The Classification and New Trends of Shared Control Strategies in Telerobotic Systems: A Survey

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***Abstract*—Shared control, which permits a human operator and an autonomous controller to share the control of a telerobotic system, can reduce the operator's workload and/or improve performances during the execution of tasks. Due to the great benefits of combining the human intelligence with the higher power/precision abilities of robots, the shared control architecture occupies a wide spectrum among telerobotic systems. Although various shared control strategies have been proposed, a systematic overview to tease out the relation among different strategies is still absent. This survey, therefore, aims to provide a big picture for existing shared control strategies. To achieve this, we propose a categorization method and classify the shared control strategies into 3 categories: Semi-Autonomous control (SAC), State-Guidance Shared Control (SGSC), and State-Fusion Shared Control (SFSC), according to the different sharing ways between human operators and autonomous controllers. The typical scenarios in using each category are listed and the advantages/disadvantages and open issues of each category are discussed. Then, based on the overview of the existing strategies, new trends in shared control strategies, including the "autonomy from learning" and the "autonomy-levels adaptation", are summarized and discussed.**

***Index Terms*—Shared Control Strategy, Telerobotic System, Classification, Semi-Autonomous Control, Cooperative Control**

I. Introduction

TELEROBOTICS, which can be traced back to 1940s and 1950s, is perhaps one of the earliest research areas in robotics [1]. Generally, a telerobotic system consists of at least one leader and one follower[1] devices that are connected via a communication network. It allows a human operator to perform complex manipulations at a distance, in order to avoid exposing the human operator to dangerous or hazardous environments. An embryo of the telerobotic system was designed by Goertz [2] to handle radioactive material from behind shielded walls. This system is controlled by an array of on-off switches to activate various motors and move various axes. However, it is slow and difficult to operate. After that, Goertz designed a pair of leader-follower robots which are mechanically linked by gears, linkages, and cables [3]. This system can allow the operator to use natural hand motions and transmit forces and vibrations via the connecting structure. It is considered to be the first truly telerobotic system and laid the foundations of modern telerobotics. However, limited by the mechanical connection, this system is difficult to achieve long-distance teleoperation.

With the development of computer networks, the internet technology makes it possible to transmit information at a long distance [4]. As a result, the telerobotic system can achieve teleoperation beyond visual range [5]. But the time delay introduced by long-distance communications brings challenges to the stability of telerobotic systems. To deal with the effects of time delay, several kinds of theories and methods have been proposed, e.g., Lyapunov-based analysis [6], network theory [7], wave variables-based method [8], energy tank-based method [9], and so on. These outcomes enable the telerobotic system to be applied in a wide spectrum of areas, ranging from search and rescue [10], space/under-water exploration [11], robot-assisted medical intervention [12], manipulation in micro-nano environments [13], and so on.

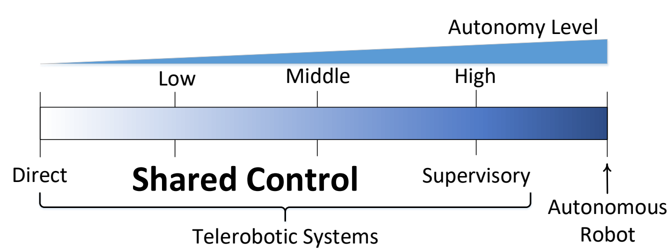

Figure 1. The spectrum of the control architectures in telerobotic systems. In which, the direct control and the autonomous control fall at the two opposite extremes and the shared control is between them.

As shown in Fig. 1, along with the evolution of telerobotic systems, the control architecture spans a spectrum, in which the *Direct Control* and the *Autonomous Control* fall at the two opposite extremes and the *Shared Control* is between them [1]. The direct control [14] implies that the remote robot is directly controlled by the human operator and no intelligence or autonomy is embedded in the system. Whereas the fully autonomous control [15], [16] means that the robot is able to fulfill tasks by relying on its own perception, decision-making, planning, and executing abilities without any human intervention. However, due to the unavoidable uncertainties

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[1]Here the conventional "master" and "slave" are all replaced by "leader" and "follower" to avoid the concern of association to racism and human subjugation.

and unpredictable events in real world, we are still far from the fully autonomous robots, except for some extreme simple tasks in extreme structured environments (e.g., pick-and-place task in industrial factory). Understandably, the *Supervisory Control* is often regarded as the substitution of autonomous control in many literatures. The supervisory control [17], [18] indicates that the user's commands and feedback occur at a very high level and the robot is required to have a substantial local intelligence or autonomy.

The shared control [19]–[21], which is between the two extremes, permits a human operator to share the control of a robotic system with an autonomous controller. The autonomous controller is embedded with some amount of autonomy/intelligence to improve task performances or reduce the operator's workload. By sharing the control between a human operator and an autonomous controller, the shared control architecture allows to utilize the human's high-level intelligence to cope with unknown and unstructured environments, as well as taking advantage of the robots' capabilities in higher power, higher precision, and so on. Not surprisingly, the shared control becomes an attractive topic since the birth of telerobotic systems. Abbink *et. al.* [22] summarized the common features of shared control across 4 different domains and proposed a consensus definition for shared control. In addition, they also provided 3 general axioms for design and evaluation of shared control solutions. However, the detailed strategies that how the control is shared between the human operator and the autonomous controller was not involved. Recently, various shared control strategies have been proposed for different purposes. But, a systematic overview to tease out their relations is still absent.

Among existing literatures, the surveys on other technologies in telerobotic systems have been provided. The first group focuses on the control theories to guarantee stability or improve transparency. For example, Hokayem and Spong [23] summarized the historical development of control theoretic approaches for bilateral telerobotic systems. Passenberg *et. al.* provided a classification of EOT-specific (Environment-, Operator-, or Task-specific) controller in [24]. Zaad and Salcudean [25] analyzed the stability and transparency performance for bilateral telerobotic systems with impedance/admittance manipulators. However, the shared control is not involved in these literatures. Shahbazi *et. al.* [26] provided a systematic review for multilateral teleoperation systems. Si *et. al.* [27] provided an overview of immersive teleoperation for manipulation skill learning and generalisation. Whereas the contents about shared control is still missing. Losey *et. al.* [28] gave a review on intention detection, arbitration, and communication aspects of shared controls for physical Human-Robot Interaction (pHRI). But the shared control strategies are also not mentioned.

However, the systematic review on shared control strategies is demanded. In previous work, Selvaggio *et. al.* [29] have collected the latest results in the field of shared control, but with a special emphasis on the adaptation of autonomy-levels in pHRI. More specifically, they distinguished the shared control (SC) and the shared autonomy (SA) by the arbitration way (The arbitration between operator's and autonomous controller's control signals is either tuned by the human operator - SC - or by the autonomous controller - SA). Similarly, Chen *et. al.* [30] summarized the development, the current challenges, and the trends of shared control strategies, but with a special focus on the ones based on telepresence technology (including haptic rendering technology and virtual reality technology). Anyhow, a systematic overview to provide a big picture for existing shared control strategies is still missing.

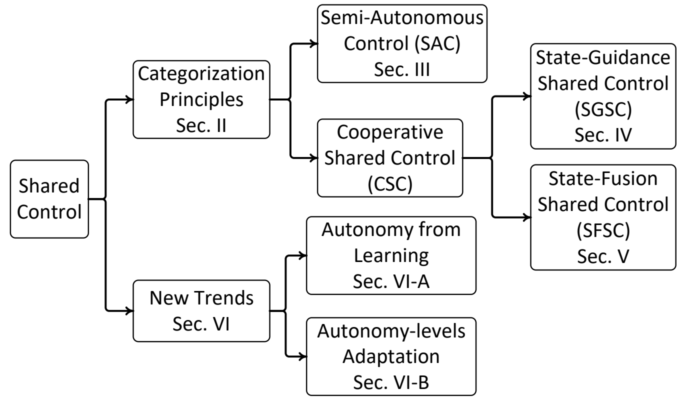

Figure 2. The organization of this survey. We classify the strategies into SAC and CSC according to whether the controlled variables are separated or not. The CSC is further divided into SGSC and SFSC according to where the intentions are mixed. Then the new trends of shared control are summarized.

