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A Survey

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After a Decade of Teleimpedance: A Survey

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***Abstract*—Despite the significant progress made in making robots more intelligent and autonomous, today, teleoperation remains a dominant robot control paradigm for the execution of complex and highly unpredictable tasks. Attempts have been made to make teleoperation systems stable, easy to use, and efficient in terms of physical interactions between the follower remote robot and the environment. In particular, the emergence of torque-controlled robots has permitted to regulate the interaction forces from a distance through direct force or impedance control, enabling them to engage in complex interaction tasks. Exploiting this feature, the concept of teleimpedance control was introduced as an alternative method to bilateral force-reflecting teleoperation. The aim was to create a feed-froward yet contact-efficient teleoperation by enriching the leader commands with desired impedance profiles while executing a task. Since then, the teleimpedance concept has found its way into a wide range of interface and controller designs, as well as application domains. Accordingly, after a decade of research progress, this survey aims to provide: first, a convenient introduction of the concept to new researchers in the field, second, consolidate the existing state-of-the-art for active researchers, third, and discuss the pros and cons of different methods in terms of interface and force feedback to provide guidelines for different applications and future developments.**

***Index Terms*—Force feedback, impedance control, stiffness command interface, teleimpedance, teleoperation.**

I. Introduction

ROBOTS enabled humans to augment their productivity in various domains. No other domain was impacted more by robots than manufacturing, where autonomous robots worked alongside humans to take over the mundane and repetitive tasks that require high speed, precision, and effort. Yet, even with the recent surge in the development of artificial intelligence and robot learning methods [1], [2], [3], [4], cognitive capabilities of robots are still far inferior to humans. This makes autonomous robots unable to cope with more complex tasks and situations that require them to deal with unstructured environments and rapid adaptation to unpredictable events. Yet, these are the conditions the robots face when working in environments outside of controlled manufacturing processes, such as inspection and maintenance of remote sites [5], robot-assisted surgery [6], [7], [8], rescue and disaster response [9], [10], ocean [11] and space exploration [12], [13], and household work [14], [15].

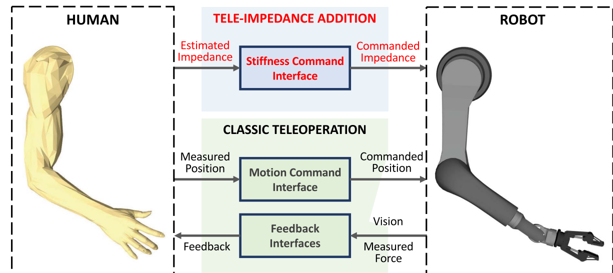

Fig. 1. Block scheme illustrating teleimpedance setup. The classic teleoperation enables the human operator to command the position of the remote robot via motion command interfaces (e.g., haptic device, optical motion capture system, inertial measurement units (IMUs), etc.) and receives feedback about the state of the robot via feedback interfaces. For example, the operator can see the remote scene through a display that steams the images from the robot's vision, and feel the forces experienced by the remote robot through force feedback generated by a haptic device. Teleimpedance offers an additional command channel that enables the operator to also directly command the impedance parameters of the robot in real time. The illustration example uses arms, however, teleimpedance is not limited to arms.

Robot cognitive capabilities can be enhanced through teleoperation, which integrates a human operator into the robot's decision-making and control loops, and combines human cognitive and adaptation capabilities with robot precision and strength. Furthermore, humans can control the robot remotely through interfaces, which enable them to perform tasks in hazardous and difficult-to-access environments. Classic teleoperation employs interfaces to capture human intent and transfer them to robot motion commands, which are sent to the robot via the network (e.g., Ethernet communication) [16], [17] (see Fig. 1). Interfaces can be as simple as buttons and joysticks, or more complex, such as motion capture systems and haptic devices that effectively measure human motion and reflect it at the remote robot. For example, the movement of a joystick can be reflected in the movement of a remote robot. Similarly, the movement of a remote robot can be linked to the movement of a human arm measured by a motion capture system.

While using interfaces based on motion capture system offer the human operator to command robot motion, they do not provide any force feedback to relay the information about the physical interaction the robot is experiencing at the remote site. On the other hand, interfaces based on haptic devices can simultaneously generate forces on the human operator and thus relay the force feedback from the remote robot force sensors. A haptic device is another kind of robot that is typically held and operated by a human arm and is called a "leader." The

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remote robot is consequently called a "follower," as it is being controlled by the "leader."[1] The system without force feedback is typically referred to as "unilateral teleoperation," while the one with force feedback as "bilateral teleoperation" [16]. Here, we use the term haptic device to refer to a grounded mechanical system, which provides forces/torques at the arm end-effector through kinaesthetic interaction and physically impedes the arms' movement. However, they are also wearable (ungrounded) types of feedback devices, which provide alternative forms of feedback (e.g., vibrotactile and pressure) and do not directly interfere with the movement of the arm [18].

While force feedback offers a human operator to sense the interaction forces experienced by the remote robot [16], [17], [19], [20], [21], the classic teleoperation systems do not permit the operator to fully control the underlying physical interaction. Physical interaction is defined by impedance, which describes the relationship between motion and forces of the limb [22] (refer to [23] for a more general survey on impedance control). In classic teleoperation, the leader can only control the motion of a typically very stiff position-controlled robotic arm that cannot adapt its impedance [16], [21]. Interacting with fragile objects in unstructured and unpredictable environments with a very stiff arm can easily lead to excessive interaction forces and consequently to the damage of the object and/or robot itself [24]. Furthermore, low impedance can improve stability in force-reflective settings [24], [25]. On the other hand, an adaptation from low to high impedance may also be necessary to stabilize the arm to unexpected external perturbations [26]. In other cases, a good combination of low and high impedance in different axes of Cartesian space is required to perform complex tasks, such as peg-in-the-hole assembly [27]. This is in agreement with the human ability to change arm impedance through different muscle activation patterns and pose [28], [29]. The human central nervous system then exploits this property to actively adapt the impedance of the limb endpoint based on the environment, leading to excellent dexterity and interaction performance [28], [29], [30], [31], [32].

The emergence of torque-controlled robots [33], [34] and corresponding low-level control algorithms [22], [35], [36] have permitted regulation of their impedance parameters in real time. To furnish these robot arms with human-like impedance adaptation capabilities in teleoperation, the concept of teleimpedance was proposed that adds an additional command channel that enables a human operator to directly command the impedance of the follower robot in real time (see Fig. 1). The term "teleimpedance" was first coined in a seminal work by Ajoudani et al. [27]. Initially, teleimpedance was referred specifically to estimating human operator limb impedance (i.e., through muscle activity measurement) and transferring it to the remote robot. Nevertheless, soon the use of this terminology was generalized to interfaces beyond the ones that estimate human operator limb impedance, such as commanding the remote robot impedance through a hand-held push-button device [37]. This extended definition would then also include some of the earlier works that used the operator's force grip to command the robot impedance [38].

It has been a decade since the term "teleimpedance" was first introduced and the field has developed into a prominent research area through many excellent scientific papers that progressed the state-of-the-art and addressed various research and application challenges. Nevertheless, despite the great importance of teleimpedance in enabling safe, stable, and highly dexterous manipulation during teleoperation, an extensive survey on the topic is missing. To bridge this gap, we aim to survey the history of the state of the art, provide a unified classification/categorization of the concepts, methods, and terms, examine the applications, and discuss the pros and cons of various teleimpedance methods with respect to contexts and applications. The survey should provide a convenient introduction to new researchers in the field, consolidate the existing state-of-the-art for existing researchers, and provide guidelines and suggestions regarding applications for potential users of the technology. The main research question that guided this survey was: *What are the tradeoffs of the existing teleimpedance methods, and how do they benefit different applications and/or fulfill specific user requirements?*

We conducted an automatic search for papers that contain the keywords *teleimpedance* and *teleimpedance* in Google Scholar and Scopus. In addition, relevant papers that were published before the term *teleimpedance* was introduced in 2011, or those published after but did not use the term, were manually searched for and included in the list (i.e., we searched for any combination of "impedance/admittance/stiffness/compliance" and "teleoperation/remote control" keywords). We then meticulously examined the list of potentially relevant papers and excluded those that did not explicitly use/study *teleimpedance* or those that only mentioned it in the literature review part of the introduction. To select among the remaining relevant papers, the most important criteria were the significance of the contribution with respect to the state-of-the-art before the publication of any particular paper. We, thus, excluded papers that made insignificant improvements to the state-of-the-art and those that presented similar (or the same) ideas multiple times. When multiple papers presented the same/similar idea, we selected the one that was published first, or in the case of evolved idea, we selected the journal version. The exceptions were some preliminary conference publications of the work that was later evolved and published in a journal for the purpose of historic narrative. In addition, we used several more general robotics and teleoperation papers for establishing a context, introducing basic concepts, and supporting our statements.

