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Human-Robot Ergonomic Handover via Deep Neural Network based Adaptive Integral Sliding Mode control

Nikolas Sacchi, Edoardo Vacchini and Antonella Ferrara

Abstract— **In this paper, we propose a strategy for performing human-robot ergonomic handover in the case of partial knowledge of the robot dynamics and in absence of assumptions about the shape or mass of the object passed. In particular, we propose a strategy for generating the reference for the manipulator and a Deep Neural Network based Integral Sliding Mode control with Adaptive discontinuous gain, in the paper referred to as DNN-AISM. The DNN weights are adapted on-line according to update laws derived directly from the theoretical analysis, without relying on previously collected data. The proposal is experimentally assessed relying on a Franka Emika Panda robot and on an Xsens MTw IMU sensor, producing highly satisfactory results.**

Index Terms— **human-robot interaction, integral sliding mode, uncertain systems**

I. Introduction

In the most recent years, the number of scenarios in which humans and robots share their workspace has been increased. In such scenarios, especially in the ones involving physical Human Robot Interaction (pHRI) [1], it is important to ensure safety for the human operators [2]. This means that not only collisions must be avoided, implementing collision avoidance strategies, e.g., the ones presented in [3]–[5], but also that the interaction must cause the minimum psychophysical stress to the human operator. Indeed, physical stress caused by repetitive work and poor posture is the main cause of muscoloskeletal disorders (MSDs), which constitutes more or less the third of all registered occupational diseases in the United States, the Nordic countries, and Japan, as studied in works like [6] and [7].

For this reason, particular attention should be put into ergonomics [8], designing comfortable and productive workspaces. In the context of pHRI, this can be translated into controlling the robotic counterpart so that it adapts to the human operator movements, while performing the task in a proficient way. One of the most common tasks which involves collaboration of humans and machines is the so-called handover, during which the human operator passes an object to the robot or vice versa. In many contexts, such an operation is performed in a fixed position and with a fixed orientation. However, such a combination may not be the most comfortable for the human operator, possibly causing bad posture and causing greater psychophysical stress if the operation is performed for long periods of time. In the last few years, several works in the literature addressed such a problem with the objective of developing strategies which ensured ergonomic handover. For example, in [9] the authors developed a methodology that learns the most ergonomic way of passing objects of a person relying on data retrieved during the interaction, while in [10] a whole-body dynamic model of the human operator is used to optimize for the position of the co-manipulation task inside the workspace.

When a robotic manipulator grasps an object, this last one exerts a generalized force on the robot joints. This can be seen as disturbance that, if not compensated, could interfere with the completion of the task. When dealing with dynamical systems affected by disturbances, Sliding Mode Control (SMC) has been proved to be an effective technique, ensuring robustness against perturbations thanks to the discontinuous control law [11].

However, classical SMC suffers from two main drawbacks, which are the presence of chattering, whose amplitude is associated to the gain of the discontinuous control, and that the robustness is ensured only when the system states are on the so-called sliding manifold, thus making the system sensible to disturbances during a first transient. To cope with this second problem, Integral Sliding Mode (ISM) control has been proposed in [12], and its validity in the robot control domain has been assessed [13].

To design an ISM controller, the knowledge of the plant is required. However, in robotic applications such a condition may not be always fulfilled, due to the difficulties in modelling terms like the Coriolis matrix and the vector of frictions. A first solution would be to treat the unknown part of the model as a disturbance and compensate it increasing the discontinuous control gain. However, this could lead to severe chattering which could damage the robot motors. Another solution is the one presented in our previous work [14], in which we proposed a Deep Neural Network based ISM (DNN-ISM) control strategy that exploits two DNNs to estimate the unknown drift term and the control effectiveness matrix of the system. The weights of the DNNs are adjusted on-line according to weight adaptation laws directly derived from Lyapunov analysis. The main drawback of the work in [14] is that it requires the knowledge of the bounds of the DNNs approximation errors residuals and the worst possible realization of the disturbance term.