Different from the aforementioned literatures, this survey aims to provide a systematic overview on the shared control strategies for telerobotic systems. Our main contributions are summarized as:

- We propose a categorization method and classify the shared control strategies into 3 categories: Semi-Autonomous Control (SAC), State-Guidance Shared Control (SGSC), and State-Fusion Shared Control (SFSC), according to the different sharing ways between human operators and autonomous controllers.
- The typical scenarios in using each category are listed and the advantages/disadvantages and open issues of each category are also discussed.
- Based on the analysis on existing strategies, we conclude the new trends of the shared control strategies, including the "autonomy from learning" and the "autonomy-levels adaptation".

As shown in Fig. 2, the rest of this paper is organized as follows. Section II gives our categorization principles. Section III, IV, and V summarize the features and typical scenarios of the SAC, SGSC, and SFSC category, respectively. The typical scenarios and their advantages/disadvantages and open issues are also discussed. Section VI summaries the new trends of the share control strategies. Section VII concludes this survey.

II. The Categorization Principle of Shared Control Strategies

By introducing an autonomous controller, the shared control architecture can assist human operators to reduce physical/mental workloads and/or improve task performances.

However, how to achieve effective assistances is non-trivial. Rather than providing assistance, an inappropriate strategy may conflict with the human operator's intention and bring negative impacts, which can deteriorate the human experience significantly. Therefore, various strategies have been proposed to provide better and effective assistance. In this survey, we would like to provide a big picture for existing shared control strategies and enumerate the typical scenarios in using different strategies.

For the convenience of analysis, we propose a categorization method according to the different sharing ways between the human operator and the autonomous controller. In many existing literatures, the "Semi-Autonomous Control" and "Shared Control" have been used interchangeable. However, we distinguish the two in this survey. We classify the shared control strategies into *Semi-Autonomous Control (SAC)* and *Cooperative Shared Control (CSC)* according to whether the controlled variables are separated or not, in which the same distinction is also adopted in [31]. Then the Cooperative Shared Control is further divided into *State-Guidance Shared Control (SGSC)* and *State-Fusion Shared Control (SFSC)* according to where the intentions of the human operator and the autonomous controller are mixed. As shown in Fig. 3, the 3 categories and their distinctions are:

- **Semi-Autonomous Control (SAC)**: The state variables controlled by the autonomous controller and the human operator are separated.
- **State-Guidance Shared Control (SGSC)**: The controlled variables of the autonomous controller and the human operator are coupled. But the autonomous controller would not control the robot directly. Instead, it provide guidance to the human operator via a Human-Robot Interface (HRI). The most common guidance is the haptic cues rendered by a haptic HRI. The haptic cues, which are often referred as *Virtual Fixtures*, can indicate the intention of the autonomous controller by constraining/guiding the human operator's control inputs.
- **State-Fusion Shared Control (SFSC)**: The state variables controlled by the human operator and the autonomous controller are also coupled. But different to SGSC, the intention of the human and the autonomous controller in SFSC is fused by an arbitration mechanism (e.g., weighted combination) after the HRI.

To make it more explicit, we would like to make a distinction for the "Shared Control" and "Shared Autonomy" after giving the definition of SFSC. In many existing literatures, these two terms have been used interchangeable. However, according to [29], the paradigm is called *Shared Autonomy* when the arbitration is tuned automatically by leveraging information from the human, the tasks, and the environments.

It is also worth to note that the strategies of the 3 categories are not incompatible. Sometimes, the same algorithm may involve more than one category. For example, the system is called "*Haptic Shared Autonomy*" according to [32] if the haptic cues are provided to the human operator after an arbitration mechanism. In this case, the states controlled by the human and the autonomous controller would be fused

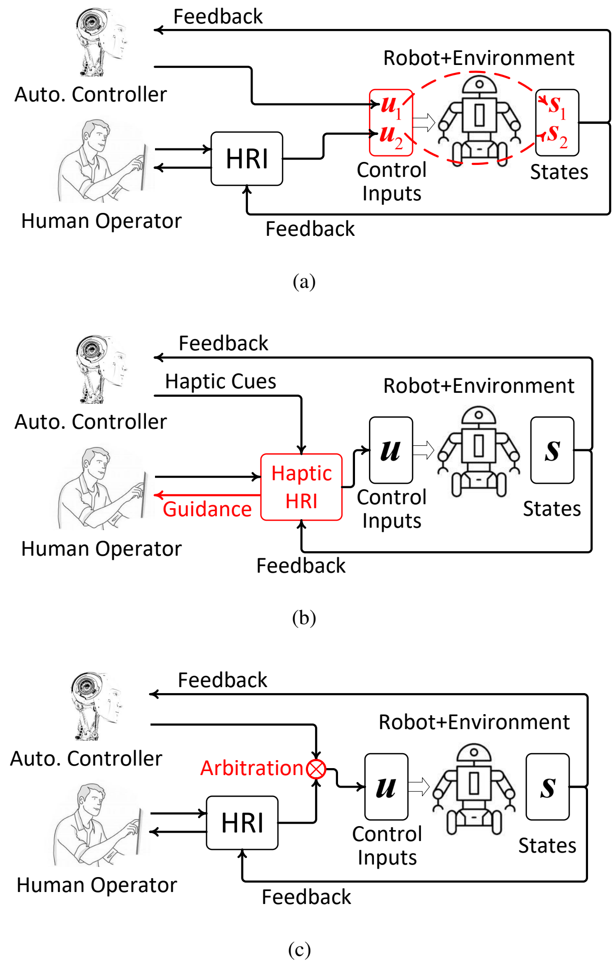

Figure 3. The architectures of the 3 categories of shared control strategies. (a) Semi-Autonomous Control (SAC): The state variables controlled by the autonomous controller $\boldsymbol{u}_1$ and the human operator $\boldsymbol{u}_2$ are separated. (b) State-Guidance Shared Control (SGSC). The controlled variables of the autonomous controller and the human operator are coupled. But the robot is still fully controlled by the human, while the autonomous controller provides guidance (e.g., rendering haptic cues to constrain the human's control inputs) to human operators to indicate its intentions. (c) State-Fusion Shared Control (SFSC). The controlled variables are also coupled. But the intention fusion is done by an arbitration mechanism (e.g., weighted combination) after the HRI.

by an arbitration mechanism, while the haptic feedback can also be rendered to the human operator to provide guidance and/or indicate the intention of the autonomous controller. More examples can be found in [33] and [34], as discussed in Section III. In this survey, we would categorize all shared strategies according to their distinctive features.

III. Semi-Autonomous Control (SAC)

In SAC, the state variables controlled by the autonomous controller and the human operator are separated. The human operator can focus on the intelligent part of a task, while the autonomous controller can handle the trivial part to assist the operator. In this section, the semi-autonomy is divided into "Low-level Autonomy" and "Parallel Autonomy" to better organize existing literatures. In the low-level autonomy, the human operator makes decisions and commands the higher-level variables, while the autonomous controller is used to handle the low-level constraints that are not intuitive to humans. In the parallel autonomy, the variables controlled by the human operator and the autonomous controller are in parallel. As shown in Table I, the typical scenarios in using the low-level autonomy and the parallel autonomy are summarized.

In early stage, the semi-autonomy is generally implemented as a *Low-level Controller* in a hierarchy architecture. To cope with unavoidable time delay, the hierarchy architecture is generally adopted in telerobotic systems. In which, the human operator makes decisions and commands the macro-task executions in the higher-layer control modules. While the autonomous controller is equipped with a certain amount of on-site autonomy to command the micro-task executions and/or handle some nonintuitive constraints (e.g., Singularity Avoidance, Joint-limits Avoidance) in the lower-layer control modules. For example, in [35], the human operator commands the task space position and velocity of the follower robot, while the autonomous controller utilizes the redundancy of the follower robot to achieve sub-task control goals, such as singularity avoidance, joint limits avoidance, and collision avoidance. In [36], a whole-body teleoperation system for a underwater mobile manipulator was presented. In this system, the operator's whole-body motion is captured and mapped to the mobile manipulator. The autonomous controller controls the manipulator to track the operator's command, while taking into account the human-robot kinematic dissimilarity (e.g., the robot's joint limit, joint velocity limit, and singularity). In [37], a switching technique-based adaptive control scheme is proposed to handle the time-varying delays and input uncertainties of a teleoperation system. The proposed teleoperation framework can autonomously achieve additional subtasks to ensure the safety and enhance the efficiency of the robot in remote site. For a whiteboard cleaning task shown in [38], the wrist position of the human operator is estimated to teleoperate the end-effector of a robot, while a low-level admittance controller is utilized to maintain contacts with the whiteboard.