We examine the teleimpedance methods and studies through several key aspects. One of the most important aspects that we can use to categorize the methods is the type of *impedance-command interface* they use. The impedance-command interface is an essential element of any teleimpedance system as it enables the operator to directly control the impedance of the remote robot in real time. Another important aspect is whether the teleoperation setup uses force feedback during impedance commanding, i.e., whether it is *unilateral or bilateral*. Having force feedback enables the operator to also feel

[1]Historically in teleoperation literature, "leader" was called "master," while "follower" was called "slave" [16], [17]. Recently, the community pushed to disuse the old terminology.

the impedance [24]. However, it comes with well-known issues related to stability and transparency [39]. Stemming from the use of force feedback and bilateral teleimpedance systems, the impedance-command interface can be categorized into *coupled or decoupled* interfaces, which pertains to the coupling between human-commanded impedance going to the remote robot and force feedback coming from the remote robot [40]. In other words, human reflexes as a result of force feedback can cause unintended changes to the commanded impedance.

The rest of this article is organized as follows. In Section II, we classify and categorize various methods based on the types of impedance-command interfaces. This is followed by Section III, where we look at the use of force feedback in teleimpedance. Next, in Section IV, we scan through different application scenarios of teleimpedance methods. Then, in Section V, we compare the pros and cons of different methods and provide guidelines and suggestions with respect to different applications and user requirements. Finally, Section VI concludes this article.

II. Teleimpedance Interfaces

Before going into details of teleimpedance interfaces, we start with a recap of the mechanical impedance concept and impedance control. The impedance is defined as a relationship between forces and motion of a mechanical structure (e.g., remote robot) at some interaction point (e.g., end-effector). The robot impedance controller is defined as [22]

$$\boldsymbol{f} = \boldsymbol{K}(\boldsymbol{x}_d - \boldsymbol{x}_a) + \boldsymbol{D}(\dot{\boldsymbol{x}}_d - \dot{\boldsymbol{x}}_a) + \boldsymbol{M}(\ddot{\boldsymbol{x}}_d - \ddot{\boldsymbol{x}}_a) \quad (1)$$

where $\boldsymbol{f} \in \mathbb{R}^6$ is the interaction force acting from the remote robot on the remote environment. Vector $\boldsymbol{x}_a \in \mathbb{R}^6$ is the actual remote robot end-effector position and vector $\boldsymbol{x}_d \in \mathbb{R}^6$ is the desired end-effector position. $\boldsymbol{K} \in \mathbb{R}^{6\times6}$, $\boldsymbol{D} \in \mathbb{R}^{6\times6}$, and $\boldsymbol{M} \in \mathbb{R}^{6\times6}$ indicate the commanded stiffness, damping, and inertia matrix, respectively. While in theory impedance can have further elements beyond the second derivative, in (1), we do not include elements beyond inertia, since practically even inertia is often not included in the control, and damping is often a relationship of the commanded stiffness in order to stabilize the system [35]. Since most of the teleimpedance methods focused on the direct control of stiffness, we refer to commanding stiffness when mentioning impedance, unless specifically stated.

To visualize the stiffness matrix (or damping and inertia), ellipsoids can be used. For example, a stiffness ellipsoid can be derived by performing singular value decomposition of the stiffness matrix

$$\boldsymbol{K} = \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{U}^T \quad (2)$$

where $\boldsymbol{K} \in \mathbb{R}^{6\times6}$ is the stiffness matrix, while $\boldsymbol{U} \in \mathbb{R}^{6\times6}$ and $\boldsymbol{\Sigma} \in \mathbb{R}^{6\times6}$ are singular vectors and values. Vectors represent the principal axes of the ellipsoid and define its orientation, while values represent the size of corresponding vectors and define the shape of the ellipsoid. Intuitively, the length of the vector in an arbitrary direction from the center of the ellipsoid to the border of the ellipsoid tells us how stiff the robot end-effector is in that direction (see Fig. 2).

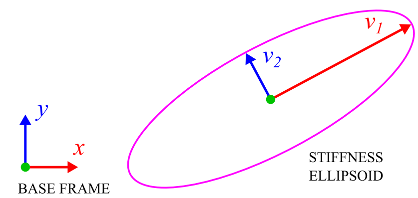

Fig. 2. Illustration of stiffness ellipsoid. The base frame in which the robot controller is operating is shown in the left-bottom corner. For the simplicity of presentation, the view is along the z-axis of the base frame (green). The ellipsoid boundary is highlighted by a magenta color. The major principal axis of ellipsoid v_1 is indicated by red color, while the minor major principal axis of ellipsoid v_1 is indicated by blue color. In this example, the robot is more stiff along v_1 and less stiff along v_2.

From the literature, we classify teleimpedance methods based on the impedance-command interface into the following five categories (see Fig. 3).

1) The first relies on a biomechanical model of the operator to estimate the arm impedance [41] and is examined in Section II-A.
2) The second is based on inducing a perturbation at the haptic device and measuring the displacement of the operator's arm [42] and is detailed in Section II-B.
3) The third is based on measuring human muscle activity, such as surface electromyography (sEMG) [27] or electrical impedance tomography (EIT) [43]. These are presented in Section II-C.
4) The fourth is based on measuring human grip force [38] and is described in Section II-D.
5) The fifth is based on external devices, such as buttons [37] and tablets [44]. These are examined in Section II-E.

It is also possible to combine these methods and create a more sophisticated impedance interface, for instance, by combining a human limb impedance model (first class) and the muscle activity signals (third class) [45], [46], or by combining perturbations (second class) and the muscle activity signals (third class) [47].

Before going into the five main categories, we provide a brief history of related research and earlier attempts leading up to implementing the teleimpedance concept. Some of the earlier attempts at adjusting the remote robot impedance actually came from pursuing to stabilize the bilateral teleoperation loop. For example, the method in [48] used a selective compliant control with a low-pass filter in the internal control loop of the remote robot. The compliance of the robot could be increased by altering the parameters of the filter, which in turn stabilized the force feedback effect on the teleoperation loop. Similarly, the study in [25] also found the advantages of low-stiffness remote robots in terms of stabilization of bilateral teleoperation. Nevertheless, these approaches cannot be classified as teleimpedance because they required offline manual tuning of parameters, and more importantly, the purpose of changing robot compliance was simply to stabilize the control loop, rather than to improve the task-related physical interaction capabilities of the remote robot. In [49], EMG was used to control the reference motion of the prosthesis, however, different stiffness levels had to be preset and were not controllable online in real time.

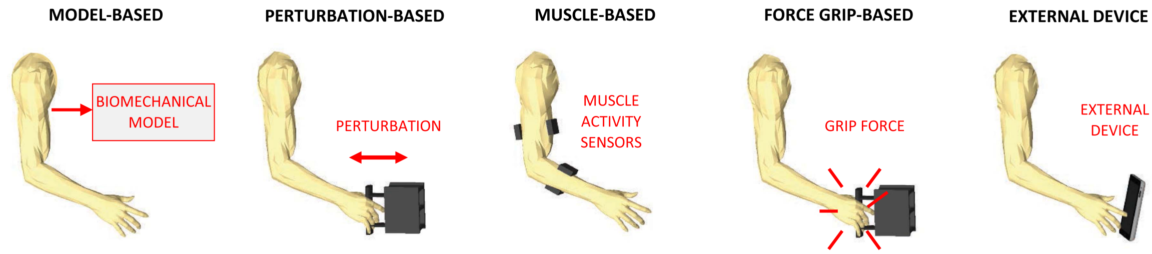

Fig. 3. Main categories of stiffness-command interfaces. Model-based interfaces use a human biomechanical model to estimate the commanded impedance. Perturbation-based interfaces perturb the operator's arm to measure the force-displacement characteristics. Muscle-based interfaces measure the activity of the operator to estimate the commanded impedance. Force grip-based interfaces measure the hand grip of the operator as an estimate. As opposed to the other four types of interfaces, the external devices enable commanding of the impedance without direct relation to the operator's biomechanics (e.g., push button). This is important regarding the coupling between the force feedback and the commanded stiffness [40] (more details follow in Section III-B).