This paper proposes a strategy for performing the human-robot handover operation in an ergonomic way, relying on readings of an Inertial Measurement Unit (IMU) placed on the back of the human operator's hand. Since the robot is

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considered as a dynamical system with partially unknown dynamics perturbed by the object grasped during the handover operation, it is controlled with a novel version of DNN-ISM controller. In particular, in this paper we introduce a DNN-ISM controller with an adaptive discontinuous gain (DNN-AISM), in order to relax the original assumption about the knowledge of the bounds of the approximation error residuals and disturbance term. The proposal is theoretical analysed and experimentally assessed relying on a Franka Emika Panda robot and an Xsens MTw IMU sensor.

Notation: Given a matrix $M \in \mathbb{R}^{n\times m}$, then $\mathrm{vec}(M) \in \mathbb{R}^{nm}$ denotes the vectorization operation. Two real matrices $A \in \mathbb{R}^{n\times m}$ and $B \in \mathbb{R}^{p\times q}$, then $A \otimes B \in \mathbb{R}^{np\times mq}$ is their Kronecker product. Given $k \in \mathbb{N}_{>0}$ matrices M_l, with $l = 1, 2, \dots, k$ with compatible dimensions, then $\prod_{l=1}^{\overleftarrow{k}} M_l = M_k M_{k-1} \dots M_1 M_0$. Given a square matrix $A \in \mathbb{R}^{n\times n}$, then $\lambda_{\min}(A)$ and $\lambda_{\max}(A)$ denote its smallest and largest singular value, respectively.

II. Preliminaries on Robot Modelling and Integral Sliding Mode Control

The aim of this section is to introduce the dynamical model of the considered robotic manipulator, along with the preliminary concepts on ISM control.

Consider an open-chain robotic manipulator characterized by $n \in \mathbb{N}_{>0}$ joints. As detailed in [15], the dynamics of the robotic arm is described by

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + F(q,\dot{q}) + G(q) = \tau + \tau_h, \quad (1)$$

where q, $\dot{q}$, $\ddot{q} \in \mathbb{R}^n$ are the vectors of the joint positions, velocities, and accelerations, respectively, $M : \mathbb{R}^n \to \mathbb{R}^{n\times n}$ is the inertia matrix, which is symmetric and positive definite, $C : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}^{n\times n}$ is the matrix of the Coriolis and centripetal effects, $F : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}^n$ is the vector collecting the friction terms, $G : \mathbb{R}^n \to \mathbb{R}^n$ represents the gravity components, $\tau \in \mathbb{R}^n$ denotes the input torques, while $\tau_h \in \mathbb{R}^n$ is the vector of the torques induced by external forces acting on the robot. In the case of the handover operation, the last term is strictly related to the object grasped by the robot during the interaction.

The model of the manipulator in (1) can be conveniently expressed in the state space formulation. In particular, defining $x = \begin{bmatrix} q^\top & \dot{q}^\top \end{bmatrix}^\top \in \Omega$, with q and $\dot{q}$ measurable through joint sensors and $\Omega \subset \mathbb{R}^{2n}$ being a compact set, and solving (1) for $\ddot{q}$, one has that

$$\dot{x} = \begin{bmatrix} \dot{q} \\ -M(q)^{-1}\left(\eta(q,\dot{q}) - \tau_h\right) + M(q)^{-1}\tau \end{bmatrix}, \quad (2)$$

where $\eta(q,\dot{q}) = C(q,\dot{q})\dot{q} + F(q,\dot{q}) + G(q)$.

When the robot manipulates objects whose dynamical parameters are not available, as it happens in the case of handover operation, the vector τ_h is unknown. Hence, the term $M(q)^{-1}\tau_h$ act as a disturbance on the dynamical system. The following assumption, common in the domain of the sliding mode control, and reasonable due to the nature of the problem, holds.

Assumption 1: There exists a constant $\bar{\delta} \in \mathbb{R}_{>0}$ such that $\sup_{x\in\Omega} \|M(q)^{-1}\tau_h\| \le \bar{\delta}$.