More examples can be found in the teleoperation of *Vehicles or Mobile Robots*. In these works, the human operator commands and/or navigates the vehicles while the autonomous controller takes care of the vehicle dynamics or other constraints. For example, in [39], the human operator can navigate a high-speed unmanned ground vehicle (UGV) freely, while the autonomous controller takes care of the safety and vehicle dynamics constraints to avoid hazards and loss of stability. To reduce the operator's workload in teleoperating a tracked vehicle, Okada *et. al.* [40] developed an autonomous controller for generating terrain-reflective motions of flippers. In this way, the human operator only needs to navigate the robot, while the autonomous control can automatically regulate the flipper's motion according to the terrain information. In [41], a semi-autonomous framework was proposed for wheelchair mobility assistance. The proposed system utilized a local motion planner driven by the operator's intention to provide progressive assistance, whenever the user is in danger of collision or at risk of disturbance to other humans. Similarly, an autonomous controller was introduced in [42] to avoid collisions with static and/or dynamic obstacles. In this framework, the autonomous controller is used to handle the vehicle dynamics by using a model predictive control (MPC) formulation.

Another group of examples can be found in the *Formation Control*. In these works, the human operator teleoperates the behaviors of the whole formation and the autonomous controller is designed to adjust the motion of each robot to

Table I
THE TYPICAL SCENARIOS IN USING THE SAC STRATEGY

	Scenarios	Ref.	States ($\boldsymbol{u}_1$) Controlled by the Human	States ($\boldsymbol{u}_2$) Controlled by the Auto. Controller
Low-level Autonomy	Manipulators	[35]	Cartesian Position and Velocity	Singularity Avoidance, Joint Limits Avoidance, and Collision Avoidance, etc.
		[36]	whole-body Motion of the Underwater Mobile Manipulator	Handling the Human-Robot Kinematic Dissimilarity
		[37]	Cartesian Position and Velocity	Additional Subtasks, e.g., Joint Limits Avoidance
		[38]	Cartesian Position	Contact Maintenance to the Whiteboard
	Vehicles or Mobile Robots	[39]	Navigating the UGV	Vehicle Dynamics Constraints
		[40]	Navigating the Tracked Vehicle	The Flipper's Motion
		[41]	Navigating the Wheelchair	Collision Avoidance
		[42]	Navigating the Vehicle	Vehicle Dynamics Constraints, Collision Avoidance
	Formation Control	[43]	The Motion of the Whole Formation	The Position Adjustment of Each Unit for Collision Avoidance and Formation Maintenance
		[44]	The Motion of a Leader robot	The Motion of the Other Robots for Formation Maintenance
		[45]	The Virtual Point (VP) of the Formation	The VPs Adjustment of Each Unit for Collision Avoidance and Formation Maintenance
Parallel Autonomy	Orientation Regulation	[46], [47]	Cartesian Position	Cartesian Position and Orientation
		[48]	Cartesian Position	Cartesian Position and Orientation, the Object's Orientation
		[49]	Cartesian Position, and Velocity	Position, Orientation, and Velocity Adjustment
		[50]	Cartesian Position	Orientation Adjustment for Grasping
		[51]	Cartesian Position	Orientation Adjustment for Moving and Grasping
	Impedance Regulation	[33]	Motion Command	Impedance Regulation according to Payload Conditions
		[52]	Motion Command	Appropriate Impedance Selection
	Dual-Arm System	[53]	The Motion of Robot A for Task Execution	The Motion of Robot B for Occlusion-free Visual Feedback
		[34]	The Position of Robot A	The Orientation of Robot A and the Pose of Robot B for Bimanual Manipulation
		[54]	The Human Movements and Gestures	The Desired Positions and Impedances for Robot A and B

handle the dynamic constraints, obstacle avoidance, and/or formation maintenance, and so on. For a human-led multi-robot system (MRS), Parker *et. al.* [43] proposed an assistive formation maintenance method to automatically allocate formation positions to each unit, which can allow a soldier to efficiently tele-operate the MRS in a cluttered environment. Cheung *et. al.* [44] proposed a leader-follower system that one of the robots is teleoperated by an operator and the other robots are autonomously coordinated to make a formation to perform a variety of tasks. In [45], Cho *et. al.* presented a semi-autonomous system composed of multiple omni-directional mobile robots. In which, the human operator commands the Virtual Points (VPs) of the formation and the autonomous parts adjust the VPs of each robot (to avoid collision and maintain formation) and control each robot to track their own VPs.

With the emerging of various strategies, the semi-autonomous control is no longer limited to the low-level autonomy. As shown in Fig. 3(a), the *Parallel Autonomy*, i.e., the variables controlled by the autonomous controller ($\boldsymbol{u}_1$) and the human operator ($\boldsymbol{u}_2$) are in parallel, has emerged. In this way, the autonomous controller can provide high-level assistance to the human operator.

The *Orientation Regulation* is the first typical example of parallel autonomy. The orientation regulation means that the autonomous controller can regulate the operators' orientation command automatically [46]–[48]. For example, considering a drilling task, the human operator controls the position of the end-effector while the autonomous controller regulates the orientation automatically to constrain the tool direction being perpendicular to a wall [31]. Owing to the semi-autonomous controller, the operator can focus on the intelligent part of a task – deciding where to drill – while the autonomous controller handles the trivial part – the perpendicular constraint. In this way, the physical and mental workload of human operators are significantly reduced, resulting in a longer working time.

Kinds of orientation regulation approach have been developed. For example, Sun *et. al.* [46], [47] provided an orientation regulation algorithm that allows the operator to solely use the operator's position command to simultaneously control the follower's position and orientation. To implement the nonprehensile object transportation, Selvaggio *et. al.* [48] proposed a shared-control approach to automatically modulate the user-specified inputs and the object's orientation to prevent the object from sliding over and/or possible falling from a tray. Gao *et. al.* [49] proposed a unified motion mapping method to regulate the operator's position, orientation, and velocity profiles automatically, based on the poses of objects of interest in the operator and robot workspaces. Khokar *et. al.* [50] presented an algorithm for orientation assistance in the execution of a grasping task, according to the recognized human intentions. In [51], the position of a robotic hand was continuously controlled by the user, while a semi-autonomy was designed to determine its orientation to assist the user for moving and grasping.

The *Impedance Regulation* is another typical example. With the development of technology, more and more researchers start to realize the importance of impedance in robotic manipulation [55]–[57]. However, the ways to identify the impedance intention are still inadequate for existing techniques. Therefore, it is natural to regulate the impedance by an autonomous controller. For example, in [33], the proposed autonomous controller can blend the operator's motion commands to avoid physical obstacles during manoeuvring and/or reduce interaction forces during contacts, which is a strategy belongs to SFSC. Beyond that, the proposed controller can also regulate the robot's impedance, which is separated to the operator's motion commands, according to different payload conditions. Thus the proposed controller also belongs to the SAC category. In [52], the autonomous controller exploits robot vision to detect the environment and select the appropriate impedance, e.g., a lower impedance for fragile objects.

