A Semi-Autonomous Tele-Impedance Method based on Vision and Voice Interfaces

Huang, Yu-Chih; Abbink, David A.; Peternel, Luka

DOI
10.1109/ICAR53236.2021.9659427

Publication date
2021

Document Version
Accepted author manuscript

Published in
Proceedings of the 2021 20th International Conference on Advanced Robotics (ICAR)

A Semi-Autonomous Tele-Impedance Method based on Vision and Voice Interfaces

Yu-Chih Huang, David A. Abbink, and Luka Peternel*

Abstract— **In tele-impedance the human can control the impedance of the remote robot through various interfaces, in addition to controlling the motion. While this can improve the performance of the remote robot in unpredictable and unstructured environments, it can add more workload to the human operator compared to the classic teleoperation. This paper presents a novel method for a semi-autonomous tele-impedance, where the controller exploits the robot vision to detect the environment and selects the appropriate impedance. For example, if vision detects a fragile object like glass, the controller autonomously lowers the impedance to increase the safety, while the human is commanding the motion to initiate and perform the interaction. If the vision algorithm is not confident in its detection, we developed an additional verbal communication interface that enables the human to confirm or correct the autonomous decision. Therefore, the method has four modalities: (i) perturbation rejection mode, (ii) object property detection mode, (iii) verbal confirmation mode, (iv) voice control mode. We conducted proof-of-concept experiments on a teleoperation setup, where the human operator performed position tracking and contact establishing tasks.**

I. Introduction

Tasks in hazardous or remote environments often require robots to perform them because such environments are unsafe or hard to reach for humans. Moreover, some of these tasks involve the interaction with dynamic environments, which could be too complex for fully autonomous robots to handle with the current artificial intelligence (AI) capacity. To make robots able to interact with dynamic environments, human adaptability and cognitive capabilities are introduced into robot systems through human-in-the-loop control. One common way to achieve this is through teleoperation. In the classic teleoperation, the human operator can control the motion of the slave robot remotely through a master device. However, the human operator can only control the motion of the robot and not its impedance, therefore it can damage the unstructured environment with high interaction forces, or cause unstable conditions when interacting with unpredictable environments.

In order to address the limited ability to interact with dynamic environments in the classic teleoperation, a concept called tele-impedance was developed that allows the human operator to control the impedance of the robot [1]. Tele-impedance includes an additional command channel that enables the human to control the impedance of the remote robot. This is realised with various interfaces, such as hand grip sensor [2], Electromyography (EMG) or [1], [3], [4] push-button [5]. Although using tele-impedance allows the robot to better interact with dynamic environments, it may significantly increase the workload of the human operator compared to the classic teleoperation setup, since he/she has an additional control task with respect to the classic teleoperation.

This problem can be alleviated by robot autonomy and shared control methods to offload the impedance control task from the human operator. There are numerous studies dedicated to developing autonomous impedance controllers, however only a few can be applied in teleoperation. Most of the autonomous impedance controllers developed with learning methods, such as reinforcement learning [6] or learning from demonstration [7], [8], cannot be used in teleoperation systems because the impedance is learned with respect to a fixed trajectory. While some methods take into account variability of multiple trajectories [9], the inferred impedance behaviour is not always optimal for interaction tasks [5]. This is not compatible with teleoperation because the human operator changes the trajectory rapidly. On the other hand, adaptive impedance controllers can be potentially applicable to teleoperation. Past research in this direction developed adaptive impedance controllers for autonomous robots based on the measured forces from the interaction with the environment [10]–[13]. However, such controllers can change the impedance only after physical interaction with the environment has been established, which might not be safe in situations where the environment is unknown, unstable or fragile.

To solve this problem, we propose and develop a novel vision-based autonomous impedance control method for tele-operation that can adjust the impedance of the remote robot prior to physical contact. The two autonomous modes are incorporated within the vision-based autonomous impedance controller. In *perturbation rejection mode*, the controller uses visual object detection to predict incoming perturbations in order to stiffen up prior to perturbation. In *object property detection* mode, the controller uses object property detection algorithms to acquire environment information without the need of physical contact. For example, if vision detects a fragile object like glass, the controller autonomously lowers the impedance to increase the safety, before the human operator initiates the interaction by commanding the motion.

Vision and visual feedback have been successfully used in robot learning, where the aim is to make robots autonomous. For example, the method [14] used visual feedback to enable the robot to learn and adjust complex behavioural semantics.

The authors are with Delft Haptics Lab of Department of Cognitive Robotics, Delft University of Technology, Mekelweg 2, 2628 CD Delft, The Netherlands.

*Corresponding author (e-mail: l.peternel@tudelft.nl)

Visual feedback was also used to infer the behaviour in interaction tasks [15], [16]. Nevertheless, to the best of our knowledge, it has not yet been exploited to adjust the impedance in semi-autonomous teleoperation, in particular based on the properties of the environment with which the remote robot should interact.