To the best of authors' knowledge, the first methods that purposely changed the impedance of the remote robot directly and in real time during teleoperation were published in 2010 by Walker et al. [38] and Howard et al. [50]. Nevertheless, these studies only focused on one degree of freedom (DoF) interface, and hence, their performance was limited. The first major work that formulated and tested the teleimpedance concept on robotic arms was published in 2011 by Ajoudani et al. [51], which was later extended into the more seminal work in 2012 [27]. As already mentioned in Section I, the work by Ajoudani, et al. was the first instance where the term teleimpedance was defined.

It is important to note that, most of the previously developed teleimpedance interfaces focused on arm-to-arm mapping of the impedance, because of the popularity and relevance of manipulation tasks. That is why in this review paper, the arm teleimpedance notation is used more frequently. Nevertheless, works that include other body parts/limbs (e.g., hand [47], [52], knee [45], or leg [53]) are introduced and discussed.

A. Interfaces Based on Biomechanical Models

Using biomechanical models of the operator [54], [55], [56], the arm impedance can be estimated and then matched in real time to the remote robot [41], [50]. Later studies further developed this approach in terms of complexity [57]. This way of estimating the operator's arm stiffness minimizes the measurements and the required external hardware. However, the method is highly reliant on the accuracy of the biomechanical model, while accurate personalized models of different operators can be difficult to obtain. Machine learning approaches, such as reinforcement learning (RL), can help in obtaining a personalisable mapping [58], nevertheless this process can also be time-consuming without a guarantee regarding the modeling accuracy (since biomechanical models usually have too many parameters, resulting in an ill-posed identification problem).

B. Interfaces Based on Perturbation

Instead of relying on biomechanical models of the operator, inducing a small perturbation by a hand-held haptic device and measuring the corresponding displacement provides a simple but effective way to estimate the human arm endpoint impedance. The stiffness is then calculated as the ratio between the induced force change and measured displacement change. This method originated from human motor control studies of limb movements [59] but was also applied for teleimpedance. For example, Gourmelen et al. [42] used such a method to probe the operator arm stiffness and send it as a command to the remote robot. Perturbations were also used in [47] but the stiffness itself was estimated from sEMG, thus combining two types of interfaces.

A rather different method in this category is based on the operator actively inducing the perturbation by wiggling the haptic device. This method originated from a robot learning from demonstration approach through kinaesthetic guidance proposed in [60], where the human wiggled the robot body to command it to become more compliant indirectly through force interaction. In [61], the principle was extended to teleimpedance, where the operator wiggled the haptic device to directly modulate the remote robot stiffness in real time. However, perturbations and wiggling of the haptic device may interfere with the task performance.

C. Muscle Activity-Based Interfaces

The work in [27] developed an interface that estimated the human arm endpoint impedance and mapped it to the remote robot endpoint impedance. This interface was based on muscle activity measurements. Human muscles have spring-like properties and act on a joint in antagonistic pairs, where different coactivation of muscles changes the stiffness of the joint [28], [29]. Through coordinated coactivations of multiple muscles, the human central nervous system (CNS) can control the endpoint stiffness in various directions [30], [31], [32]. The endpoint stiffness properties of the arm are typically represented by a stiffness ellipsoid, where the length of a vector from the center of the ellipsoid to the surface indicates how stiff the arm endpoint is in that direction of Cartesian space (see Fig. 2). By measuring a set of eight dominant muscles in the arm through sEMG, the method in [27] estimated the human arm endpoint stiffness ellipsoid and then use it in real time to command the robot endpoint stiffness ellipsoid.

The interface in [27] enabled a complex multi-DoF control of the robot impedance. However, the disadvantage was that it had to be calibrated around a specific human arm configuration. Furthermore, equipping eight sEMG electrodes is a tedious process. To alleviate these two issues, a new interface was proposed in [62], where only two dominant antagonist muscles were measured instead and used an estimate of stiffness trend to scale the size of the stiffness ellipsoid. This is possible due to a phenomenon called muscle synergies, where the CNS controls multiple muscles in a coordinated manner with a lower dimensional input [63], [64], [65]. More importantly, the new interface included a motion capture system that measured the configuration of the human arm, achieving two things: the workspace was not limited to the vicinity of one calibrated arm configuration, and the extra configuration information was used to determine the orientation of the stiffness ellipsoid.

There were also some other simplifications of muscle activity type of interface. For example, in [15], only a single muscle was used to scale the size of the stiffness ellipsoid, while the orientation was kept fixed. Both the works in [15] and [62] used sophisticated and expensive sEMG measuring systems intended for research use. A step toward reducing the cost and complexity of sEMG measurement was made in [66] and [67], where the interface was based on a low-cost commercially available arm brace with integrated electrodes. On the other hand, a completely different system to measure muscle activity, called EIT, was used in [43] and [68].

Nevertheless, simplifications are not always feasible when impedance estimation precision and control complexity are desired. In such a case, real-time sEMG measurements can be combined with a biomechanical model to achieve such functionality [46].

D. Interfaces Based on Grip Force

Due to the intuitive nature of using human arm stiffness estimation to control robot stiffness, muscle activity-based interfaces are by far the most common type found in research papers. However, muscle activity measurement comes at the price of wearable sensors and complex calibration procedures. One alternative type of interface is based on measuring the human operator's grip force by a sensor attached to the haptic device [38], [69]. The higher grip force corresponds to higher stiffness of the remote robot. Studies in human motor control showed that grip force is highly correlated with the neuromuscular impedance [70], [71], [72], thus providing a good substitute for muscle activity measurements. While this type of interface does not require wearable sensors and complex calibration procedures, it has disadvantages too. Since force grip is essentially one DoF variable that gives an overall arm stiffness estimation trend, it cannot control all the aspects of the stiffness ellipsoid at the remote robot. The human operator can essentially only scale the ellipsoid size whose orientation and shape are fixed, as in a simplified muscle activity system without additional arm configuration measurement [15]. Furthermore, force grip regulation may not be trivial and can easily lead to muscle fatigue in sustained use of such interface [73], [74]. Nevertheless, arguably this problem also applies to muscle activity-based interfaces as well [75].

E. Interfaces Based on External Devices

A third major type of interface is based on external devices, where external refers to the human neuromechanical system and its properties, such as muscle activity and force grip. The first of such interfaces was based on a continuous push button operated by a finger, where the position of the button is measured by a linear potentiometer and then mapped to a commanded stiffness of the remote robot [24], [37]. In other words, the more the operator presses the button, the stiffer the robot becomes. This method provides simplicity and low-cost equipment, but can also control only one DoF at a time and, thus, is best suited when the shape and orientation of the stiffness ellipsoid are fixed. While using an extra input to switch between modalities related to scaling size, shape, and orientation of the stiffness ellipsoid is feasible, it is time-consuming and unintuitive for highly dynamic tasks [44]. Impedance parameters can be tuned with a computer mouse in a computer program interface [76], however, this can be similarly ineffective for fast tasks. A somewhat different way of commanding impedance is to use a voice interface [77]. In this case, the human can use language or sound to adjust the remote robot impedance parameters in real time. Yet, similarly to the previous two cases, it is not best suited for highly dynamic tasks.

To command the size, shape, and orientation of the stiffness ellipsoid simultaneously with an external device, an interface based on a virtual ellipsoid that is generated on an off-the-shelf tablet was proposed in [44]. Here, the human operator forms and adjusts the geometric aspects of a virtual ellipsoid, which is then commanded in real time to the remote robot. Similar functionality can be achieved by a foot-operated interface, where the operator shapes the ellipse via a mechanical disc interface [78]. While the more sophisticated muscle activity interfaces can also simultaneously control the size, shape, and orientation of the stiffness ellipsoid [27], [62], the ability to do so independently from each other is limited by the human neuromechanical system. The arm endpoint stiffness is dependent on the arm configuration [62], [79] and there is a strong coupling effect between muscle activities through synergies [63], [64], [65].