Another interesting semi-autonomy is presented in *Dual-Arm Systems*. In [53], the proposed system is composed of two robot arms where one is for task execution, while the other is equipped with an eye-in-hand camera. The human operator commands the motion of one robot to fulfill a given task and the autonomous controller commands the motion of the other one to provide occlusion-free visual feedback. Selvaggio *et. al.* [34] proposed a dual-arm system that one robot is partially controlled by the operator and the other one is controlled by an autonomous controller to perform a bimanual task. Also, the autonomous controller is able to regulate the orientation of the teleoperated robot to keep the gripper oriented toward the object (Orientation Regulation). In [54], a bimanual tele-manipulation system that can be switched between a direct control mode and a shared control mode was proposed. In the shared control mode, an autonomous controller can take the movements and gestures of just one arm as inputs and generate the desired position references and impedances for the two individual end-effectors of the bimanual manipulator.

By controlling separate variables, the SAC can provide auxiliary assistance to human operators. The SAC is a straight-forward way in combining the human's cognitive skills (e.g., perception of the complex environment, decision-making) and the higher power/precision abilities of robots. Therefore, the SAC attracts a lot interest in the field of shared control.

However, there are still many challenges in SAC. In the low-level autonomy, the autonomous controller is usually used to handle the low-level constraints that are not intuitive to humans. In this way, the human operator can better focus on the task itself, without paying extra efforts to the limits of the robot or the environments. Then the open questions are: How does the semi-autonomy affect the user's experience because it reduces the human operator's control authority over the robot? What are the effects of the semi-autonomy to the stability and transparency?, and so on. In the parallel autonomy, the autonomous controller can take over parts of the mission objectives and introduce higher-level intelligence to the system. But it also opens some questions: How to automatically determine which variables are controlled by the human operator and which variables are controlled by the autonomous controller? How to evaluate the user's satisfactions and correspondingly adjust the autonomy levels seamlessly? And, the most important one (according to our opinion) is: how to provide the expected assistance according to the operator's intentions, i.e., assistance-as-needed. To address these problems, an essential challenge is how to correctly recognize the operator's intentions according to the user's inputs, the tasks, and the environments. Although kinds of case-by-case solutions have been proposed for intention cognition (e.g., hybrid gaze-brain machine interface-based [58], EEG-based [59], and learning-based [60] methods, etc.), an efficient, universal, and robust human intention detection method with situation-awareness (environment and/or task situations) is still an open research field.

IV. State-Guidance Shared Control (SGSC)

Different to the strategies adopted in SAC, the controlled variables of the autonomous controller in SGSC are the same as the ones of the human operator. But the autonomous controller would not control the robot directly. Instead, it provide guidance to the human operator via a HRI. The guidance can be designed in different modalities, such as visual, auditory, vibrotactile, haptic cues, and so on, as summarized in Table II.

The visual and/or auditory feedback are the classical and most commonly used guidance. In early stage, these guidances are limited to some low-level and discrete warning signals, to indicate that the human's actions are wrong or the system has reached to limits of the task domains, and to remind the operator to change his/her behaviors for maintaining system stability. Examples for warning signals can be found in the Advanced Driver Support Systems (ADAS) [61] in providing parking assistance or cruise control for a intelligent car/vehicles. Gradually, researches start to realize the importance of continuous communications between human operators and autonomous controllers. Therefore, kinds of visual interfaces are designed to display the intended behaviors of the autonomous controllers to human. For example, Seppelt *et. al.* [62] created a visual representation approach to continuously indicate the intended behaviors of an Adaptive Cruise Control (ACC) to the human driver, rather than providing imminent crash warnings when the ACC fails. This design can promote faster and more consistent braking responses when braking algorithm limits were exceeded, resulting in safe following distances and no collisions. Kofman *et. al.* [63] presented a robot vision guidance system to perform fine alignment and centering of the gripper with the object by using the continuously acquired images from the end-effector-mounted camera. Once the alignment and centering are completed, the system is transformed into a semi-autonomous mechanism that the operator can only control the motion along the image-depth direction to move toward or away from the object, while the other motions are controlled by an autonomous controller. With the development of virtual/augumented reality technologies, the visual guidance become more intuitiveness and friendly to human operators. Fichtinger *et. al.* [64] presented an image overlay system which can display the CT image to a semitransparent mirror and make the CT image float "inside" the patient with correct size and position. Thus the optimal path for a needle can be identified from the CT image and rendered to the mirror to provide guidance for physicians. Huegel *et. al.* [65] introduced a visual guidance scheme for target hitting tasks in a virtual environment. The guidance is rendered as two colored regions (to indicate the target axis and the trajectory error, respectively) whose intensities diminish independently as performance improves in each of the two measures. The colored regions eventually fade to the background color when the progression of the guidance diminishes to zero. Caccianiga *et. al.* [66] investigated and compared the training performances of a needle insertion task in virtual reality environment by using visual, haptic and visuo-haptic guidance, respectively. In this work, the visual guidance is represented by a multi directional real-time visual cue carrying information about the displacement of the controlled rings. The experimental results validated that the visual and haptic guidance both played a significant role in error reduction.

With the development of wearable devices, the cutaneous guidance by using vibrotactile feedback has been risen as another important modality [86]. For example, Tanaka *et. al.* [67] designed a vibrotactile guidance mechanism for a collaborative operation system, in order to improve the collaborative operations. In this system, a 7-DoF robotic arm with a gripper is collaboratively controlled by two users, with one user (Operator A) controlling the arm and the other one (Operator B) controlling the gripper. The cutaneous guidance, which promotes the recognition of the actions of a partner, is given to the wrist of Operator B based on the position data of operator A. Kim *et. al.* [68] developed a vibrotactile device, called ErgoTac, to provide a directional guidance at the body segments to adjust its wearer's pose towards a more ergonomic and healthy posture when performing heavy lifting or forceful exertion tasks. Bai *et. al.* [69] designed a wearable vibrotactile glove and constructed a vibrotactile potential field to generate vibration stimulus for guiding the operators in teleoperation and virtual environments. Basu *et. al.* [70] proposed to use vibrotactile motors to provide cutaneous guidance cues for the training of percutaneous needle insertion tasks. Brygo *et. al.* [71] applied the cutaneous guidance to the balance control of a teleoperated humanoid robot. These examples have demonstrated the effectiveness and benefits of cutaneous guidance by using vibrotactile feedback. However, the above examples are still case-by-case studies. How to determine the layout position, the stimulus pattern, and the vibration magnitude, etc., of vibrotactile motors, is still an open problem.

Recently, the haptic guidance is attracting more and more interests with the development of haptic technologies. A wide variety of haptic devices have been developed [87]–[91], including many commercial ones, e.g., the Omega.x series produced by Force Dimension [92], the Phantom Omni/Desktop/Premium produced by 3D SYSTEMS [93], and the Virtuose 6D produced by Haption [94]. These available haptic devices make it possible to achieve continuous and direct physical human-robot interaction (pHRI), which can be used to provide more intuitive and friendly communication between human and robots. In addition, compared with the visual and vibrotactile guidance, the physical interaction can directly change the human operator's behaviors/actions. Not surprisingly, more and more work has shown the benefits of

Table II
DIFFERENT MODALITIES USED IN THE SGSC STRATEGY

Modality	Typical Scenarios	Ref.	Main Features
Visual/Auditory	Driver Support System	[61]	Discrete warning signals to indicate human's wrong actions or system's limits
	Adaptive Cruise Control	[62]	Visual representation to continuously display the intended behaviors of ACC
	Object Grasping	[63]	Vision guidance to perform fine alignment and centering of gripper with the object
	Medical Needle Insertion	[64]	Overlay the CT image and the optimal path with the patient
	Target Hitting Training	[65]	Two colored regions to show guidances for target axis and trajectory error
	Medical Needle Insertion	[66]	Compare visual guidance with haptic and visuo-haptic guidance
Vibrotactile	Collaborative Operation	[67]	Indicate Operator A's actions to Operator B for better collaboration
	Ergonomic Posture Adjustment	[68]	Provide directional guidance to adjustment worker's posture to reduce fatigue and injury
	Vibrotactile Glove	[69]	Vibration Stimulus for guiding the operators in teleoperation or virtual environment
	Medical Needle Insertion	[70]	Training of percutaneous needle insertion tasks
	Balancing of Humanoid Robots	[71]	Indicate the status of a teleoperated humanoid robot to operators
Haptic	Target Pursuing and Obstacle Avoidance	[72]	Repulsors for obstacles and attractors for target
		[73]	Generate escape points to drive robots away from obstacles
		[74], [75]	Generate virtual fixtures automatically by using a stereo camera system
	Object Grasping	[76]	Attractor to drive the operator toward the target object
		[77]	Best grasp candidate is selected as an attractor based on a ranking metric
		[78]	Smooth and continuous switching among multiple grasp candidates
		[79]	Set grasp candidates as attractors and obstacles as repulsors
	Desired Trajectory Tracking Task	[80]	Set a reference trajectory learned by GMM as attracting field
		[81]	Set reference trajectories learned from experts as attracting field for peg-in-hole
	Others	[82]	Impedance virtual fixtures for needle passing and knot typing tasks in surgical system
		[83]	Steer the manipulator away from its kinematic constraints
		[84]	Provide haptic support to minimize the operator's workload
		[85]	A feature-based user interface to specify the virtual fixture components

haptic guidance and various haptic SGSC strategies have been proposed to assist human operators.