In addition, a completely autonomous impedance controller is not a desirable approach in human-in-the-loop systems, where the human operator cannot override its decision, when it is not correct due to unreliable sensory data. In such a case, a shared control method is required to provide the human with a suitable degree of authority over the robot autonomy. Many studies investigated the concept of shared control in teleoperation with different purposes, such as teaching through shared control [17]–[19], assistive shared control [20]–[22], or collaborative shared control [23]. However, most of these studies focus mainly on motion control, and only a few considered impedance control [3], [12]. Although in [3] and [12] impedance control was considered, both studies do not have vision-based impedance capability and require robots to perform physical interactions with the environment to make adjustments of impedance.

To facilitate a degree of shared control between the human operator and the vision-based autonomous impedance controller, we developed a voice-based impedance control interface that adds two additional modalities to the method. *Verbal confirmation mode* enables the human operator to interact with the vision-based autonomous impedance controller and override its decisions if necessary. This is particularly crucial when the vision detection algorithm has lower estimation accuracy or when it is not certain in its decision. For example, when the vision detection is uncertain due to unreliable sensory data, the controller prompts the human operator for a confirmation through verbal interaction. Finally, if the human for some reason wishes to set the impedance himself/herself, *voice control mode* delegates the impedance control entirely to the human.

To demonstrate the main features of the proposed method we conduct proof-of-concept experiments. The experiments are performed on a teleoperation setup with a Force Dimension Sigma7 haptic device as the slave robot, a computer mouse as the master device, and a camera for visual feedback. The experiments consist of two tasks that show the performance of each modality of the proposed method: rejecting external perturbations in a position tracking task and establishing contact with different objects.

II. Control method

A. General Control Scheme

The block scheme of the proposed vision and voice based semi-autonomous impedance control method is shown in Fig. 1. The human operator controls the motion of the robot through a master device. The method has four modalities: (i) *perturbation rejection mode*; (ii) *object property detection mode*; (iii) *verbal confirmation mode*; (iv) *voice control mode*. The two autonomous modes (mode i, ii) are part of the vision-based autonomous impedance controller, where the controller processes the data from the camera with vision algorithms and determines the proper impedance command for the robot. The impedance command is generated by a Cartesian impedance control method. During the teleoperation, the human operator can assess the situation through visual feedback and, if needed, activate the voice-based impedance control interface to override the robot impedance value with the verbal confirmation mode (*mode iii*) or the voice control mode (*mode iv*).

B. Robot Stiffness Control

We used the Cartesian impedance control method on Sigma7 robot, which has 7 degrees of freedom (DoF). However, in this study we only focused on controlling the impedance in translational axes of Cartesian space, therefore the following derivation only considers 3 DoF. The robot's physical interaction at the end-effector was controlled as:

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

where $\boldsymbol{f} \in \mathbb{R}^3$ is the end-effector force exerted by the robot on the environment, $\boldsymbol{x}_d \in \mathbb{R}^3$ and $\boldsymbol{x}_a \in \mathbb{R}^3$ are the desired and the actual end-effector position of the robot. The stiffness matrix $\boldsymbol{K} \in \mathbb{R}^{3x3}$ is controlled by either the autonomous impedance controller or the human operator as diag$\{\boldsymbol{k}\}$ where $\boldsymbol{k} = [k_x \ k_y \ k_z]$. The damping matrix $\boldsymbol{D} \in \mathbb{R}^{3x3}$ was designed based on the stiffness matrix $\boldsymbol{K}$ at each time-step as:

$$\boldsymbol{D} = 2\boldsymbol{D}_\xi\sqrt{\boldsymbol{K}} \tag{2}$$

where $\boldsymbol{D}_\xi \in \mathbb{R}^{3x3}$ is a diagonal matrix that contains the damping factors, which were set to 0.7 for critical damping.

III. Vision-based autonomous impedance controller

A. Perturbation Rejection Mode

If position errors can lead to unstable conditions or damage to the environment, it is important for the robot to closely follow the trajectory in a position tracking task. For example, in a drilling task, the robot should hold its position perpendicular to the drilling direction under external perturbations in order to minimise the damage on the environment and prevent breaking the drill. To reject perturbations, the robot needs to increase its stiffness when a perturbation or its potential cause is detected. The proposed perturbation rejection mode detects the incoming perturbation through vision and increases the impedance beforehand in order to minimise its effect on the position tracking error. The advantage of the proposed perturbation rejection mode is that it does not require a physical contact to adjust the impedance and can do so before any interaction occurs, unlike most of the existing adaptive impedance controllers mentioned in the introduction.