F. Traded/Shared Control Interfaces

While an operator can have full control over the impedance of the remote robot, there is also an option to share or trade control over it with the robot's autonomous controller. Traded control refers to a case when one agent (e.g., either human or robot) takes over the control of a whole aspect, while shared control refers to a case when two or more agents share the control over the same aspect (e.g., human 50% and robot 50%) [80], [81]. These concepts can be applied to teleimpedance.

For example, in the method proposed in [82], the robot autonomy took over the aspect of controlling the stiffness, while the human controlled the reference motion. The remote robot used torque sensors to measure physical interaction with the environment to adjust the stiffness to stabilize the task. This is similar to the approach in [26] where the stiffness of the robot increased when perturbations were detected to reject them, however, it was not done in teleoperation as in [82].

In [77], the robot autonomy also took over the control over the stiffness, and the human controlled the reference motion. However, in this case, the remote robot used a vision system

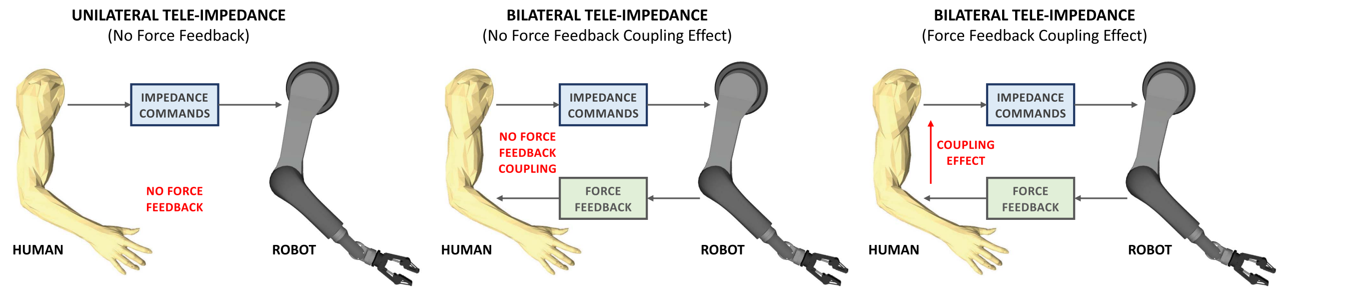

Fig. 4. Force feedback related categorizations. The main division is between the teleimpedance setups that do not employ force feedback (unilateral) and those that employ it (bilateral). The secondary division is whether there is a coupling effect between force feedback and commanded stiffness. This division is naturally only relevant for bilateral setups since unilateral setups do not employ force feedback.

to detect objects and their properties, with which the operator interacted (or intended to) in order to autonomously adjust optimal stiffness. For example, if the detected object was glass that has fragile and nonelastic properties, the stiffness of the remote robot decreased in order to make sure the object was not damaged when the human moved the end-effector to interact with it. The advantage of vision-based semiautonomous stiffness control [77], compared to interaction-based [82], is that the stiffness can be adjusted before the interaction with the object takes place and can be safer. However, a vision system is typically more complex and costly compared to using already integrated robot torque sensors.

III. Force Feedback

Typically human operator heavily relies on visual feedback to perform various tasks with teleoperated robots. However, in tasks involving physical interactions visual feedback alone provides only limited information about what is happening in the remote environment. To increase the telepresence and immersion of human operators in the remote environment, force feedback can be generated at the haptic device. In other words, we reproduce the forces measured at sensors attached to the remote robot at the human operator's hand.

A. Unilateral Versus Bilateral Setup

The teleimpedance formulation of [27] did not consider the use of force feedback (see Fig. 4 left). However, there is a sound argument for using a unilateral setup with teleimpedance, since the ability to command impedance can simplify the control of interaction with the remote robot and the environment [27], [83]. Furthermore, force feedback adds complexity in terms of extra expensive hardware (i.e., haptic device). Wearable vibrotactile interfaces are typically much cheaper, however, they do not provide the kinaesthetic interaction type of force feedback as grounded haptic devices.

In the context of teleimpedance, one of the first works to use force feedback with real-time commanding of impedance was in [38]. The experimental setup consisted of a single DoF robot, thus, the full potential of teleimpedance was not exploited. Later on, the force feedback was introduced to teleimpedance for multi-DoF in controlling full-scale industrial robotic arm [37]. Since then, the force feedback was regularly applied in teleimpedance methods [24], [39], [66], [67].

While force feedback increases the immersion of the operator in the remote environment, it can also cause issues related to transparency [20], [84] and closed-loop stability of the teleoperation system under time delays [48], [84], [85], [86], [87], [88]. Transparency gives us an idea of how well can a teleoperation system reproduce the interaction impedance, experienced by the remote robot interacting with the remote environment at the haptic device side where it is felt by the human operator. For example, a very stiff wall is more difficult to reproduce as the interaction involves very high-frequency components in the force signal, which can be difficult to handle by the control system (e.g., the sampling rate should be very high, delays should be low, etc.). In another example, low damping and inertia are also difficult to reproduce as they require very good compensation of the intrinsic dynamics of the haptic device, otherwise, the human operator predominantly feels the dynamics of the haptic device, rather than the remote environment. Closed-loop stability ensures that the teleoperation system remains stable. Two major factors that are detrimental to the stability are the delays in the communication and low sampling rate. While there is plenty of the literature on the topic of stabilizing the classic bilateral teleoperation system, the work in [39] analyzed this challenge specifically for teleimpedance.

B. Force Feedback Coupling Effect

Force feedback can also affect the interface for commanding the remote robot impedance. The study in [40] introduced the concept of "coupling effect" in force feedback teleimpedance and defined it as *the loss of a degree of control over the commanded stiffness as a result of a neuromechanical dependency between force feedback and operator's commanded stiffness*. With this effect present, the commanded impedance sent to the remote robot is a sum of voluntary impedance changes and involuntarily impedance changes that can result from unexpected force feedback (see Fig. 4 middle and right).

The teleimpedance interfaces were categorized into those who are affected by this effect, called "coupled interfaces," and those who are not affected by the effect, called "decoupled interfaces." In a coupled impedance-command interface, which is based on sEMG or EIT measurements, the measured muscle activity increases when the arm stiffens up in order to counter unexpected force feedback induced by the bilateral nature of the system. The increased human arm stiffness, as a result of increased muscle activity, simultaneously affects the stiffness of the remote robot through the impedance command channel. This hypothetically causes a temporal mismatch between the intended remote robot stiffness (required to perform a given task) and the actual commanded remote robot stiffness. While this temporal stiffness mismatch due to the coupling effect takes away some degree of the operator's control over the remote robot impedance, it might not necessarily negatively affect the task performance on the robot side. For example, if the remote robot experiences undesired perturbations, the force feedback might make the human naturally stabilize the remote robot through the coupling effect.

The coupled interfaces include the ones that are based on biosignals, such as sEMG measurements [27], [39], [67] or EIT [68]. Besides voluntary changes in muscle activity, the sEMG or EIT also measures involuntarily changes in muscle activity due to reflexes induced by unexpected force feedback. This is reflected in the commanded impedance to the remote robot as well. A potentially interesting exception is when muscle activity measurements are used in combination with vibrotactile feedback devices [18], [89], [90]. Unlike haptic devices that provide force feedback by directly displacing the operator's arm end-effector, vibrotactile cuffs only vibrate or squeeze the skin. Nevertheless, this kind of feedback might still partially affect muscle activity.

Due to grip force being highly correlated with the neuromuscular impedance [70], [72], the interfaces based on grip force can be similarly subject to the coupling effect. The same can be argued for the interfaces based on induced perturbation [42], [47] where the force feedback would corrupt the measurement of the position from which the commanded impedance is estimated.

On the other hand, external devices [37], [44] do not have any direct connection to the neuromechanical properties of the arm that is being subject to the force feedback. In such a case, involuntary changes of the viscoelastic properties of the operator's limb due to reflexes do not affect the commanded impedance because there is no coupling effect between the force feedback and the stiffness commanding method. While this can be an advantage when a precise stiffness is to be commanded, it can also be a disadvantage since they cannot exploit the rapid response of reflexes.

Most of the previous research in teleimpedance used coupled types of impedance-command interfaces [15], [27], [62]. Since they are mostly used in a unilateral teleoperation setup, the coupling effect was not present. Whenever the concept of teleimpedance is used in a bilateral setup [24], [37], [38], [39], [67], the coupling effect becomes important. When a human limb is unexpectedly perturbed, reflexes can cause an involuntary stiffening of the limb [91].