In order to deal with systems subject to uncertainties, it is possible to design an ISM controller

$$\tau = \tau_0 + \tau_r \in \mathbb{R}^n, \quad (3)$$

where $\tau_0 \in \mathbb{R}^n$ is a control law which stabilizes the system in the case of $\tau_h = 0_n$, while $\tau_r \in \mathbb{R}^n$ is the discontinuous robustifying term defined as

$$\tau_r = -\rho \frac{\sigma(x)}{\|\sigma(x)\|}, \quad (4)$$

with $\rho \in \mathbb{R}_{>0}$ being the discontinuous control gain, and $\sigma : \Omega \to \mathbb{R}^n$ being the so-called integral sliding variable. This last one is defined as

$$\sigma(x) = \sigma_0(x) + z(x), \quad \sigma(x(t_0)) = 0, \quad (5)$$

where $t_0 \in \mathbb{R}_{\ge 0}$ is the initial time instant, $\sigma_0 : \Omega \to \mathbb{R}^n$ is the conventional sliding variable, and $z : \Omega \to \mathbb{R}^n$ is the so-called transient variable. In particular, in the domain of SMC theory, it is common to define the former term as the linear combination of the system states, i.e.,

$$\sigma_0 = C\left(x - x^\star\right), \quad C = \begin{bmatrix} C_1 & C_2 \end{bmatrix}, \quad (6)$$

with C_1, $C_2 \in \mathbb{R}^{n\times n}$ being symmetric and positive-definite matrices selected by the controller designer and $x^\star = \begin{bmatrix} (q^\star)\top & (\dot{q}^\star)^\top \end{bmatrix}^\top \in \Omega$ being a desired state for the robot. As for the transient variable z, it is defined so that $z(x(t_0)) = -\sigma_0(x(t_0))$ and with dynamics

$$\dot{z} = -C \begin{bmatrix} \dot{q} - \dot{q}^\star \\ -M(q)^{-1}\eta(q,\dot{q}) + M(q)^{-1}\tau_0 - \ddot{q}^\star \end{bmatrix}. \quad (7)$$

As detailed in [12], if the discontinuous control gain ρ is designed so that it dominates the worst realization of the external disturbances, then a sliding mode $\sigma = 0$ is established for each $t \ge t_0$.

Despite the effectiveness of the ISM methodology, it presents two main drawbacks. The former is that it requires the complete knowledge of the manipulator dynamics, which is not always possible, mostly due to the difficulties in modelling $\eta(q,\dot{q})$. The latter is that, considering the worst realization of the disturbance $\bar{\delta}$, there is the risk of applying a discontinuous control law with unnecessary high gain on the system, which, in the case of the robot, could cause damage to the motors. In the next sections, modifications to the classical ISM which address such problems are presented.

III. Preliminaries on Deep Neural Networks for Dynamics Approximation

The aim of this section is to introduce the use of DNNs as approximators for the unknown dynamics and the related notation. In this paper, it is considered the case of a robotic manipulator with partially unknown dynamics, performing handover of object with unknown dynamic properties. In other words, the terms $\eta(q,\dot{q})$ and τ_h are not available to the controller designer.

According to the universal approximation property [16] and taking into account the considerations in [17], it exists an ideal DNN $\Phi : \Omega \rightarrow \mathbb{R}^n$, with $k \in \mathbb{N}_{\geq 2}$ hidden layers, such that

$$\eta(q, \dot{q}) - \tau_h = \Phi(x) + \varepsilon_\Phi(x), \tag{8}$$

where $\varepsilon_\Phi : \Omega \rightarrow \mathbb{R}^n$ is the function approximation error. Each layer of the DNN is characterized by $L_j \in \mathbb{N}_{>1}$ neurons, with $L_0 = 2n$, and $L_{k+1} = n$. The DNN can be expressed in a more detailed manner as

$$\Phi(x) = V_k^\top \phi_k \circ \cdots \circ V_1^\top \phi_1 \circ V_0^\top x, \tag{9}$$

where $V_j \in \mathbb{R}^{L_j \times L_{j+1}}$, with $j = 0, 1, \ldots, k$, are the ideal weights of the network, while $\phi_j(\cdot)$, with $j = 1, 2, \ldots, k$ are the activation functions, chosen so that they are Lipschitz continuous. Due to the bounded nature of the term estimated by the network (9), the following assumption can be introduced.

Assumption 2: There exist unknown constants $\bar{v}, \bar{\varepsilon} \in \mathbb{R}_{>0}$ such that $\|V_j\| \leq \bar{v}$ and $\sup_{x \in \Omega} \|\varepsilon_\Phi(x)\| \leq \bar{\varepsilon}_\Phi$, for $j = 0, 1, \ldots k$.