In order to identify the perturbation with vision, we employed an object detection algorithm to detect any unknown objects that are moving within the camera view, and an object tracking algorithm to track the position of the robot. The system identified the perturbation when the minimum

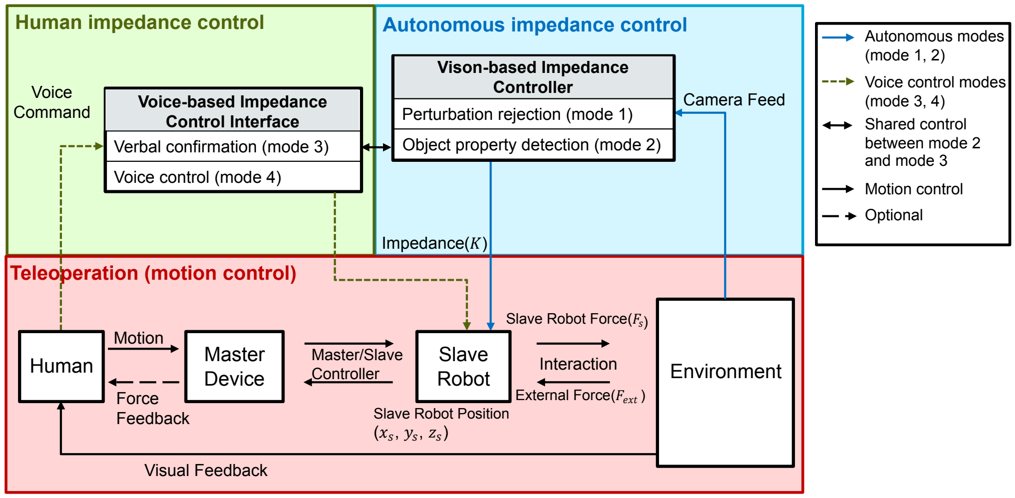


Fig. 1: Block diagram of the semi-autonomous impedance control method based on vision and voice interfaces. The bottom block (red) is the teleoperation framework for motion control. The upper half is the impedance control loop. The autonomous impedance control block (blue) contains the vision-based autonomous impedance controller with the perturbation rejection mode ((*mode i*) and the object property detection mode (*mode ii*). The human impedance control block (green) contains the voice-based impedance control interface with the verbal confirmation mode (*mode iii*) and voice control mode (*mode iv*).

distance between the detected object motion and the robot is less than a preset safe distance. The robot then increased its stiffness in order to minimise the effect of disturbance on the position tracking task.

B. Object Property Detection Mode

Humans often use their visual cues and experience to estimate the properties of an object, and adjust their neuromuscular impedance to interact with it in a natural manner. Inspired by this behaviour, we designed the object property detection mode to adjust the impedance according to the detected object and its material.

We used two databases from the literature for object material recognition: Flickr Material Database (FMD) [24] and the Materials in Context Database (MINC) [25]. FMD contains 10 categories with 100 samples in each category, while MINC contains 23 categories with at least 14000 patches in each category. We selected ten materials (Glass, Leather, Metal, Paper, Plastic, Stone, Concrete, Wood, Ceramic, Rubber) from these databases and categorised them into groups by their properties: elasticity and fragility. Based on the material properties, we established the relationship between the material and the desired robot impedance, which was used by the autonomous impedance control method.

The results are shown in Table I. We categorised the selected materials into three groups: "Rigid, Fragile", "Rigid, Non-Fragile", "Elastic, Non-Fragile", where each group was assigned a corresponding impedance value. For example, if the material is in the "Rigid, Fragile" group, the robot should interact with a low impedance in order not to damage the object. If the material is in the "Rigid, Non-Fragile" group, the robot can have a higher impedance as there is less chance of damaging the object. If the material is in the "Elastic, Non-Fragile" group, the robot should have a medium impedance to ensure a sufficient damping that can stabilise the elastic property of the object.

TABLE I: Material property and prescribed impedance

Material	Elasticity	Fragility	Impedance
Glass	Rigid	Fragile	Low
Leather	Elastic	Non-Fragile	Medium
Metal	Rigid	Non-Fragile	High
Paper	Rigid	Fragile	Low
Plastic	Rigid	Non-Fragile	High
Concrete	Rigid	Fragile	Low
Stone	Rigid	Non-Fragile	High
Wood	Rigid	Non-Fragile	High
Ceramic	Rigid	Non-Fragile	High
Rubber	Elastic	Non-Fragile	Medium

Ideally, the object property detection algorithm should be a material recognition algorithm. However, material recognition algorithms are not as widely available, well developed and precise as object detection algorithms. Since this study did not focus on vision and visual recognition itself, but rather on the impedance control method, we instead used an object detection algorithm YOLOv3 and linked the material to a specific detected object.

IV. Voice-based Impedance Control Interface

A. Verbal Confirmation Mode

To deal with situations where the detection algorithm might not be sufficiently accurate or reliable, we developed a verbal confirmation mode within the voice-based impedance control interface. This mode allows the robot to offload the impedance control task, but the human operator still has the ability to intervene when the robot is not confident. It is activated automatically by the robot control system when the confidence score of the detection is lower than a predefined threshold, or when the robot incorrectly identifies the object. The robot then verbally announces the detected material to the human operator, who is required to either confirm the detection results by saying "yes" or override the results by saying the correct material.