IV. Applications

This section examines different applications of teleimpedance. We identified the following four key application areas: teleoperation of robotic arms and hands, control of physical human–robot collaboration, control of exoskeletons and prostheses, and learning from demonstration. An illustration of these application areas is provided in Fig. 5.

Different tasks and conditions require different arm impedance settings for successful execution. We identified the following four key scenarios that prescribe the specific impedance settings:

1) operation in unknown/fragile environments (i.e., conditions do not suddenly change but are not known in advance);
2) operation in unpredictable environments (i.e., general conditions may be known but there are unexpected perturbations);
3) optimizing the control in terms of closed-loop stability and resolution;
4) achieving energy efficiency and transfer.

In the first scenario, the robot is interacting with an unknown environment [27], [69], fragile objects [77], [92], or humans [15], thus, the safety of interaction becomes an important aspect. In this case, the preferred stiffness of the robot is low so that the interaction forces are low if the reference position accidentally goes too far inside the environment. One could argue that in most cases low stiffness is preferred since due to redundancy in the force control through impedance [24], a certain desired force can be achieved by just commanding a larger displacement between the reference and the actual position of the robot. However, the other three scenarios are an example where that is not the case.

In the second scenario, the robot is performing a task in an unpredictable environment, where the critical aspect is to maintain accuracy and robustness [26], [30], [31], [32]. For example, the robot can be subject to external perturbations that can have an adverse effect on position tracking, thus, stiffness of the robot should increase to better reject the external forces.

In the third scenario, we want to optimize the control of the remote robot for human operators. One aspect is interaction force control through the difference between the commanded reference and the actual position of the robot end-effector. To maximize the resolution of force control concerning the difference between the reference and actual positions, the stiffness should be decreased [24]. For example, if the operator commands high stiffness while maintaining the desired interaction force between the robot end-effector and the environment, any tremor in the operator's arm will cause oscillations in the commanded reference position, which in turn will result in large oscillations of the desired force, according to the Hooke's law. Another control aspect that can be optimized is force feedback related stability. Commanding low stiffness was shown to reduce the stability issues of the teleoperation loop [24], [25].

In the fourth scenario, the robot needs to perform energy-efficient (e.g., swinging, walking, etc.) or explosive tasks (e.g., throwing, hammering, etc.), thus, variable impedance control is needed to store and release the energy. However, this approach requires variable stiffness actuators (VSA) or variable impedance actuators (VIA) with actual mechanical spring elements between the motors and links [93], [94], [95]. While

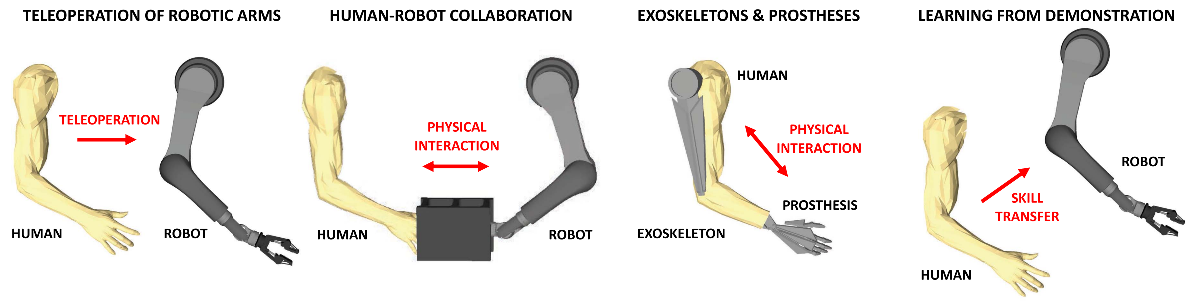

Fig. 5. Main applications categories of teleimpedance. Teleoperation of robotic arms is the largest application category, which stems from the fact that most tasks involve manipulation. Another important category is a physical human–robot collaboration where the teleimpedance principle is used to give the robot direct cues about the human intentions. Teleimpedance is also useful in the control of exoskeletons and prosthetic limbs, as it gives the operator the ability to better control their interaction properties. Finally, teleimpedance is used in learning from human demonstration, where the operator can teach robots complex interaction skills. The examples depict arms as a representative example, but of course such applications are not limited to these limbs.

VSA/VIA have been more commonly applied in legged robots, such as quadrupeds and humanoids, where energy transfer is important during locomotion [94], their application to robotic arms is still very rare and experimental (e.g., DLR David [96]). The standard robotic arms do not have VSA/VIA, but instead emulate variable impedance behavior through torque-controlled electric motors [33], [34]. For this reason, so far there is little to no application of teleimpedance for the energy efficiency/transfer scenarios, and our focus will primarily be on the first two scenarios.

A. *Teleoperation of Robotic Arms and Hands*

The most common application of teleimpedance is in the teleoperation of robotic arms and hands to execute various manipulation tasks. Since physical contact with the environment is an essential component of manipulation, teleimpedance facilitates the modulation of interaction characteristics through real-time adjustment of the robotic arm's impedance. In the following sections, we will take a look at various tasks and how they are solved through teleimpedance.

1) Peg-in-the-Hole: Peg-in-the-hole is a common assembly task where a peg has to be inserted into a tight hole to fit two parts together. For example, in [27], sEMG-based interface was used to control the stiffness of the remote robotic arm performing a peg-in-the-hole task. The operator approached the hole with a low stiffness to minimize the interaction forces at the contact and then gradually increased the stiffness to add force that overcame the friction between the peg and the hole. In [69], a force grip-based interface was used for a similar task but also considered orientation during the insertion. Commanding low orientation stiffness during the insertion prevented large forces and potential peg jamming. By keeping the stiffness low, the peg could freely align with the orientation of the hole, reducing the amount of commanded position coordination requirements by the operator. Even if the human did not align the orientations perfectly, the peg self-aligned with the hole under the interaction forces.

2) Slide-in-the-Groove: Complementary to peg-in-the-hole is the slide-in-the-groove task that is also commonly found in the assembly. In this case, a section of one part is inserted and slid into a groove of another part to fit the two parts together. For example, in [24], teleimpedance was employed for the operator to perform slide-in-the-groove with a remote robotic arm. The operator lowered the translational impedance before the insertion so that the parts freely aligned and slid into the groove. If high stiffness was commanded and there was any slight misalignment, the controller would not permit the parts to freely fit into each other. Thus, like in the peg-in-the-hole task, it is essential to keep the stiffness low to simplify the assembly. When the insertion is complete, the operator kept the stiffness low to guard against any sudden perturbations and displacement of the part. With high stiffness, any such event would produce huge forces for relatively small displacement that could damage the parts or even the robot.

3) Bolt Screwing: Screwing a bolt is an essential assembly task that involves a screwdriver to tighten bolts. Unlike many other tasks, this one is characterized by rotational movements that require corresponding adjustments of rotational stiffness. For example, in [24], the robotic arm held a screwdriver, and the operator used teleimpedance to screw a self-tapping bolt into a wooden object. The insertion of the screwdriver into the bolt head followed a similar principle as in peg-in-the-hole and slide-in-the-groove tasks: the stiffness should be kept low so that if screwdriver orientation is not perfectly aligned with the bolt head orientation, the screwdriver will conform to the shape of the environment under pressing force.

4) Cutting: Cutting is a very common task in handcraft and food preparation. For example, in [67], [92], teleimpedance was used to cut vegetables with the robotic arm that held a knife. The operator used sEMG-based interface to command low stiffness during the approach phase in order to establish contact with the vegetable. Then, the stiffness was increased to make the cut.

5) Catching Objects: Catching objects is also a good example of tasks that require variable impedance control. If an object is caught with high stiffness, it is likely to cause high-impact forces and bounce off. On the other hand, if the stiffness is too low, it might perturb the arm too far from the reference position and cause safety issues. In [27], teleimpedance was used to catch a ball with a remote robot, where the operator commanded low stiffness of the robotic arm at the time of the impact to prevent the ball from bouncing off. Then, immediately afterwards the operator increased the stiffness to make sure the robot was not displaced too far from the reference position. A similar task was studied in [97], however, the key difference was in the complexity, as the ball had to be caught in-between the fingers of the gripper while in motion, rather than simply stopping it using the palm.