The ideal network is unknown, hence the estimate of the unknown drift dynamics is provided by an approximation of the ideal DNN, i.e.,

$$\widehat{\Phi}(x) = \widehat{V}_k^\top \phi_k \circ \cdots \circ \widehat{V}_1^\top \phi_1 \circ \widehat{V}_0^\top x, \tag{10}$$

with $\widehat{V}_j \in \mathbb{R}^{L_j \times L_{j+1}}$ being the estimate of the ideal weights. In order to simplify the subsequent analysis, it is possible to express the output of each layer of $\Phi(x)$ and $\widehat{\Phi}(x)$ in a recursive fashion as

$$\Phi_j = V_j^\top \phi_j(\Phi_{j-1}), \qquad \widehat{\Phi}_j = \widehat{V}_j^\top \phi_j(\widehat{\Phi}_{j-1}), \tag{11}$$

for $j = 1, 2, \ldots, k$, while $\Phi_0 = V_0^\top x$ and $\widehat{\Phi}_0 = \widehat{V}_0^\top x$.

In order to develop the adaptation laws for the estimated weights in (10), the approximation error associated to each layer $j = 0, 1, \ldots k$ is defined as $\widetilde{\Phi}_j = \Phi_j - \widehat{\Phi}_j$. Relying on (11), adding and subtracting $V^\top \widehat{\phi}_j$, and defining $\widetilde{V}_j = V_j - \widehat{V}_j$, such an error can be expressed as

$$\widetilde{\Phi}_j = \widetilde{V}_j^\top \phi_j(\widehat{\Phi}_{j-1}) + V_j^\top(\phi_j(\Phi_{j-1}) - \phi_j(\widehat{\Phi}_{j-1})), \tag{12}$$

with $\widetilde{\Phi}_0 = \widetilde{V}_0^\top x$. The term $\phi_j(\Phi_{j-1})$ is unknown. However, it can be approximated using Taylor approximation around $\widehat{\Phi}_{j-1}$. In particular, it holds that

$$\phi_j(\Phi_{j-1}) = \phi_j(\widehat{\Phi}_{j-1}) + \phi_j'(\widehat{\Phi}_{j-1})\widetilde{\Phi}_{j-1} + \mathcal{O}^2(\widetilde{\Phi}_{j-1}), \tag{13}$$

where $\phi_j'(\widehat{\Phi}_{j-1}) \in \mathbb{R}^{L_j \times L_j}$ is the Jacobian of $\phi_j(\cdot)$ computed in $\widehat{\Phi}_{j-1}$, while $\mathcal{O}^2(\widetilde{\Phi}_{j-1})$ denotes the terms of order two [18]. For sake of readability, it is possible to define $\phi_j := \phi_j(\Phi_{j-1})$, $\widehat{\phi}_j := \phi_j(\widehat{\Phi}_{j-1})$, and $\widehat{\phi}_j' := \phi_j'(\widehat{\Phi}_{j-1})$. Exploiting $V_j = \widehat{V}_j + \widetilde{V}_j$ and substituting (13) into (12), one obtains

$$\widetilde{\Phi}_j = \widetilde{V}_j^\top \widehat{\phi}_j + \widehat{V}_j^\top \widehat{\phi}_j' \widetilde{\Phi}_{j-1} + \Delta_j, \tag{14}$$

where $\Delta_j := \widetilde{V}_j^\top \widehat{\phi}_j' \widetilde{\Phi}_{j-1} + V_j^\top \mathcal{O}^2(\widetilde{\Phi}_{j-1})$. Then, since $\widetilde{V}_j^\top \widehat{\phi}_j \in \mathbb{R}^{L_{j+1}}$, it holds that $\widetilde{V}_j^\top \widehat{\phi}_j = \mathrm{vec}(\widetilde{V}_j^\top \widehat{\phi}_j) = \mathrm{vec}(\widehat{\phi}_j^\top \widetilde{V}_j I_{j+1})$, thus, the identity $\widetilde{V}_j^\top \widehat{\phi}_j = (I_{L_{j+1}} \otimes \widehat{\phi}_j^\top)\mathrm{vec}(\widetilde{V}_j)$ is valid [19]. Substituting this last one in (14), the approximation error can be written as