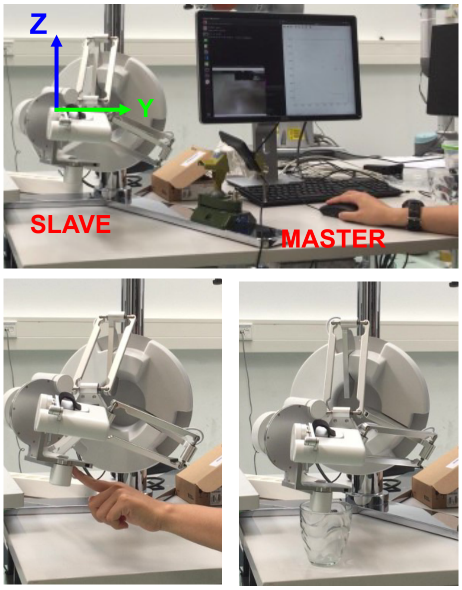


Fig. 2: Photos from the experiments. The photo on the top shows the human operator controlling the slave robot through the master device (computer mouse). The photo on the bottom left shows the position tracking experiment. The humanapplies physical perturbations on the end-effector of the robot. The photo on the bottom-right shows the contact establishing experiment, where the human operator controlled the robot to approach the object. The robot base frame orientation is illustrated by the blue arrows for y-axis and z-axis. The x-axis follows the right-handed coordinate system.

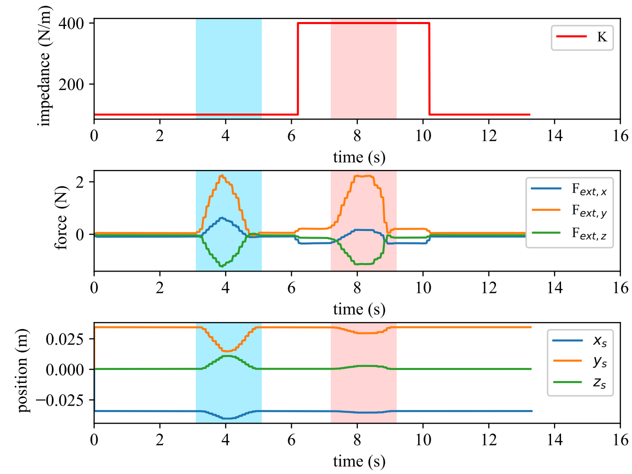


Fig. 3: Experiment results using the perturbation rejection mode (*mode i*) during the position tracking task. The blue shaded area shows when the robot is perturbed with the mode disabled. The red shaded area shows when the robot is perturbed with the mode activated. The first graph shows the commanded impedance $\boldsymbol{K}$. The second graph shows the external force exerted on the slave robot. The third graph shows the end-effector position of the slave robot (x_s, y_s and z_s).

The object property detection mode and the verbal confirmation mode both have the same drawback; the impedance values can only be switched discretely between the predefined values. This can be sufficient in many cases. For example, when the robot is approaching an object, setting an approximate impedance level is usually sufficient to establish a safe contact for a given material. However, if the interaction task is very complex after the contact is established, the human operator might need to further adjust the impedance in a continuous fashion.

B. Voice Control Mode

To complement the verbal confirmation mode, we developed the voice control mode that gives the human operator the ability to adjust the impedance value continuously and hands-free. Unlike the verbal confirmation mode, which is activated automatically based on the robot vision confidence, the voice control mode can be activated or deactivated by the human operator through language commands (i.e., ”activate/deactivate voice control”). Once the mode is activated, the impedance control is assigned entirely to the human operator, who can then adjust the impedance by making high-pitch or low-pitch tones; high-pitch increases the impedance, while the low-pitch decreases the impedance. The proposed voice control mode changes the impedance value with a fixed rate (i.e., change of diagonal elements of $\boldsymbol{K}$), which is determined by a predefined increment size parameter. The audio data is processed at each time-step to adjust the impedance in the following manner:

1) Receive audio data from the microphone.
2) Perform fast Fourier transform (FFT) on the audio data.
3) Get the top three nominal frequency signals, f_1, f_2, f_3 (large to small amplitude).
4) Calculate the average amplitude of f_1, f_2, f_3.
5) If the average amplitude is less than a noise threshold, then no impedance changes will be made. Otherwise, the voice command frequency f_c will be calculated to best represent the current tone: $f_c = \frac{3f_1+2f_2+f_3}{6}$.
6) If f_c is higher than the threshold frequency f_{th}, the impedance $\boldsymbol{K}$ increases by the predefined increment size. In the opposite case, the impedance $\boldsymbol{K}$ decreases by the increment size.

V. Experiments

To demonstrate the proposed vision and voice based semi-autonomous impedance control method in real-world applications, we performed several proof-of-concept experiments on a teleoperation setup (see Fig. 2). The setup included Force Dimension Sigma7 as slave robot, a computer mouse as a master device, and a camera for robot vision. The human operator controlled the $y-z$ plane motion of the Sigma7 by the computer mouse. Force feedback was not important to this study and was therefore not implemented. The method derived the appropriate impedance from the processed camera feed and sent the command to the Sigma7. The experiments involved two tasks, where adjusting the impedance of the robot is crucial or beneficial: a position tracking task and a contact establishing task.