6) Reaching in Cluttered Spaces: Movement tasks are not always in direct physical interaction with the environment. For example, if you are carrying a glass from a counter to the table you are moving in the air. If you then reach for the glass on the table, the task similarly involves moving in the air. However, in realistic unpredictable environments, there can be sudden and unexpected perturbations that can negatively affect the position tracking [26], [30], [31], [32].

In [83], the reaching task was performed via teleimpedance using sEMG interface. Since the remote robot was subject to external perturbations from the environment, the operator had to command high stiffness of the robotic arm in order to ensure the desired movement trajectory was followed. In [42], teleimpedance with the perturbation-based stiffness estimation method was employed to perform a drawing task with the remote robot. Thus, the robotic arm could be stiffened up to maintain the desired path for the drawing.

7) Grasping: The previously examined tasks focused on manipulating the environment with a tool that was already grasped by the robotic arm. However, grasping objects is also an important aspect of manipulation [98], where different objects may require different stiffness strategies to perform them optimally. For example, in [99], teleimpedance was used to control the stiffness of a compliant robotic hand in grasping debris during an earthquake rescue operation. In [90], a dual-arm teleimpedance was employed to grasp a large box with both hands in order to lift and carry it.

B. Physical Human–Robot Collaboration

Some tasks require multiple agents to coordinate their actions to execute them together. In particular, physical human–robot collaboration is a scenario where a human and a robot team up to perform tasks that involve physical interactions [81], [100], [101]. Similar to any other physical interaction task, impedance regulation becomes crucial in the coordination of the team effort among the agents [102]. Here, we examine physical human–robot collaboration cases where robot stiffness is directly controlled by the human in real time through a dedicated interface during the task execution. Indirect impedance modulation through interaction forces [60], [103] is not considered as it cannot be classified as teleimpedance.

One of the most representative tasks of such coordination is a two-agent sawing task. In [15], operator used sEMG interface to teleoperate a robotic arm that was collaborating with another human in a wood sawing task. An ideal strategy for performing a collaborative human–robot sawing task is to vary the stiffness in a way that when the human pulls the saw the robot should be compliant in order not to obstruct the human effort. If the robot was stiff and the reference positions of the human and the robot were not perfectly matched (and they are almost impossible to match in practice), the robot would either drag the human back or bend the saw when pushing too fast. Thus, when the human was being stiff and pulling the saw, the robot stiffness was commanded as low. Once the saw reached the human side and the human became complaint, the robot stiffness was increased to pull the saw back to the robot side.

Adjusting the robot stiffness through teleoperation is one way to ensure the correct collaborative coordination. However, this method is very complex and we prefer the robot to be able to collaborate without being controlled by another operator via a full teleoperation setup. In [100], a control method was proposed based on sEMG interface, where impedance commands are taken directly from the collaborating human rather than another external operator. The control method has two modes. The first mode is called mirrored teleimpedance and is similar to standard teleimpedance in the teleoperation scenario. For example, if a human and a robot have to collaborative turn a valve, which entails simultaneous effort, the high stiffness of the human is mirrored in the high stiffness of the robot. The second mode is called reciprocal teleimpedance, where the commanded impedance to the collaborative robot is reciprocal to that of the human. For example, in a sawing task, the robot becomes compliant when a human is stiff, and vice-versa.

The sawing task was also explored by later works in physical human–robot collaboration. In [104], sEMG interface was used in combination with reciprocal mode to perform the collaborative task. In [43], EIT interface was used instead. The study in [105] used sEMG interface in combination with mirrored mode to coordinate collaborative human–robot object carrying. The robot used the information from the human stiffening trends to adjust the robot by stiffening or relaxing during the lifting and placing actions. For more related work on the use of sEMG in direct physical human–robot collaboration, refer to a survey in [106].

In [107], a combination of perturbations and EMG was employed to adjust the collaborating robot's impedance in real time. The method was tested on experiments involving assembly and bed-making tasks.

C. Exoskeletons and Prostheses

The applications examined so far primarily focused on robots assisting healthy humans in performing various tasks. However, robots can also assist impaired humans. Two representative examples of such robots are exoskeletons and prosthetic limbs. The former are robots attached to the human limbs that assist in movements, while the latter are robots that replace lost limbs.

The method presented in [45] used sEMG interface to measure the activity of dominant muscles of the human leg and use it to estimate the stiffness trend. This trend was then scaled and mapped to a task-dependent stiffness related to the agreement with the desired degree of assistance provided by a leg exoskeleton. The experiments were conducted on standing-up and sitting-down tasks. The work in [53] also used sEMG interface to estimate human stiffness and then used it for an impedance matching on the leg exoskeleton. In [108], the patient's contralateral (healthy) arm was employed to estimate the impedance via sEMG interface, which was then used to control the impaired arm.

The research in [47] explored the use of teleimpedance for the control of prosthetic limbs using a combination of perturbations and sEMG interface to adjust the stiffness. The experiments were conducted on a generic setup involving a haptic device controlling a one-DoF remote robotic limb, which served as a starting point for potential applications to either prosthesis or exoskeleton.

In [89], teleimpedance with sEMG was used to control the grasping actions of a prosthetic hand. The setup used Pisa/IIT Softhand [109], which has some intrinsic mechanical compliance but the stiffness of the grasp is controlled actively via an electric motor. The human commanded the postural and stiffness synergies to the prosthetic hand in real time.

The work in [52] used teleimpedance with sEMG to control a prosthetic hand. Unlike Pisa/IIT Softhand, their prosthetic hand was actuated by VSA, which enabled more complex variable stiffness behaviors. Such an approach enabled better energy efficiency compared to stiffness being modulated only by control. An extension of this work later used also a prosthetic forearm in addition to the prosthetic hand, increasing the complexity and capability of the setup [110].

D. Learning From Demonstration

Robot learning from demonstration is one of the most popular ways to obtain autonomous robotic skills [1], [2]. In contrast, to manual programming, it is a much more intuitive and faster method to generate autonomous robot behavior, i.e., a policy. Unlike RL, where a robot obtains new skills through trail-and-error exploration [3], [4], learning from demonstration keeps human in the loop, which is a good guarantee for the safety of the learning process and usefulness of the learned skill.

A demonstration can be done in the following two main approaches: through kinaesthetic guidance and teleoperation. In the former, the human holds the robotic arm and physically guides it while the data (e.g., position, force) is collected to be used in learning the policy. However, one of the key disadvantages of this approach is that the human arm is physically coupled with the robotic arm during the demonstration, and induces extra dynamics that are then not present during the autonomous robot task execution. Thus, there can be a mismatch between the policy and the task. More importantly, it is difficult for a human to also demonstrate other parameters, such as impedance. In that respect, demonstration through teleimpedance has a clear advantage, at the expense of a more complex setup.

In [15], teleimpedance with sEMG interface was used to demonstrate skills for a collaborative sawing task. The operator simultaneously commanded the reference position of the remote robot and modulated its stiffness behavior during the collaboration. The reference position and the stiffness were encoded separately by dynamic movement primitives (DMPs) [111]. The parameters of the DMPs were learned online during the demonstration by locally weight regression (LWR) [112]. The phase and frequency of periodic task execution were controlled by adaptive oscillators [113]. When the robot felt confident in reproducing the demonstrated skill, the human demonstrator was disconnected from the teleoperation loop and the robot continued to collaborate with the human partner autonomously.

A similar teleimpedance-based learning approach was proposed in [24] for demonstrating assembly tasks. The key difference was that instead of using sEMG interface to control the robotic arm stiffness, a hand-held push button interface was employed. This study also showed an advantage of demonstrating stiffness behavior directly through teleimpedance, as opposed to implying it from the inverse of variation in multiple demonstrations obtained through kinaesthetic guidance, as shown in [14] and [114]. For example, in a slide-in-the-groove task, the environment provides a constraint for a movement and, thus, demonstrations are naturally very repetitive, thus, low variation would result in high stiffness during the sliding, which can be dangerous when external perturbations occur. Using teleimpedance, the operator can directly demonstrate low stiffness to optimize for safety, without being constrained by the type of environment.