$$\widetilde{\Phi}_j = (I_{L_{j+1}} \otimes \widehat{\phi}_j^\top)\mathrm{vec}(\widetilde{V}_j) + \widehat{V}_j^\top \widehat{\phi}_j' \widetilde{\Phi}_{j-1} + \Delta_j, \tag{15}$$

with $\widetilde{\Phi}_0 = (I_{L_1} \otimes x^\top)\mathrm{vec}(\widetilde{V}_0)$. Finally, relying on [20, Lemma 1], it is possible to iterate and obtain the expression of the approximation error for the last layer of the DNN, i.e.,

$$\widetilde{\Phi}_k = \sum_{j=0}^{k} \Lambda_j \mathrm{vec}(\widetilde{V}_j) + \sum_{j=1}^{k} \Xi_j \Delta_j, \tag{16}$$

where the terms $\Xi_j \in \mathbb{R}^{n \times L_{j+1}}$ and $\Lambda_j \in \mathbb{R}^{n \times (L_j L_{j+1})}$ are defined as

$$\Xi_j = \prod_{l=j+1}^{\overleftarrow{k}} \widehat{V}_l^\top \widehat{\phi}_l', \quad \Lambda_j = \Xi_j (I_{L_{j+1}} \otimes \widehat{\phi}_j^\top), \tag{17}$$

with $\Lambda_0 = \Xi_0 (I_{L_1} \otimes x^\top)$.

IV. The Proposed Ergonomic Handover Strategy

The main objective of the proposed strategy is to control the robot so that it reaches the most comfortable pose for the human operator, grasps an object with unknown shape and mass, and places it into a predefined location. The aim of this section is to describe how such task is performed.

As the above description suggests, it is possible to divide the task into two phases: the *hand reaching* phase and the *object placement* phase. The hand reaching strategy, summarized in the block scheme depicted in Fig. 1, is now described.

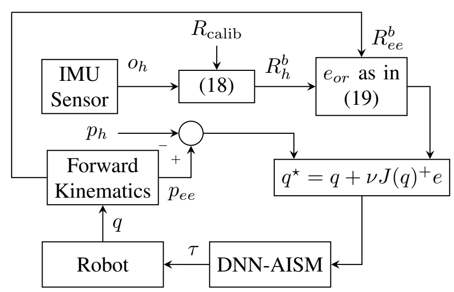

Fig. 1: The block diagram of the hand reaching strategy.

In this paper, we assume that the position $p_h \in \mathbb{R}^3$ in which the human operator places the hand for performing the handover operation is known a priori. For example, it could be defined before the start of the task by hand guiding the robot end-effector into a position which is considered comfortable for the operator. On the other hand, the comfortable orientation for the hand cannot be assumed a priori, since it could depend on different aspects, such as the shape of the object passed during the interaction. In this work, such an orientation is determined relying on readings of an IMU sensor placed on the back of the operator's hand. In particular, such a sensor provides a set of orientation angles $o_h = \begin{bmatrix} \alpha & \beta & \gamma \end{bmatrix}^\top$ with respect to its own frame at the moment of the calibration. As suggested from Fig. 1, the values of p_h and o_h are used as starting point in the calculation of a reference $q^\star \in \mathbb{R}^n$ for the manipulator joint positions, following the procedure which described hereafter.

At first, the rotation matrix $R_h^b \in SO(3)$, which expresses the orientation of the operator's hand with respect to the fixed base frame is calculated as

$$R_h^b = R_{\text{calib}} R_z(\gamma) R_y(\beta) R_x(\alpha), \quad (18)$$

where R_x, R_y, $R_z \in SO(3)$ represent the basic rotations around the sensor axes, while $R_{\text{calib}} \in SO(3)$ is the matrix which express the orientation of the hand frame with respect to the base frame at the moment of the calibration.