A. Position Tracking Task

In the position tracking task, the goal was to control the robot to hold a reference position during the external perturbations. Ideally, the robot should be compliant to avoid large interaction forces that might damage the robot. However, in some cases, where small position errors could lead to unstable or dangerous conditions (e.g., drilling task

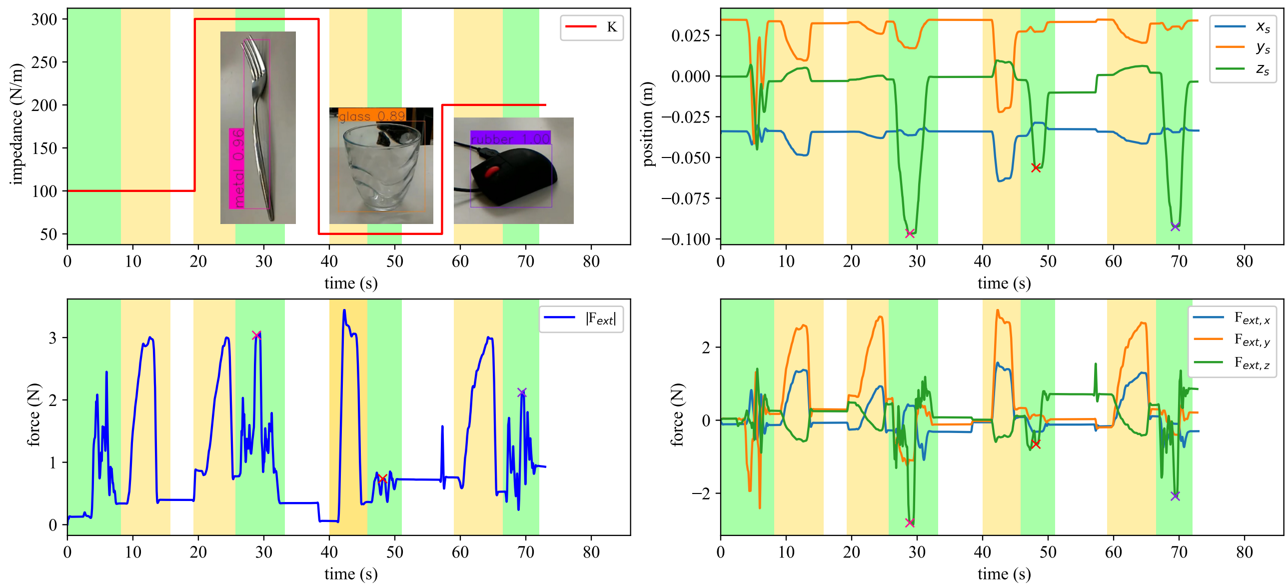


Fig. 4: Experiment results using the object property detection mode (*mode ii*) during the contact establishing task. The green shaded area indicates when the human operator is moving the slave robot by teleoperation. The yellow shaded area indicates when the robot is perturbed with external forces. The white area indicates when the object in front of the robot changed. The 'x' marker indicates the robot position and the interaction force between the robot and the object when contact is first established. The top left graph shows the impedance command $\boldsymbol{K}$ received by the slave robot. The top right graph shows the position of the slave robot end-effector (x_s, y_s and z_s). The bottom left graph shows the absolute magnitude of external force $\boldsymbol{F}_{ext}$ exerted on the slave robot end-effector. The bottom right graph shows the components of $\boldsymbol{F}_{ext}$.

or surgical task), the priority is to minimise position error caused by the perturbations, therefore the robot impedance should be increased in the direction of the perturbation. By considering such cases in our experiment, the strategy of the *perturbation rejection mode* was designed to reject external perturbations by stiffening up the robot.

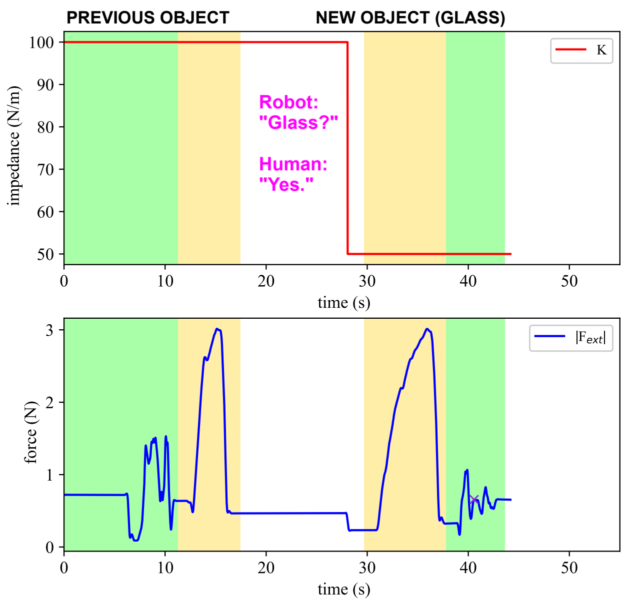
The human operator controlled the robot position in order to hold the desired reference position with the initial impedance $\boldsymbol{K}$ set to 100 N/m. The human then applied an external force mainly along the x-y plane to perturb the robot. When the perturbation was detected by the proposed vision-based method, the controller increased the impedance $\boldsymbol{K}$ from 100 N/m to 400 N/m. The results of the experiment are shown in Fig. 3. The robot was first perturbed without the perturbation rejection mode activated (blue area). Then the robot was perturbed again with approximately the same external force while the perturbation rejection mode was activated (blue area). The displacement difference under perturbations can be seen in the third graph. The displacement of the second perturbation was much smaller than the displacement of the first perturbation, because the vision-based impedance controller increased the robot impedance as result of detected perturbations.