An approach combining demonstrations through teleimpedance and DMPs was also presented in [67]. The operator used sEMG interface to demonstrate stiffness modulation skills in cutting and lift-and-place tasks. The method focused on the generalization of the demonstrated stiffness as encoded by DMPs. The method in [97] also used an sEMG interface to teach the robot how to catch a ball. To encode the demonstrated skill, Gaussian mixture regression (GMR) was used.

An sEMG-based teleimpedance setup was used for transferring skills from tutor human to tutee human [66]. In this case, the tutor was operating the haptic device that was controlling the remote robotic arm, which was coupled with the tutee's arm. The tutor could then guide the tutee's movements in and also adjust the stiffness of the remote robot.

As mentioned earlier, the teleimpedance principle can also be applied in physical human–robot collaboration. In such a case, the derived collaborative robot behavior can also be learned online during the task execution. For example, this was done using an sEMG interface and DMPs for collaborative sawing and polishing tasks [75]. A particular case of physical human–robot collaboration is kinaesthetic teaching, where sEMG interfaces were also applied to transfer impedance skills to the robotic arms [115], [116], [117].

Finally, the stiffness behavior of the remote robot can be learned for traded/shared control applications. For example, in [82], semiautonomous variable stiffness control was learned from human demonstration using a combination of Gaussian mixture models (GMM) and GMR. The remote robot could react to perturbations from the environment as detected by the torque sensors, while the operator was controlling its motion.

V. Discussion

A. Stiffness-Command Interface

The stiffness-command interface is the central element of any teleimpedance system, as it provides the operator with the ability to change the impedance of the remote robot in real time. We classified the five main types of stiffness-command interfaces in the literature (see Table I for an overview). Furthermore, we

TABLE I
COMPARISON OVERVIEW OF THE MAIN TELEIMPEDANCE METHODS

study	stiffness command interface	motion command interface	application / task	unilateral / bilateral	setting up complexity[a]	stiffness command DoF[b]	coupling effect[c]	machine learning[d]
[41]	biomechanical model	motion capture	movement tracking	unilateral	high	one DoF[e]	decoupled	N/A
[58]	learned model	motion capture	movement tracking	unilateral	high	one DoF[e]	decoupled	RL
[46]	biomech. model + multi sEMG	haptic device	movement tracking	bilateral	very high	multi DoF	coupled	N/A
[42]	perturbation at haptic device	haptic device	drawing	bilateral	low	multi DoF	coupled	N/A
[61]	wiggling of haptic device	haptic device	opening a drawer	bilateral	low	multi DoF	coupled	N/A
[27]	multielectrode sEMG	motion capture	peg-in-the-hole, ball catching	unilateral	high	multi DoF	decoupled	N/A
[15]	single-electrode sEMG	motion capture	collaborative sawing	unilateral	medium	one DoF	decoupled	DMP+LWR
[45]	multielectrode sEMG	direct interaction	sit-to-stand (exoskeleton)	direct interaction	high	multi DoF	coupled	N/A
[110]	multielectrode sEMG	extracted from sEMG	object grasping	direct interaction	high	multi DoF	coupled	N/A
[90]	two arm braces with multi sEMG	motion capture	dual-arm object grasping	unilateral (vibro-tactile)	medium	one DoF	decoupled	N/A
[83]	multielectrode sEMG	motion capture	arm reaching	unilateral	medium	multi DoF	decoupled	N/A
[100] [75]	pair-electrode sEMG + arm configuration	direct interaction	collaborative sawing, valve turning, and polishing	direct interaction	medium	multi DoF	coupled	DMP+LWR
[62]	pair-electrode sEMG + arm configuration	motion capture	drilling	unilateral	medium	multi DoF	decoupled	N/A
[67] [92]	two arm braces with multi sEMG	haptic device	plugging-in, and cutting	bilateral	medium	multi DoF	coupled	DMP
[97]	one arm brace with multi sEMG	motion capture	ball catching	unilateral	medium	one DoF	decoupled	GMR
[105]	pair-electrode sEMG	direct interaction	collaborative carrying	direct interaction	medium	one DoF	coupled	N/A
[43]	EIT	direct interaction	collaborative sawing	direct interaction	medium	multi DoF	coupled	N/A
[38]	grip force	haptic device	touching an object	bilateral	low	one DoF	coupled	N/A
[69]	grip force	haptic device	peg-in-the-hole	unilateral	low	one DoF	decoupled	N/A
[24]	push button	haptic device	slide-in-the-groove, and bolt screwing	bilateral	low	one DoF	decoupled	DMP+LWR
[44]	virtual ellipsoid on a tablet	haptic device	touching an object	unilateral, and bilateral	low	multi DoF	decoupled	N/A
[82]	semiautonomous (torque sensing)	haptic device	touching an object	bilateral	low	multi DoF	decoupled	GMM+GMR
[77]	semiautonomous (vision)	haptic device	touching an object	unilateral	low	multi DoF	decoupled	N/A

[a]Related to stiffness-command interfaces in terms of wearable sensors and calibration process (i.e., how quickly can a new operator start using it). The criteria we used to score the interfaces were as follows. Biomechanical models require considerable effort to be personalized, thus the baseline score is high. Wearable devices require some time to be equipped depending on the type and number of their components. A couple of EMG sensors (or an integrated brace) do not take so much time to be equipped, but still are subject to calibration, thus the baseline score is medium. Multiple electrodes are more complex to be equipped and calibrated, thus, the baseline score is high. The combination of biomechanical models and multiple electrodes sums up the individual baseline scores and results in a higher score. Other "grab-and-use" external devices that require no calibration have low baseline scores.
[b]One DoF stiffness command can still control various aspects of the ellipsoid (size, shape, orientation), however, not simultaneously. Multi-DoF typically refers to commanding the full aspect of the ellipsoid.
[c]Refers to the coupling effect between the force feedback and the commanded stiffness as defined in [40].
[d]If machine learning was applied to derive an autonomous robot behavior or human impedance estimation, what kind of algorithms were used.
[e]Can be extended to command multiple DoF of stiffness ellipsoid but experiments were conducted with one.

identified other aspects of the teleimpedance system that form a particular method to be applied. Here, we examine the pros and cons of each method with respect to specific scenarios and applications.

Stiffness-command interfaces based on sEMG [15], [27], [46], [67], [83], [110] and EIT [43] offer very intuitive control for the operator, since the operator can just naturally stiffens up or down its own arm. This can be further made more intuitive if telepresence and immersion of the operator into the remote environment in increased. Thus, compared to unilateral setup, the bilateral setup has an advantage in this respect as the operator can naturally react to the force feedback. This improves the quickness of adaptation to the interaction with the environment due to exploiting human reflexes [40], which can be very useful in tasks that involve rejecting external perturbations, such as precise reaching, drilling, and ball catching. However, the users should be aware that the coupling effect may also change the commanded stiffness unintentionally as a result of a reflex [40]. Finally, using sEMG interface the operator can easily provide multiple DoF stiffness commands to the robot. For example, all three axes of the stiffness ellipsoid can be controlled at the same time, which is essential in complex tasks requiring high dexterity, such as assembly with a robotic arm and walking with an exoskeleton.

However, sEMG interfaces fall into the category of wearable devices, which have several common disadvantages. One of the principal is the time and effort required to equip the sensors on the human body, especially when measurements of many muscles are needed [27], [46], [110]. In the case of sEMG, this is further complicated by the fact that electrodes have to be placed precisely on specific muscles, which requires knowledge of biomechanics as well. Typical operators working in industrial environments often do not possess such expertise. Simplification can be done by placing electrodes only on a couple of dominant muscles to estimate a general stiffness trend [15], [62]. However, to enable multiple DoF stiffness commands, operator arm configuration has to be measured [62], which can add additional wearable markers for the motion capture system. Markerless camera-based motion capture system (e.g., MS Kinect) is an alternative option [67], however, this typically come at the expense of measurement accuracy, and may not be suitable for very precise tasks, such as robotic surgery.

Electrode placement issues can be alleviated by arm braces and arm straps with integrated sEMG [67] or EIT [43] sensors, which can simply be slid on the arm and/or forearm and then adjusted to fit the muscle locations with the preconfigured sensors inside the brace/strap. However, there is still a calibration process needed to normalize the measured muscle voltage into muscle activity and set the correct operator-specific stiffness mapping parameters. Last but not least, poorly designed and nonpersonalized wearable devices can cause discomfort to the operators and they may be less motivated to use the interface for this reason. Thus, good design and personalization are very important to achieve good comfortability. Nevertheless, personalization may be a difficult process. Thus, sEMG interfaces might not be suitable for scenarios where quick equipping is critical (e.g., disaster response, rescue), and where the operator has to perform the task for a long time, as the wearable system might cause discomfort.