Then, the orientation error between the the operator's hand and the actual orientation of the end-effector, is denoted as $e_{\text{or}} \in \mathbb{R}^3$ and computed as in [21, Chapter 3]. In particular, define $R = (R_{ee}^b)^\top R_h^b \in SO(3)$, with $R_{ee}^b \in SO(3)$ being the rotation matrix which describes the end-effector orientation with respect to the base frame, then

$$e_{\text{or}} = -\theta R_{ee}^b \begin{bmatrix} W_{32} & W_{13} & W_{21} \end{bmatrix}^\top, \quad (19)$$

where $\theta = \cos^{-1}\left(\frac{1}{2}(\text{tr}(R) - 1)\right) \in \mathbb{R}$, while $W \in \mathbb{R}^{3\times 3}$ a skew-symmetric matrix defined as $W = \frac{1}{2\sin(\theta)}\left(R - R^\top\right)$.

The vector of the pose error $e \in \mathbb{R}^6$ can be then defined as $e = \begin{bmatrix}(p_{ee} - p_h)\top & e_{or}^\top\end{bmatrix}^\top$, where $p_{ee} \in \mathbb{R}^3$ denotes the position of the end-effector with respect to the base frame.

At this point, the reference for the joint positions $q^\star \in \mathbb{R}^n$ is computed according to

$$q^\star = q + \nu J(q)^+ e, \quad (20)$$

where $q \in \mathbb{R}^n$ is the vector of the actual joint positions, $\nu \in R_{>0}$ is a design parameter, while $J(q)^+ \in \mathbb{R}^{n\times 6}$ is the Moore-Penrose pseudo-inverse of the geometric Jacobian matrix of the manipulator and it is computed as $J(q)^+ = J(q)^\top \left(J(q)J(q)^\top\right)^{-1}$. The joint reference is then passed to the DNN-AISM controller, described in detail in the next section. As soon the $\|e\|$ is sufficiently small, the end-effector is controlled so that it grasps the object. If the grasping procedure is carried out successfully, the robot is controlled to fulfill the second phase of the task, i.e., the object placement phase.

In such a phase, the robot is controlled to reach a predefined location configuration $q_{\text{place}} \in \mathbb{R}^n$, hence a reference $q^\star = q_{\text{place}}$ is provided to the DNN-AISM controller. As soon as $\|q - q^\star\|$, the end-effector is controlled so that it releases the object. As soon the object is released, the robot is controlled again as in the first phase.

V. The DNN-AISM Control Scheme

The objective of this section is to present the DNN-AISM control scheme depicted in Fig. 2, used to drive the robot toward the reference configuration.

The use of the DNN in (10) allows to estimate the dynamics of the transient variable in (7) as

$$\dot{\hat{z}} = -C \begin{bmatrix} \dot{q} - \dot{q}^\star \\ -M(q)^{-1}\widehat{\Phi}(x) + M(q)^{-1}\tau_0 - \ddot{q}^\star \end{bmatrix}, \quad (21)$$

and hence define the sliding variable as $\sigma = \sigma_0 + \widehat{z}$. The nominal part of the control law $\tau_0 \in \mathbb{R}^n$, appearing in (21) and (3), is chosen so that it stabilizes the robot around the reference configuration $q^\star \in \mathbb{R}^n$, whose definition is detailed in Section IV. In particular, τ_0 is designed as

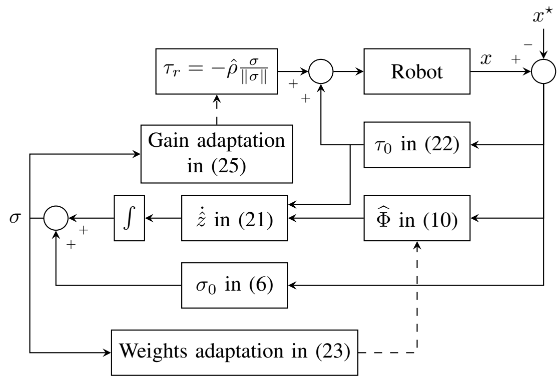

Fig. 2: The block diagram of the proposed DNN-AISM control.