To achieve effective assistance, the haptic SGSC strategies usually set some attractors or repulsors to guide or constrain the operator's commands. The attractors can assist the operator in moving the robot towards desired points or along desired paths/surfaces. The repulsors can prevent the robot from entering into forbidden regions of the workspace. These attractors or repulsors are often referred as *virtual fixtures* [95], [96]. Metaphorically, a virtual fixture plays a role of ruler when the human operator draws a straight line. With the help of a ruler, a human can draw faster and straighter [1].

The first typical scenario in using virtual fixtures is the *Target Pursuing and Obstacle Avoidance*. For example, Luo *et. al.* [72] exploited an artificial potential field for a mobile robot to avoid obstacles according to the repulsive force and attractive force. The force feedback can drive the human partners to update their control intention with predictability. Gottardi *et. al.* [73] presented a haptic shared control framework by utilizing an improved artificial potential field, in which the escape points, which are dynamically generated around the obstacles, are set as virtual attractors to drive the robot away from obstacles. Another interesting example is presented in [74] and [75]. In this work, the authors made use of a stereo camera system, which can provide accurate pose estimations of objects, to generate virtual fixtures automatically. A great benefit is that it can fast adapt to different manipulation tasks without the need of tedious programming job. Therefore, the methods to set virtual fixtures automatically are attracting a rising interest in the field of shared control.

The *Object Grasping Task* is another common scenario in using virtual fixtures. In early stage, Howard *et. al.* [76] presented a haptic rendering algorithm to generate forces that drive the operator toward the target object, whose position is extracted from a visual image. Gradually, researchers try to select the grasping configurations as attractors to improve the success rate of grasping. For example, in [77], to assist the object grasping task, a best grasp candidate is selected based on a ranking metric. Then the haptic forces are provided to human operators for reach-to-grasp trajectory guidance. Also, the end-effector orientation is automatically corrected by the autonomous controller while reaching towards the grasp (Semi-Autonomy). In [78], the guiding haptic cues are generated for a set of potential grasp candidates to assist the operator in approaching and grasping the objects from a cluttered and unknown environment. The goal of this work is to provide smooth and continuous feedback as the user switches from a grasp candidate to the next one, or from one object to another one. Another example for using virtual fixtures is found in [79]. To avoid collisions during a grasping, Parse *et. al.* proposed a shared control system that can provide the operator with force cues during reach-to-grasp phase. And then it can also provide force cues informing the operator of grasping configuration which allows a collision-free autonomous post grasp movement.

The third typical scenario in using virtual fixtures is the *Desired Trajectory Tracking Task*. For example, Ewerton *et. al.* [80] proposed to construct a potential field, which determines the haptic cues, for a reference trajectory plan based on Gaussian Mixture Model (GMM) over demonstrated trajectories. The learned GMM can be updated smoothly based on the updated belief over the plans. And new plans can also be learned when the operator does not follow any of the proposed plans or after changes in the environment. Similarly, in [81], a force-based haptic guidance reference trajectories for peg-in-hole insertion task can be extracted from the expert's demonstrations by imitation learning method. The guidance trajectories are superimposed to the inputs of the operator and

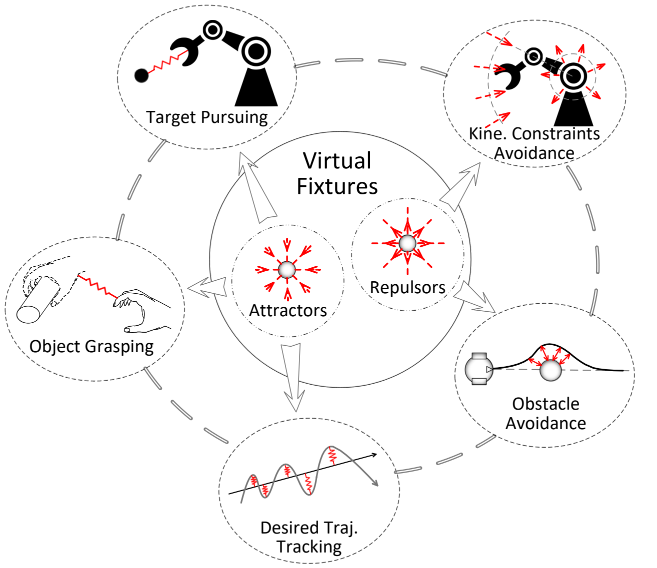

Figure 4. The typical scenarios in using the haptic SGSC strategy. The attractors or repulsors are usually set to guide or constrain the operator's commands. The guidances are marked by red springs (attractors) or arrows (repulsors).

used to generate haptic feedback to assist the operator.

The virtual fixtures can also be found in kinds of tasks. For example, Chen *et. al.* [82] provided an impedance virtual fixture framework in *Surgical System*. By introducing virtual plane fixture and virtual circle fixture, which are designed based on the frequently used motion patterns in suturing, the performance on task execution time and accuracy are improved a lot in the needle passing and knot typing subtasks. In [83], the haptic guidance is embedded in a task-prioritized control architecture to *steer the manipulator away from its kinematic constraints* for a redundant manipulator. Rahal *et. al.* [84] proposed to provide haptic support to minimize the operator's workload and *improve the operator's comfort* during a teleoperated manipulation task. To achieve this goal, the authors proposed an estimation approach to evaluate the operator's comfort by using an inverse kinematic model of the human arm. Then the active haptic constraints are provided to operators along the directions that can improve their posture and increase their comfort. Another important work is recently presented in [85]. To overcome the limitations of pre-defined or hand-coded virtual fixtures, an interactive virtual fixture generation method, which represents virtual fixtures as a composition of components, are presented. A feature-based user interface allows the human operator to intuitively specify the virtual fixture components. These works mean that the "autonomy from learning" and the "autonomy-levels adaptation" are new trends in the filed of shared control.

The typical scenarios in using the haptic SGSC strategies are summarized in Fig. 4. Compared with other strategies, the haptic SGSC strategies can provide physical interactions with human operators, which brings many benefits: 1) The autonomous controller can indicate its intentions to the operator and modify the operator's behaviors directly. 2) It can provide physical support to the human operator, which is helpful in reducing the operator's workload both in physical (e.g., relieving muscle fatigue) and mental (e.g., task cognition) aspects. However, the SGSC strategies also suffer the following disadvantages: 1) A haptic device, which is unavailable in many scenarios, is essential in the SGSC strategies. 2) Due to the haptic interaction with human operators, the stability problem may arise when time delay occurs in the system. 3) Although the haptic guidance is beneficial for task execution when no inaccuracies are presented in the guidance model, the inaccuracies and uncertainties are unavoidable in real applications. As revealed in [97], the inaccuracies may degrade task execution significantly. Therefore, how to handle the unavoidable inaccuracies and uncertainties in the guidance model is still an open issue. 4) The defining of virtual guidance model is often a laborious work requiring expert knowledge. Also the wide variety of tasks make the manual coding a daunting work. Any changes in the tasks would lead to substantial strategy modifications and bring tedious interruptions and setting up times. Therefore, how to automatically define the guidance model is still a worthy problem.