B. *Contact Establishing Task*

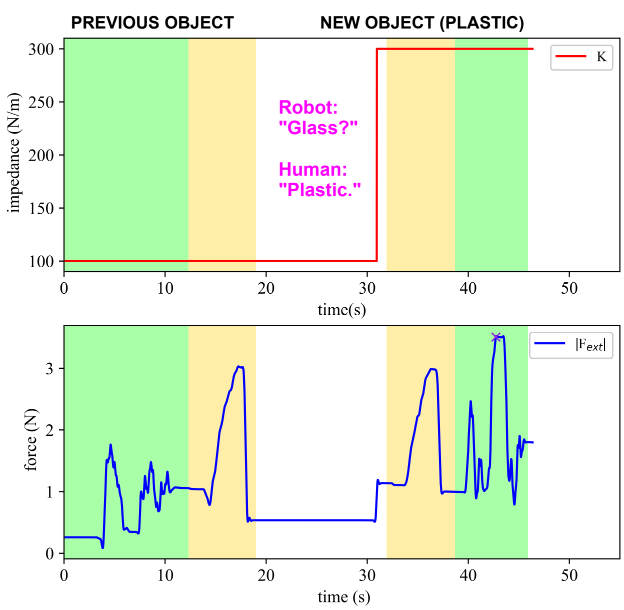
In the contact establishing task, the goal was to approach and establish contact with different objects. If the object property is unknown to the human operator due to lack of visual feedback, or the exact position of the object is unknown due to sensory uncertainty, the robot should approach the object slowly and compliantly. However, if the robot can obtain knowledge about the object property beforehand through our system, it can set the appropriate impedance and approach the object slightly faster and without a considerable risk of unsafe interaction. During this task, the *object property detection mode* and the *verbal confirmation mode* were used to approach different objects with the proper impedance. Additionally, the *voice control mode* was used by the human operator to command the impedance continuously while interacting with the objects.

Different objects were placed in front of the robot, with which it had to interact. The human operator controlled the motion of the remote robot and approached each object. Prior to contact, the proposed vision-based autonomous impedance control method changed the impedance of the robot according to the detected object through visual feedback. To visualise the commanded impedance for the results, the robot was perturbed by the human with approximately the same amount of force. The purpose of these experiments was to demonstrate different modes of the semi-autonomous impedance control method in three different scenarios, with different amounts of robot autonomy.

In the first scenario, the vision algorithm had a good accuracy (high confidence in detection) and therefore did not need human intervention. The object property detection mode was demonstrated by establishing contact with three different objects that represent metal, glass, and rubber. The results are shown in Fig. 4. The top left graph shows that the robot had an initial impedance $\boldsymbol{K} = 100$ N/m, which later changed to 300 N/m, 50 N/m, and 200 N/m based on the detected material (metal, glass, and rubber, respectively).



(a) Unreliable detection case



(b) False detection case

Fig. 5: Results of the second scenario voice confirmation mode (*mode iii*). The figure description is similar to that of Fig. 4.

The bottom left graph shows that approximately 3N of external forces were applied to the robot after the impedance value changed. The effect of the impedance change can be visually confirmed by observing the difference in position displacements under the same amount of force (the yellow shaded area in the top right graph).

In the second scenario, the vision algorithm had poor performance and required the human operator to confirm the detected material or command the correct material. The scenario included two cases: (a) the vision has low confidence in detection of the new object, (b) the new object

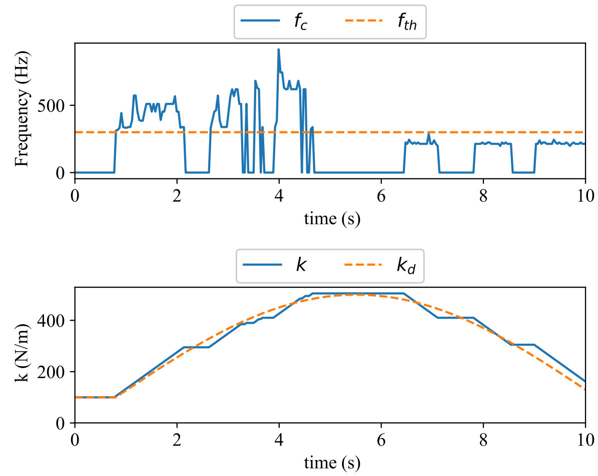


Fig. 6: Results of the third scenario that demonstrates the voice control mode (*mode iv*). The top graphs show the voice command frequency f_c and the threshold frequency f_{th}. The bottom graphs show the desired impedance profile k_d and the impedance commanded by the user k.