Stiffness-command interfaces based on the operator's biomechanical model [41] do not necessarily require haptic devices, and thus, can be used in a unilateral setup. However, the configuration of the arm has to be measured and used as an input for the biomechanical model [57]. The tradeoff between precise marker-based and imprecise camera-based motion capture systems comes into play again in this case. If used in bilateral setup, the haptic device could be used to estimate the operator arm configuration [118], nevertheless redundant joint DoF of the human arm can be a problem. More importantly, the model-based approach is only as good as the accuracy of the model is, and the model has to be personalized to an individual operator. Often precise personalized models are difficult to obtain, thus, this method may not be suitable when there are many possible operators, or when model accuracy cannot be trusted. On the other hand, it can be an excellent option when there is a single operator for whom we can obtain an accurate personalized model.

Repurposing the haptic device as a teleimpedance interface in perturbation-based methods [42], [47], [61] can avoid the abovementioned problems, however, perturbations may interfere with the task performance while haptic devices are typically expensive hardware. Using external devices, such as human grip force sensor [38], [69] or buttons [24] offers a simple and inexpensive way to command remote robot stiffness since no wearable sensors are needed and hardware is cheap. For example, the interface based on controlling a virtual ellipsoid on a tablet [44] can be used by almost everyone due to the widespread use of smartphones. Since these kinds of devices do not require long equipping and calibration times, they might be preferred when quick setup is needed, such as rapidly employing rescue robots in a disaster response scenario, or in industrial settings where switching between different tasks/operators is more common.

Nevertheless, external devices typically enable only one-DoF stiffness commands, where either the operator has to switch between individual axes to command one by one, or all axes of the ellipsoid are scaled dependently. Alternatively, some more complex preplanned and preprogrammed dependence between the axes can be used. This can be effective in tasks where stiffness adjustments are required in a single axis or dependently in all axes, such as pushing an object, slide-in-the-groove, and valve turning. However, they may not be suitable for complex assembly tasks where independent multiaxis stiffness modulation is required. The independent command of all aspects of the stiffness can be achieved by a virtual ellipsoid manipulated on a tablet device [44]. However, this may require considerable cogitative attention from the operator, thus commanding fast changes is way more intuitive with interfaces based on biosignals, such as sEMG or EIT [15], [27], [43], [46], [67], [83], [110]. The intuitiveness and link to neuromechanical functioning of a human operator are especially important in the exoskeleton and prosthesis applications [53], [89], [108], thus, we recommend using interfaces based on biosignals for such purposes.

B. Unilateral Versus Bilateral Setup

When teleimpedance setup is already bilateral, a haptic device can be exploited as a stiffness-command interface [42], [61]. This alleviates some disadvantages of sEMG interfaces, as there are no wearable sensors involved and very little calibration procedure. However, this approach is only viable for bilateral teleoperation systems, and a good haptic device can often be even more expensive than an sEMG measurement system. Thus, the application is reasonable when force feedback is critical to a successful task execution, which warrants the haptic device. On the other hand, wearable devices [18], [89], [90] provide a more affordable alternative to haptic devices, at expense of providing a vibrotactile type of feedback as opposed to kinaesthetic interaction type of feedback.

It is reasonable to employ interfaces based on the wiggling of the haptic device [61] for bilateral teleoperation systems. This method is very easy to apply, however, while performing the wiggling motion to demonstrate the stiffness, the force feedback coming from the remote environment can interfere with the desired wiggling action. In such a case, it might be preferred to temporarily switch to unilateral mode while the stiffness is being commanded in order to avoid conflict.

C. Coupling Effect

Some external devices [24], [44] do not have the force feedback coupling effect, which can be an advantage in tasks where a certain stiffness has to be maintained at all costs. For example, interacting with human tissue during telesurgery requires the remote robot to be very complaint not to cause damage. Coupled interfaces, such as sEMG and perturbation based, can invoke unexpected reflexes in the operator's arm, which can involuntary increase the commanded remote robot stiffness to unsafe levels [40]. However, on the other hand, they also do not take the advantage of human reflexes to facilitate rapid stiffness adaptations when needed [40]. Thus this tradeoff should be considered with respect to the task requirements.

Beyond that, although bilateral teleimpedance control can potentially provide an intrinsically safe way to control a remote robot (due to the human-in-command compliance control concept), however, measurement errors (e.g., reflected by sensor faults and noisy measurements) and undesired involuntary muscular activities (i.e., through the coupling effect) may cause adverse effects. Since such errors and reflex-like behaviors usually happen quite fast, human voluntary control may be too slow to compensate for them. In such cases, robot behaviors can be unexpected and potentially dangerous. This calls for sophisticated monitoring and "filtering" techniques to take into account such measurement inconsistencies, and the role of machine learning to capture and discard them can be quite important. While this is still an open issue, traded/shared control approaches [26], [77], [82] can be exploited for the robot to temporarily take over when the system experiences errors and detrimental reflex-like behaviors.

D. Personalization

Personalizing human impedance models in teleimpedance control would result in better impedance matching and, therefore, would increase the performance of the task, especially when a user can feel the remote environment through kinaesthetic feedback. However, this can lead to a higher computational cost in an identification stage, where human models are identified and calibrated (see, e.g., [39]). Nevertheless, since teleimpedance control regulates remote interaction forces through the adaptation of both position commands and impedance values, trajectory adjustments can compensate for impedance matching inaccuracies up to a certain extent. Obviously, the overall performance depends on the required complexity in the regulation of the interaction forces and torques in Cartesian space: such personalization would have less impact in simpler tasks, where a simple keyboard button can be sufficient.

E. Gaps and Future Directions

One of the major future research directions in teleimpedance is to expand the impedance-command interfaces to directly control parameters beyond stiffness (i.e., damping and inertia). So far most of the interfaces only enable real-time commanding of stiffness, while the damping is typically automatically adjusted based on the commanded stiffness, and inertia is neglected.

Another major future research direction is to employ teleimpedance in combination with VSA/VIA hardware, since it enables better energy efficiency and more explosive actions. Most of the existing research in teleimpedance has focused on hardware that uses control-based impedance modulation, rather than VSA/VIA. This is most likely due to control-based impedance modulated robotic arms being much more common and accessible. The few works that explored teleimpedance with VSA are typically in the exoskeleton and prosthetic applications, where custom-built hardware is more common [52], [110].

Most of the teleimpedance work has been done on human-like robotic arms. A potential extension of existing research is to examine also robots that have less human-like morphology, such as tentacles or quadrupeds. The main challenge in this direction is how to control the impedance of extra DoF that are not familiar to humans. Foot-operated impedance-command interfaces could help to that end [78].

Finally, while the field has gained considerable prominence in terms of research, most of the work so far has been done in laboratory settings reaching middle technology readiness levels. The key future step is to work on the maturity, acceptability, and usability of such interfaces, enabling a wider adoption in real-world applications. Another critical aspect is to make such interfaces affordable, intuitive, and quickly (re)deployable with minimum setting times.

VI. Conclusion

In this article, we provided an overview of the teleimpedance concept, its means of implementation, and relevant application scenarios. Overall, teleimpedance studies suggest that such an enriched unilateral communication interface subsumes the advantages of unilateral position-based and bilateral force-reflecting teleoperation, in terms of robustness to communication delays and physical interaction performances. Visual feedback is necessary to perform the task, but this communication channel does not interfere with the data that is needed to control the robot. One major limitation of the current studies is that teleimpedance control has been demonstrated only in quasi-static interaction tasks, where the design of the damping parameter was strictly related to the commanded stiffness matrix. The generality of this control interface in more dynamic scenarios (e.g., through inertia shaping) has not been explored. This can be a crucial requirement for tasks that require dynamic interactions with uncertain environments or envision planned impacts between the robot and the remote world. Another interesting direction can be the integration of RL in control of the follower robot, which can use the commanded impedance profile as the first *best guess*, and refine it in real time based on the sensory information of the robot. This can contribute to higher task execution performances, as well as reduce the cognitive load on the leader.

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