V. State-Fusion Shared Control (SFSC)

In SFSC, the state variables controlled by the human operator and the autonomous controller are fused by an arbitration mechanism after the HRI. Compared with the SGSC, the autonomous controller in SFSC does not rely on rendered haptic cues to indicate its intention. Instead, the arbitration mechanism is crucial for SFSC strategies [98]. We summarized the existing arbitration mechanisms in Fig. 5 and Table III.

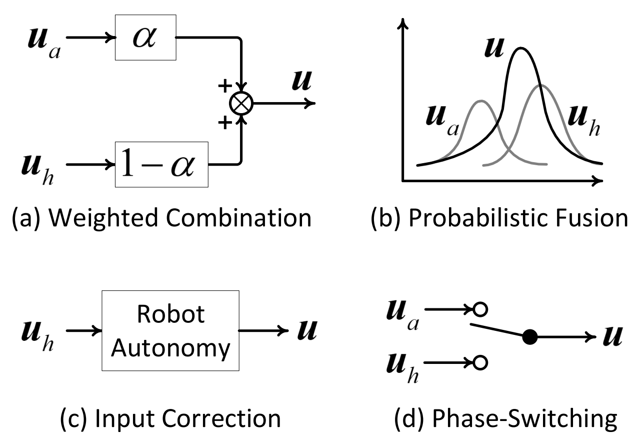

Figure 5. (a) The Weighted Combination Mechanism. The inputs from the human ($\boldsymbol{u}_h$) and the autonomous controller ($\boldsymbol{u}_a$) are superimposed linearly to determine the control signal ($\boldsymbol{u}$), according to their authority weights (α). The authority weights can be tuned either manually or automatically. (b) The Probabilistic Fusion Mechanism. The inputs from the human and the autonomous controller are modelled as probabilistic distributions. They are fused together by a probabilistic model. (c) The Input Correction Mechanism. The robot autonomy accepts the human's commands as inputs, and then supervises and corrects them according to a certain autonomy. (d) The Phase-Switching Mechanism. The robot is controlled by the human operator or the autonomous controller, respectively, in different phases. The switching can be done either manually or automatically.

The most straightforward arbitration mechanism in mixing the state variables is the *Weighted Combination Mechanism*. The weighted combination means that the inputs from the human operator and from the autonomous controller are superimposed linearly according to their authority weights. Many ways to allocate the authority weights have been proposed. For example, Kim *et. al.* [99] described a telerobotic shared control framework for micro-injection task, in which the authority weight between the operator and the controller is determined by a quantitative evaluation method using a model of speed/accuracy trade-offs in human movement. Malysz *et. al.* [100] introduced an application specific task-space weighting matrix to adjust the relative weight of autonomous control with respect to manual control. Balachandran *et. al.* [101] proposed an adaptive authority allocation method based on Bayesian filters. The adaptation was established based on a metric derived from an adaptive EKF's state covariance which depended on the real sensor measurements. The metric can be used to evaluate the manipulation performance. This allows the autonomous controller to execute the tasks and yield control authority to the operator only when the performance degrades.

Among existing methods, a notable way to allocate the authority weights is the trust-based method proposed by Saeidi *et. al.* in [102] and [103]. They introduced a computational two-way trust model to enable a trust-based weighted combination scheme for a mobile robotic system. The inputs of the manual and the autonomous controller are scaled with a function of computational human-to-robot trust. And then the haptic force feedback is dynamically scaled with a function of computational robot-to-human trust. Furthermore, in [104], the authors from the same team also designed a decision pattern correction algorithm based on a nonlinear MPC. This algorithm is used to help a human operator gradually adapt to the authority allocation pattern to improve the overall performance. However, how to build an appropriate trust model is still an open field. Many factors related to the human, the tasks, and the environments, need to be considered. Also, how to maintain the computational tractability of the trust model, is another exciting area.

Another group of examples for weighted combination mechanism can be found in dual-user systems. For example, Liu *et. al.* [105] proposed a dual-user teleoperation system for hands-on medical training. In this system, the robot is cooperatively controlled by an expert surgeon and a trainee one. The control authority between the two users, which is represented by a dominance factor α ($0 \le \alpha \le 1$), is chosen according to their relative levels of skills and experience. The dominance factor α can be adjusted manually/automatically in 3 modes: training mode ($\alpha = 1$), guidance mode ($0 < \alpha < 1$) and evaluation mode ($\alpha = 0$). Motaharifar *et. al.* [106] also presented an online authority adjustment method for a surgical training haptic system. This system can work in two modes (trainee-dominant and trainer-dominant modes) and allow the trainer to transfer the task authority to and from the trainee in real-time. Although the control in dual-user system is shared between two human operators, the similar authority allocation mechanism can be shifted to the case that the control is shared between a human operator and an autonomous controller.

Except for the weighted combination mechanism, another important arbitration mechanism is the *Probabilistic Fusion Mechanism*. In probabilistic fusion mechanism, the inputs from the human operator and the autonomous controller are both modelled as probabilistic distributions and described by probability density functions. The arbitration of the two inputs are replaced by the fusion of the two probability density functions according to Bayes rules. A common density function is the normal/Gaussian distribution which can be totally characterized by a mean and a variance. Here the mean indicates the desired values for the controlled variables and the variance is used to depict the human operator or the autonomous controller's confidence to the task. Of course, other probabilistic distributions, e.g., exponential distribution, can also be chosen depending on the requirements of applications. Ezeh *et. al.* [107] proposed a probabilistic fusion mechanism to combine the human's intended trajectory and the autonomous planner's trajectory for a wheelchair. The proposed approach works by modelling the two trajectories as a joint probability distribution, rather than the weighted combination of the two

Table III
EXISTING ARBITRATION MECHANISMS USED IN THE SFSC STRATEGY

Arbitration Mechanism	Sub-Category	Ref.	Main Features
Weighted Combination	Authority Allocation	[99]	Authority weight is determined by a quantitative evaluation method using human movement data
		[100]	A task-space weighting matrix to adjust the relative weight between human and robot autonomy
		[101]	A Bayesian filter-based allocation method depending on manipulation performance
		[102]–[104]	A weighed combination scheme based on human-to-robot and robot-to-human trust model
	Dual-User System	[105]	A dominance factor is chosen according to users' levels of skills/experience to determine authority
		[106]	Online authority adjustment method depending on training performance
Probabilistic Fusion	– –	[107]	Model the input trajectories from human and autonomous planner as a joint probability distribution
		[108]	A similar work with considering the wheelchair's dynamics
Input Correction	Predict-then-Act	[109]	Correct human's input to automatically handle obstacles avoidance via a MPC
		[110]	Predict the manipulation target by learned manipulation skills and correct the human's input to accelerate the approaching task
		[111]	Detect the reaching intention and accelerate the reaching and grasping behaviors; Determine the single- or dual-arm coordinated movements based on object size
	Workspace Limits	[112]	Correct human's position inputs to avoid unreachable commands
		[113], [114]	A partial orientation regulation method for rotational DoF deficiency in remote side
Phase Switching	– –	[115]	Direct control in approaching phase and Autonomous control for sub-task
		[116]	Human can determine the intervention level at different situations

values. The velocity probabilities in the next time is generated by a dynamic window approach (DWA) according to the joint probability distribution in current time. A similar work, which came from the same team, was provided in [108] to consider the wheelchair's dynamics.