is made of plastic but the vision falsely identifies it as glass. The verbal confirmation mode was used to handle both cases of this scenario before the robot physically interacted with the new object. The results are shown in Fig. 5. The robot had an initial impedance $\boldsymbol{K} = 100$ N/m in both cases. In (a), the impedance changed to 50 N/m after confirming the detected glass object by saying ”yes”. In (b), the impedance increased to 300 N/m after overwriting the false detection by saying ”plastic”.

In the third scenario, the human operator had to take over the impedance control and change the impedance continuously. This scenario imitates the situation when the vision is unavailable (e.g., dark room) or when switching discretely between the predefined impedance values is no longer sufficient for the interaction task. The human operator was asked to command a reference impedance profile. The results in Fig. 6 show that the impedance increases when the extracted human voice frequency $f_c \geq f_{th}$, and decreases when $f_c < f_{th}$.

VI. Discussion

The main advantage of the vision-based autonomous impedance controller is that it can adjust the impedance of the robot before making contact with the environment. The object property detection mode can adjust the impedance according to the detected material using visual feedback. The perturbation rejection mode can detect the perturbation and increase the impedance of the robot prior to physical contact in order to guarantee a precise position tracking during the perturbation. If the environment is fragile or unstable, adjusting the impedance prior to contact can minimise chances of damage to the environment, and can prevent entering unstable conditions. On the other hand, the existing adaptive impedance control methods [10]–[13] adjust the impedance based on the measured physical interaction through force or proprioceptive sensors on the robot, which can be risky in fragile or unstable environments.

However, there are also disadvantages to the two vision-based modes. The disadvantage of the perturbation rejection mode is that the interaction forces cannot be measured, therefore force sensor-based methods are better suited for force tracking tasks. The disadvantages of the object property detection mode are that the detection results can sometimes have low accuracy, and that the impedance changes are discrete.

These disadvantages were for the most part addressed by developing the voice-based interface with two modes that allow the human operator to interact with the vision-based autonomous impedance controller. The human operator can correct the object detection results with the verbal confirmation mode when the vision algorithm is performing poorly. On the other hand, the voice control mode enables the human operator to take full control over the impedance when changing the impedance discretely is no longer sufficient.

Unlike the state-of-the-art interfaces based on EMG [1], grip force [2] and button [5], the voice-based impedance command interface does not require a limb to operate it and is essentially a hand-free approach. It was shown that the EMG-based interfaces have a coupling effect between between the force feedback (if implemented) and the commanded stiffness; i.e., physical interaction with the limb of the human operator can affect the commanded impedance [26]. Since the proposed method is based on vision and voice, there is no direct physical contact between the human limb and the impedance-command interface and such effect is not present.

In future, we will perform a human factors study that will go beyond this proof of concept. Furthermore, we will introduce several improvements to the proposed method. One such improvement can be in the form of a more complex object trajectory prediction system for the perturbation rejection mode. Additionally, the developed material property mapping can be expanded to include more properties (i.e., beyond elasticity and fragility).

References

[1] A. Ajoudani, N. G. Tsagarakis, and A. Bicchi, "Tele-impedance: Teleoperation with impedance regulation using a body-machine interface," *The International Journal of Robotics Research*, vol. 31, no. 13, pp. 1642–1656, 2012.

[2] D. Walker, R. Wilson, and G. Niemeyer, "User-controlled variable impedance teleoperation," in *2010 IEEE International Conference on Robotics and Automation (ICRA)*, May 2010, pp. 5352–5357.

[3] L. Peternel, T. Petrič, E. Oztop, and J. Babič, "Teaching robots to cooperate with humans in dynamic manipulation tasks based on multi-modal human-in-the-loop approach," *Autonomous robots*, vol. 36, no. 1-2, pp. 123–136, Jan 2014.

[4] C. Yang, C. Zeng, P. Liang, Z. Li, R. Li, and C. Su, "Interface design of a physical human-robot interaction system for human impedance adaptive skill transfer," *IEEE Transactions on Automation Science and Engineering*, vol. 15, no. 1, pp. 329–340, Jan 2018.

[5] L. Peternel, T. Petrič, and J. Babič, "Robotic assembly solution by human-in-the-loop teaching method based on real-time stiffness modulation," *Autonomous Robots*, vol. 42, no. 1, pp. 1–17, Jan 2018.

[6] J. Buchli, F. Stulp, E. Theodorou, and S. Schaal, "Learning variable impedance control," *The International Journal of Robotics Research*, vol. 30, no. 7, pp. 820–833, 2011.