$$\tau_0 = -M(q)\left(\widehat{\Phi}(x) + K_p(q - q^\star) + K_d\dot{q}\right), \quad (22)$$

with K_p, $K_d \in \mathbb{R}^{n\times n}$ being diagonal matrices with positive entries. The weights of the DNN $\widehat{\Phi}$ are characterized by dynamics given by

$$\text{vec}(\dot{\hat{V}}_j) = \text{proj}\left(\Gamma_j \Lambda_j^\top M(q)^{-\top} C_2^\top \sigma\right), \quad (23)$$

where $\Gamma_j \in \mathbb{R}^{L_j L_{j+1} \times L_j L_{j+1}}$ is the diagonal matrix with positive entries and it represent the learning rate, while proj denotes the projection operator defined as in [22, Appendix E] and it ensures that that $\text{vec}(V_j) \in \mathcal{B}_j$, with $\mathcal{B}_j$ being $\mathcal{B}_j = \left\{\theta_j \in \mathbb{R}^{L_j L_{j+1}} : \|\theta_j\| \leq \bar{v}\right\}$.

The presence of Assumption 2, the use of proj operator in (23), and the fact that the activation functions $\phi_j(\cdot)$ are chosen with bounded gradients, imply the validity of the following fact

Fact 1: There exist an unknown constant $\bar{c} \in \mathbb{R}_{>0}$ such that $\|\sum_{j=1}^k \Xi_j \Delta_j\| \leq \bar{c}$.

Since from Assumption 2 and Fact 1 it is only possible to conclude that the approximation error ε and the residual term $\sum_{j=1}^k \Xi_j \Delta_j$ are bounded, it is possible to say that there exist a ISM controller gain $\rho^\star \in \mathbb{R}_{>0}$ that is able to dominate such terms.

Since $\rho^\star$ is unknown, an estimate of it can be used, having

$$\tau_r = -\hat{\rho}\frac{\sigma}{\|\sigma\|}, \quad (24)$$

where $\hat{\rho}$ is characterized by the dynamics

$$\dot{\hat{\rho}} = \mu\|\sigma\|\lambda_{\max}\{C_2 M(q)^{-1}\}\,\text{sign}(\|\sigma\| - \varepsilon_\sigma), \quad (25)$$

with $\hat{\rho}(t_0) = 0$, $\mu \in \mathbb{R}_{>0}$ being the adaptation rate, $\varepsilon_\sigma \in \mathbb{R}_{>0}$ being a leaking factor which allows $\hat{\rho}$ to decrease when $\|\sigma\| < \varepsilon_\sigma$. Then, it is convenient to define the error between the optimal and the estimated gain, i.e., $\tilde{\rho} = \rho^\star - \hat{\rho}$.

To facilitate the subsequent analysis, it is possible to provide a formulation for $\dot{\sigma} = \dot{\sigma}_0 + \dot{\hat{z}}$. In particular, considering

$\dot{q}^\star = \ddot{q}^\star = 0_n$, substituting (21), (3), (9), (10), and then (16), it holds that

$$\dot{\sigma} = -C_2 M^{-1}\left[\sum_{j=0}^{k}\Lambda_j \mathrm{vec}(\widetilde{V}_j)+\sum_{j=1}^{k}\Xi_j\Delta_j+\varepsilon-\tau_r\right], \quad (26)$$

with the dependence on q and x being omitted for sake of readability. The main theoretical result about the DNN-AISM controller is now introduced.

Theorem 1: Consider the robotic manipulator described by the dynamics in (2), the control law $\tau = \tau_0 + \tau_r$, with τ_0 and τ_r defined respectively as in (22) and (24), the sliding variable $\sigma = \sigma_0 + \hat{z}$, with $\hat{z}$ as in (21), the weight adaptation law (23) and the discontinuous gain dynamics (25). Then, a practical sliding mode on $\Omega_\sigma \coloneqq \{\sigma \in \mathbb{R}^n : \|\sigma\| \le \varepsilon_\sigma\}$ is enforced.