The third arbitration mechanism is the *Input Correction Mechanism*. The input correction means that the autonomous controller accepts the commands of the human operator as inputs, and supervises the commands, and modifies the commands when it is necessary. Generally, the robot autonomy is used to handle constraints that are non-intuitive to human operators. But different to the low-level controllers in SAC, the robot autonomy in SFSC controls the same variables with the human operator. For example, in [109], the human operator's position references are corrected in real time by an autonomous controller to consider obstacles avoidance constraints via a MPC. In [110], a method was proposed to assist the human operator in manipulation tasks. In this method, the task-parameterized hidden semi-Markov model is used to extract the manipulation skill from several human demonstrations. The learned skills is utilized to predict the manipulation target and then correct the input of the operator to provide manipulation assistance. In order to increase the task execution efficiency for prolonged and repetitive operations, Laghi *et. al.* [111] presented a shared-autonomy to assist the operators in reaching and manipulation of objects. In this work, a visual perception system is introduced to monitor the operator's actions. When the reaching intention of an operator towards a target object is detected, the robot trajectory is corrected autonomously to accelerate the reaching and grasping behaviors. In addition, based on the detected size of a target object, single- or dual-arm coordinated movements are autonomously generated without the need for additional human interventions. These methods are all based on a *predict-then-act* paradigm. Thus an essential presupposition for these methods is the correct prediction of the user's goals. However, when the prediction is with less accuracy or lower confidence, they may not assist the user or give little assistance.

Another group of examples in using the input correction mechanism is the *Workspace Limits*. The robot autonomy in these examples plays a role of legitimacy inspector. When the inputs are illegitimate for the remote robot, the robot autonomy would correct the inputs to avoid dangerous behaviors. For example, Li *et. al.* [112] proposed a real-time motion mapping approach that can correct the operator's position inputs when the commands are out the scope of the robot's reachable workspace. The resultant commands can guarantee the safe and smooth motion of the follower robot. Also, to address the telerobotic systems with rotational DoF deficiency in remote side, they proposed a partial orientation regulation method [113], [114] to automatically prevent the rotational motion along the missing DoF, while persevering the remaining motions. Please note that the partial orientation regulation shown in [113], [114] is different to the orientation regulation methods discussed in Section III. For SAC strategies, the orientation is fully controlled by the autonomous controller. However, the partial orientation regulation means that the orientation command is still governed by the operator, while the autonomous controller is used to discard the unreachable components. In another word, the orientation is collaboratively determined by the operator and the autonomous controller. Therefore, the partial orientation regulation is classified into the SFSC category in this survey.

The fourth arbitration mechanism is the *Phase-Switching Mechanism*, in which the robot is controlled by the human operator or the autonomous controller, respectively, in different phases. For example, in [115], the operator can command the robot to reach the desired location via direct control at the initial phase. Then, depending on the recognized intention, the sub-task is recognized and finally the robot itself takes over the control to accomplish the task. Yu *et. al.* [116] reported another example that the human can determine the intervention level at different situations. Different to conventional telerobotic system that the autonomous controller is designed to assist the human operator, in this work the robot is mainly controlled by the autonomous controller. The human operator can intervene to assist the autonomous controller when it is necessary. The autonomous controller adopts the potential field method to achieve target pursuing and obstacle avoidance. However, the goals of target pursuing and obstacle avoidance may conflict with each other and lead to the stuck in some certain positions (deadlock zone). When the robot gets stuck, the human intervention is introduced to guide the robot in departing the deadlock zone. In this work, the human intervention and the robot autonomy were smoothly fused together through an impedance/admittance model. Besides, the human operator is able to adjust the invention levels to provide flexible assistance.

According to the arbitration is done manually or automatically, the probabilistic fusion mechanism and input correction mechanism can be classified as "Shared Autonomy", and the weighted combination mechanism and the phase-switching mechanism can also be classified as "Shared Autonomy" if the weights/switching is done automatically by leveraging information extracted from the human, the tasks, and the environments. Further, the haptic cues can also be embedded into a shared autonomy paradigm and result in a "haptic shared autonomy" framework. As revealed in [32], haptic cues are great helpful in improving the system legibility and the situation awareness of the human, which may increase the trust toward the system. Therefore, our intuition is that the haptic shared autonomy would be a worthy explored field in telerobotic systems.

Although some arbitration mechanisms have been proposed for specific tasks, the design of a general arbitration mechanism is still a bottleneck in SFSC. There are still many open challenges in the designing of a arbitration mechanism. **When the arbitration is manually tuned by the human operator, the following questions arise**: how to inform the operator the intentions of the autonomous controller? How to evaluate the human's trust and confidence? How to adjust the behaviors of the autonomous controller exploiting the human's understanding of the tasks/environments? How to provide effective assistance to improve the human's experience, and so on. **When it is automatically tuned by the autonomous controller, the open questions are**: how to determine the required amount of robot autonomy in the system? how to adjust the autonomy-levels by leveraging the information extracted from the human, the task, and/or the environment? how to predict the human's future behaviors and goals? how to let users be aware of what the system is doing, why, and what it will do next? how does the arbitration mechanism affect the user's trust and their willingness to use the system? and so on.

Compared with the SAC that provides auxiliary assistance to human operators, the autonomy in SFSC can be more diverse and in a higher level. Compared with the SGSC, the SFSC leaves room for vision-based user-interfaces since the haptic cues are not essential in the SFSC. Moreover, the SFSC has an innate and essential advantage in seamless autonomy-levels adaptation. Therefore, the SFSC architecture provides a promising intermediate to promote the evolution from a teleoperation system to a fully autonomous system.

VI. New Trends in Shared Control Strategies

The shared control architecture is designed to combine the cognition skills of the human with the robustness and precision abilities of robots. However, our ultimate goal is to promote the evolution from a teleoperation system to a fully autonomous system. Although this goal is still far away, a cheerful phenomenon is that the autonomy level in shared control is increasing, e.g., from low-level autonomy to parallel autonomy, from auxiliary assistance to cooperative assistance.

In addition, we collect, merge, and cluster the current open questions of the 3 categories as two groups, as shown in Fig. 6. To pave the evolution from a teleoperation system to a fully autonomous system, more and more efforts are required to perform to reduce the dependency on human intervention and make the robot behavior more like a human. To achieve this goal, the following two questions are especially important: 1) How to automatically design or acquire the autonomy; 2) How to automatically and seamlessly adapt the different autonomy levels as needed. Therefore, we summarize the following desirable trends in the development of shared control strategies: 1) Autonomy from Learning: The robot autonomy tends to be acquired automatically based on learning methods, rather than being manually encoded. 2) Autonomy-levels Adaptation: The autonomy level tends to be adapted seamlessly by leveraging information extracted from the human, the tasks, and/or the environments.

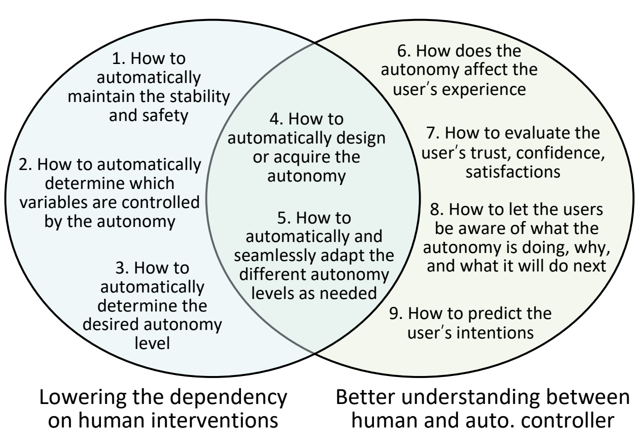

Figure 6. We collect, merge, and cluster the open questions of the 3 categories as two groups. In the first group, the goal is to lower the dependency of the telerobotic system on human interventions. In the second group, the goal is to promote the better understanding between human and the autonomous controller and make the robot behavior more like a human.

A. Autonomy from Learning

In early stage, the robot autonomy is pre-defined or manually encoded according to a specific tasks. However, as stated before, the design and implementation of the pre-defined or manually encoded autonomy is often a laborious work requiring expert knowledge [98]. Also, the diversity of tasks makes the manual coding a daunting work since any changes in the tasks/environments would lead to substantial modifications and bring tedious interruptions and setting up times [31]. Therefore, the autonomy learning becomes an attractive research field with the development of various learning methods [27].