[7] K. Kronander and A. Billard, "Online learning of varying stiffness through physical human-robot interaction," in *2012 IEEE International Conference on Robotics and Automation (ICRA)*, May 2012, pp. 1842–1849.

[8] F. J. Abu-Dakka, L. Rozo, and D. G. Caldwell, "Force-based variable impedance learning for robotic manipulation," *Robotics and Autonomous Systems*, vol. 109, pp. 156–167, 2018.

[9] S. Calinon, I. Sardellitti, and D. Caldwell, "Learning-based control strategy for safe human-robot interaction exploiting task and robot redundancies," in *2010 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Oct 2010, pp. 249–254.

[10] C. Yang, G. Ganesh, S. Haddadin, S. Parusel, A. Albu-Schäffer, and E. Burdet, "Human-like adaptation of force and impedance in stable and unstable interactions," *Robotics, IEEE Transactions on*, vol. 27, no. 5, pp. 918–930, Oct 2011.

[11] A. Brygo, I. Sarakoglou, N. Tsagarakis, and D. G. Caldwell, "Tele-manipulation with a humanoid robot under autonomous joint impedance regulation and vibrotactile balancing feedback," in *2014 IEEE-RAS International Conference on Humanoid Robots*, Nov 2014, pp. 862–867.

[12] L. Muratore, A. Laurenzi, E. M. Hoffman, L. Baccelliere, N. Kashiri, D. G. Caldwell, and N. G. Tsagarakis, "Enhanced tele-interaction in unknown environments using semi-autonomous motion and impedance regulation principles," in *2018 IEEE International Conference on Robotics and Automation (ICRA)*, May 2018, pp. 5813–5820.

[13] P. Balatti, D. Kanoulas, N. Tsagarakis, and A. Ajoudani, "A method for autonomous robotic manipulation through exploratory interactions with uncertain environments," *Autonomous Robots*, vol. 44, no. 8, pp. 1395–1410, 2020.

[14] K. Ramirez-Amaro, E. Dean-Leon, and G. Cheng, "Robust semantic representations for inferring human co-manipulation activities even with different demonstration styles," in *2015 IEEE-RAS 15th International Conference on Humanoid Robots (Humanoids)*. IEEE, 2015, pp. 1141–1146.

[15] L. Peternel, L. Rozo, D. Caldwell, and A. Ajoudani, "A method for derivation of robot task-frame control authority from repeated sensory observations," *IEEE Robotics and Automation Letters*, vol. 2, no. 2, pp. 719–726, Apr 2017.

[16] C. A. V. Perico, J. De Schutter, and E. Aertbeliën, "Combining imitation learning with constraint-based task specification and control," *IEEE Robotics and Automation Letters*, vol. 4, no. 2, pp. 1892–1899, 2019.

[17] L. Peternel and J. Babič, "Humanoid robot posture-control learning in real-time based on human sensorimotor learning ability," in *Robotics and Automation (ICRA), 2015 IEEE International Conference on*, 2013, pp. 5309–5314.

[18] M. A. Zamani and E. Oztop, "Simultaneous human-robot adaptation for effective skill transfer," in *2015 International Conference on Advanced Robotics (ICAR)*. IEEE, 2015, pp. 78–84.

[19] L. Peternel, E. Oztop, and J. Babič, "A shared control method for online human-in-the-loop robot learning based on locally weighted regression," in *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Oct 2016, pp. 3900–3906.

[20] J. Kofman, Xianghai Wu, T. J. Luu, and S. Verma, "Teleoperation of a robot manipulator using a vision-based human-robot interface," *IEEE Transactions on Industrial Electronics*, vol. 52, no. 5, pp. 1206–1219, Oct 2005.

[21] A. D. Dragan and S. S. Srinivasa, "A policy-blending formalism for shared control," *International Journal of Robotics Research*, vol. 32, no. 7, pp. 790–805, Jun. 2013.

[22] E. You and K. Hauser, "Assisted teleoperation strategies for aggressively controlling a robot arm with 2d input," in *Robotics: science and systems*, vol. 7, 2012, p. 354.

[23] N. Amirshirzad, A. Kumru, and E. Oztop, "Human adaptation to humanrobot shared control," *IEEE Transactions on Human-Machine Systems*, vol. 49, no. 2, pp. 126–136, April 2019.

[24] L. Sharan, R. Rosenholtz, and E. Adelson, "Material perception: What can you see in a brief glance?" *Journal of Vision*, vol. 9, pp. 784–784, 08 2010.

[25] S. Bell, P. Upchurch, N. Snavely, and K. Bala, "Material recognition in the wild with the materials in context database," in *IEEE conference on computer vision and pattern recognition*, 2015, pp. 3479–3487.

[26] L. M. Doornebosch, D. A. Abbink, and L. Peternel, "Analysis of coupling effect in human-commanded stiffness during bilateral tele-impedance," *IEEE Transactions on Robotics*, vol. 37, no. 4, pp. 1282–1297, 2021.