative of our field and highlights the requirements for proper shared control that creative interface designers can integrate into their human-robot interaction interfaces.

### VIII. CONCLUSIONS

The diversity in application fields for shared control solutions, with its accompanying lack of consensus in definitions, and methodologies for design and evaluation, was the inspiration for the proposed definitions, axioms, and a suggestion for a unifying hierarchical shared control framework. This framework is not merely conceptual, but constructed to guide the design and evaluation of shared control within, around and beyond system operational and functional boundaries. The framework addresses the need for *out-of-scope design and evaluation* because supporting transitions in and out of the design scope are most critical for safe introduction of systems into the real world. Examples from four different HRI disciplines show how shared control at different task levels and different behavior levels fit within the STOE-KRS framework.

The three main *design elements* of the proposed shared control framework are:

1. Shared control should implement continuous interaction between human and robot to facilitate robust mutually aware interaction (*constituting enhanced operation at a particular task level*).
2. Shared control should communicate the proximity to task boundaries, environmental constraints, or system limits to facilitate a need for adaptation in control strategy or adaptation in the cooperation balance (*constituting efficient sharing and trading of human and robot control at each task level*).
3. Shared control should be complemented with information about the motivation for operational limitations, decision boundaries or strategic choices to facilitate understanding of the system and promote learning towards a skill-based interaction (*constituting*

*effective learning of system functioning and the situation limitations that plague it*).

The three main *evaluation elements* of the proposed framework are:

1. Support systems should be evaluated to demonstrate that the performance-effort balance shows a positive shift within the targeted task domain as defined by situated operational and functional support boundaries (*constituting proof of superiority under predetermined conditions*).
2. Support systems should be evaluated to demonstrate that transitions across task boundaries, designed system boundaries, and unexpected changes in system performance due to hardware changes are quickly recognized, and adjustments in human involvement are promptly and efficiently achieved (*constituting proof of superiority in recognition and recovery of out-of-scope transitions and conditions*).
3. Support systems should be evaluated to demonstrate learning, by showing a shift towards proactive interaction in response to changes in system functionality or reliability (*constituting proof of superiority in learning dynamics*).

The proposed framework forms a coherent way of approaching these design and evaluation elements. It can be applied to shared control, but also to traded control solutions as part of truly cooperative human-machine systems.

In a future where the machines we work with become increasingly capable of sensing, decision-making, and physical (inter)action, we need increasingly intelligent ways to communicate and interact with these robots. We agree with [21] that “...as the frontiers between automation and operators blur, it becomes increasingly critical that automation designers realize that they are not building technology, but relationships.” Echoing Wiener, communication and control are essential to foster such relationships.

The concept of shared control has great potential to design communication and control between human and robot. Unfortunately, the widespread application of shared control across different disciplines has grown more quickly than the underlying theories and design & evaluation principles. It is high time to start thinking in, on, and out of the boundaries of our domains to realize the full potential of shared control. We hope that this review paper and its proposed definition, axioms and framework for design and evaluation for support systems serves as a useful starting point towards that goal.

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**David A. Abbink (M'05, SM'14)** received his M.Sc. degree in Mechanical Engineering at the Delft University of Technology in 2002. He received his Ph.D. degree in 2006, for his thesis on a force feedback gas pedal to support drivers with car following. He continued his research at Delft, funded by Nissan, Boeing, and personal grants 'VENI' and 'VIDI'. His research interests include haptics, shared control, human-automation interaction, operator modeling and identification. David is currently an associate professor at the Delft Haptics Lab, and co-founded the IEEE SMC Technical Committee on Shared Control.



**Tom Carlson. (M'10)** obtained his MEng (2006) and Ph.D. (2010) from the Electrical Engineering Department at Imperial College London. He then began researching brain-computer interfaces as a postdoctoral scientist at EPFL, Switzerland. Tom is currently a Senior Lecturer at University College London, in Aspire Create, the Centre for Rehabilitation Engineering and Assistive Technology. His research focuses on the use of shared control in assistive technologies, in particular, to empower end-users to control devices through novel interfaces, such as brain-machine interfaces. Tom also co-founded the IEEE SMC Technical Committee on Shared Control.



**Mark Mulder. (M'04-'14)** received his MSc. in Aerospace Engineering from the Delft University of Technology in September 2000 and his Ph.D., on haptic driver support systems, in January 2007 and worked as a postdoc at the Delft Haptics Lab until 2014. That year, in addition to his engineering work, he also became an MD. Currently, he is specializing in internal medicine at Erasmus Medical Center in Rotterdam and a visiting researcher at the Delft Haptics Lab. His research interests include driver support systems, haptic guidance systems, neuromuscular control and modeling and medicine. Mark co-founded the IEEE SMC Technical Committee on Shared Control.



**Joost C. F. de Winter** received the MSc degree in aerospace engineering and the Ph.D. degree (cum laude) from the Delft University of Technology, Delft, the Netherlands, in 2004 and 2009, respectively. His research interest is human factors and statistical modeling, including the study of individual differences, driver behavior modeling, and research methodology. He is currently an associate professor at the faculty of Mechanical, Maritime and Materials Engineering at the Delft University of Technology.



**Farzad Aminravan** Farzad Aminravan received his M.Sc. in Mechanical Engineering at Tehran Polytechnic in 2008. He received his Ph.D. on hierarchical control and decision support systems from the University of British Columbia in 2014. Farzad is currently a systems consultant at Industrial Software Solutions in Vancouver, British Columbia. His research interests are multi-agent and supervisory control systems and application of human-machine interfaces in surgical and service robots.



**Tricia L. Gibo** received her B.S. degree from the University of Southern California (California, USA) in 2007, and her M.S. and Ph.D. degrees from The Johns Hopkins University (Maryland, USA) in 2009 and 2013, respectively, all in mechanical engineering. She was previously a postdoctoral research fellow at Delft University of Technology (Netherlands) from 2014–2017. Her research interests include human motor learning, human-robot interaction, human factors, and haptics. She received the Graduate Research Fellowship from the US National Science Foundation in 2007 and the Link Foundation Fellowship in Advanced Simulation and Training in 2011. Tricia is currently a senior human factors specialist for medical technology at UL.



**Erwin R. Boer (M'95)** received his M.S. degree in Electrical Engineering from Twente University of Technology in The Netherlands in 1990 and his Ph.D. also in Electrical Engineering from the University of Illinois in Chicago in 1995; both in the area of manual control. Currently, he is an associate professor in Mechanical Engineering at Delft University of Technology in The Netherlands and has his own automotive research company Entropy Control, Inc. in La Jolla California. His research focus is the design of multi-sensory human-machine interaction experiences that enhance control of dynamical systems and on the design of virtual environment for medical diagnosis and rehabilitation.