The research on manipulation skill learning and generalisation in robotics has gained increasing attention over past decades [117]. Especially, the imitation learning (or Learning from Demonstration, LfD), which is an important branch in skill learning, has achieved many important progresses [118]. The existing imitation learning methods include: the Gaussian Mixture Model (GMM) or Gaussian Mixture Regression (GMR) [119], the Hidden (Semi-)Markov Model (HMM/HSMM) [120], [121], the Dynamic Movement Primitives (DMP) [122], the Stable Estimator of Dynamical Systems (SEDS) [123], the Probabilistic Movement Primitives (ProMP) [124], the Task-Parameterized GMM (TPGMM) [125], and the Kernelized Movement Primitives (KMP) [126], etc.. These methods have been applied to the autonomy learning for shared control. Several examples had been stated above, e.g., the [80] and [81] given in Section IV (SGSC), the [110] given in Section V (SFSC).

More examples can also be found. For example, Raiola *et. al.* [127] proposed a framework that can enable non-expert users to design virtual guides through demonstrations based on GMM (Although the proposed framework was designed for a co-manipulation robot instead of a telerobotic system, it can be transferred to a shared control strategy easily). In [18] and [128], Havoutis and Calinon presented an autonomy learning method based on the task-parametrized hidden semi-Markov models (TP-HSMM) method. The autonomy is extracted from demonstrated motions and then it is used to assist the operator in an underwater teleoperation scenario. Furthermore, Tanwani *et. al.* [129] presented an imitation learning framework based on TP-HSMM that can learn the sequential structure in the demonstrations. Lu *et. al.* [130] proposed a DMP-based skill learning and transfer framework for the generalization between two or more different tools.

Other learning methods can also be found in the autonomy acquisition. For example, Odroodgar *et. al.* [131] presented a controller which can enable a rescue robot to continuously learn from its own experiences based on a hierarchical reinforcement learning (RL) method. The proposed learning method can improve the overall performance in exploration of unknown disaster scenes. Rahman *et. al.* [132] proposed to use a supervised machine learning method to learn the dexterous surgical skill knowledge from a DESK dataset, which includes a wide variety of compact image representations with kinematic features. Liu *et. al.* proposed a learning method to learn the Chinese cooking art stir-fry skills from demonstrations. [133].

Learning methods make it easier to design, implement, and set a robot autonomy, especially for non-experts. We believe that the autonomy acquisition from learning is a desirable trend and can speed up the development of shared control significantly. It also pave the way for the evolution towards a fully autonomous robot. But it also raises new challenges for safety and stability certification, which is still an open field to be further studied in the future. Moreover, although the learning-based methods have achieve great success in learning skills in linear space (e.g., position space), there are still many difficulties and challenges in learning skills in non-linear space (e.g., orientation [134], impedance [135], etc.). Thus the extension for autonomy acquisition from linear space to non-linear space would be another important topic.

B. Autonomy-levels Adaptation

Although robot autonomy can provide great assistance to human operator, the intuitiveness of the system would be reduced owing to the concession in control authority from human to robots. To provide contextual or personalize assistance, the level of the robot autonomy is desirable to be able to change seamlessly based on internal/external information. The importance of seamless autonomy-levels adaptation had also been discussed in many comprehensive literatures [136], [137]. Therefore, we believe that the autonomy-levels adaptation is a key step to be taken in the future.

However, how to trigger the adaptation is non-trivial. As stated before, the SFSC has an innate and essential advantage in seamless autonomy-levels adaptation owing to the arbitration mechanism. The arbitration can be either manually tuned by the human operator or automatically tuned by the autonomous controller. When it is manually tuned, the user-friendly interface may be a key technology for the implementation of the autonomy-levels adaptation. For example, Pruks *et. al.* [85] presented a feature-based user interface that allows the human operator to intuitively specify the virtual fixture components to generate desired virtual fixtures. When it is automatically tuned, the adaptation is performed by leveraging information extracted from the human, the tasks, and/or environments. In [29], the adaptation approaches are divide into two categories according to the source of information that triggers the adaptation: 1) The ones that extract information from the human [138], [139]; and 2) The other ones that extract information from the environment (including the task) [18], [101]. More details can be found in [29]. In summary, we believe that the design of a more advanced arbitration mechanism may be a promising solution for the seamless autonomy-levels adaptation.

How to determine the desired autonomy level in a telerobotic system is another complex problem. There are cases that the human operator wants to get more guidance during the task execution, e.g., the desired trajectory tracking task. However, there are also cases that human operator hope to have more control authority over the system, e.g., the telesurgical operation for an expert surgeon. The desired autonomy level may depend on many factors, including the operator's experience/skill level/ability (e.g., [84], [99]), the different types/phases of the tasks (e.g., [115]), the environmental information (e.g., [101]), and so on. This is still an open problem with no unique answer, but worthy to be explored in the future work.

The implementation of seamless autonomy-levels adaptation will bring many benefits to the evolution of the telerobotic system. This adaptation may make robots behave more like a human and promote the human-robot interaction much closer to the human-human collaboration. Thus, although there are still many challenges in this field, we believe it will be another desirable trend.

VII. Conclusion

To this end, the literatures discussed in this survey is visualized as Fig. 7. We classified the existing shared control strategies into 3 categories: Semi-Autonomous Control (SAC), State-Guidance Shared Control (SGSC), and State-Fusion Shared Control (SFSC), according to their distinctive features. The typical scenarios in using each category are summarized and the advantages/distantages and open issues of

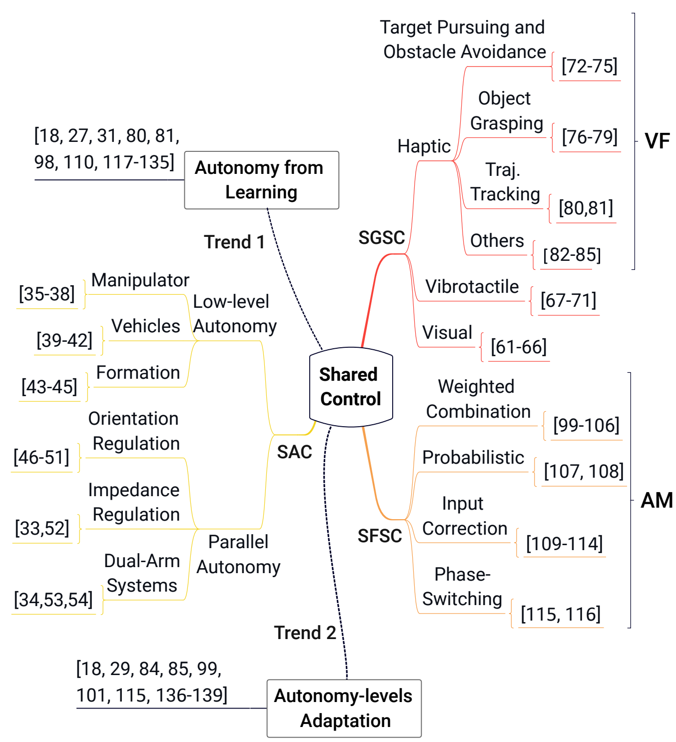

Figure 7. The existing strategies are classified into 3 categories: SAC, SGSC, and SFSC. The representative literatures are listed in each category. Two trends (Autonomy from Learning and Autonomy-levels Adaptation) are summarized. (VF: Virtual Fixtures. AM: Arbitration Mechanism.)

each category were discussed. Two desirable trends, "autonomy from learning" and "autonomy-levels adaptation", were also summarized after a systematic review. We believe that this survey captured the most important features in shared control. In addition, for some terms that have been used interchangeable in many literatures, e.g., the "Semi-Autonomous Control" versus "Shared Control", the "Shared Control" versus "Shared Autonomy", we summarize and clarify their fine distinctions to provide a unified understanding on the same term and facilitate discussions in robotic society.

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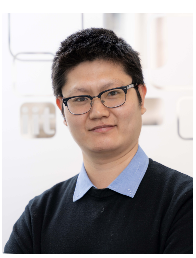

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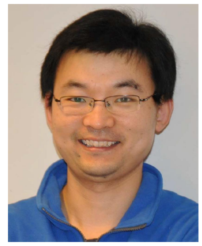

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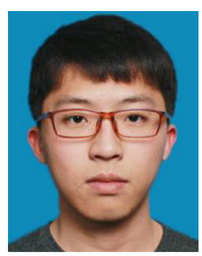

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