Proof: The above theorem can be proven by performing Lyapunov analysis on the candidate function

$$\mathcal{L}(x) = \frac{1}{2}\sigma^\top\sigma + \frac{1}{2}\sum_{j=0}^{k}\mathrm{vec}(\widetilde{V}_j)^\top\Gamma_j^{-1}\mathrm{vec}(\widetilde{V}_j) + \frac{\tilde{\rho}^2}{2\mu}, \quad (27)$$

inspired by the adaptive control theory [23], and whose time derivative is given by

$$\dot{\mathcal{L}}(x) = \sigma^\top\dot{\sigma} - \sum_{j=0}^{k}\mathrm{vec}(\widetilde{V}_j)^\top\Gamma_j^{-1}\mathrm{vec}(\dot{\hat{V}}_j) - \frac{\tilde{\rho}\dot{\hat{\rho}}}{\mu}. \quad (28)$$

Substituting (26) and then (24), the above equation can be written

$$\dot{\mathcal{L}} = -\sigma^\top C_2 M^{-1}\Big\{\sum_{j=0}^{k}\Lambda_j\mathrm{vec}(\widetilde{V}_j) + \sum_{j=1}^{k}\Xi_j\Delta_j + \varepsilon_\Phi\Big\} + \\ -\hat{\rho}\sigma^\top C_2 M^{-1}\frac{\sigma}{\|\sigma\|} - \sum_{j=0}^{k}\mathrm{vec}(\widetilde{V}_j)^\top\Gamma_j^{-1}\mathrm{vec}(\dot{\hat{V}}_j) - \frac{\tilde{\rho}\dot{\hat{\rho}}}{\mu}.$$

Since from [22, Appendix E] it holds that, given a generic vector $\psi \in \mathbb{R}^{L_j L_{j+1}}$, it holds that $-\mathrm{vec}(\widetilde{V}_j)\Gamma^{-1}\mathrm{proj}(\psi) \le -\mathrm{vec}(\widetilde{V}_j)\Gamma^{-1}\psi$. Then, if the adaptation law (23) is substituted in the above equation, the term $\sum_{j=0}^{k}\Lambda_j\mathrm{vec}(\widetilde{V}_j)$ is canceled and it holds that

$$\dot{\mathcal{L}} \le -\sigma^\top C_2 M^{-1}\Big\{\sum_{j=1}^{k}\Xi_j\Delta_j + \varepsilon_\Phi\Big\} - \frac{\tilde{\rho}\dot{\hat{\rho}}}{\mu} + \\ -\hat{\rho}\sigma^\top C_2 M^{-1}\frac{\sigma}{\|\sigma\|}. \quad (29)$$

Then, substituting $\hat{\rho} = \rho^\star - \tilde{\rho}$ and bounding the first term of the above inequality with its worst realization, i.e., the one which makes $\dot{\mathcal{L}}$ positive, (29) can be written as

$$\dot{\mathcal{L}} \le \|\sigma\|\lambda_{\max}\{C_2M^{-1}\}(\bar{c}+\bar{\varepsilon}_\Phi) - \rho^\star\lambda_{\min}\{C_2M^{-1}\}\|\sigma\| + \\ +\tilde{\rho}\sigma^\top C_2 M^{-1}\frac{\sigma}{\|\sigma\|} - \frac{\tilde{\rho}\dot{\hat{\rho}}}{\mu}. \quad (30)$$

By virtue of the adaptation law and initial condition for the gain reported in (25) it is possible to state that $\tilde{\rho} > 0$ for all $t \ge t_0$.

Define now the ideal discontinuous controller gain $\rho^\star \in \mathbb{R}_{>0}$ as one which dominates the residual approximation terms as

$$\rho^\star > \frac{\lambda_{\max}\{C_2M^{-1}\}(\bar{c}+\bar{\varepsilon}_\Phi)}{\lambda_{\min}\{C_2M^{-1}\}} + \varrho,$$

with $\varrho \in \mathbb{R}_{>0}$ being an arbitrary constant. This allows us to rewrite the above inequality as

$$\dot{\mathcal{L}} \le -\varrho\|\sigma\| - \tilde{\rho}\|\sigma\|\lambda_{\max}\{C_2M^{-1}\}\,\mathrm{sign}\,(\|\sigma\|-\varepsilon_\sigma) + \\ +\tilde{\rho}\lambda_{\max}\{C_2M^{-1}\}\|\sigma\|.$$

It is now essential to distinguish among two cases.

First, if $\|\sigma\| > \varepsilon_\sigma$, one has that $\mathrm{sign}\,(\|\sigma\|-\varepsilon_\sigma) = 1$, and thus $\dot{\mathcal{L}}$ can be rewritten as

$$\dot{\mathcal{L}} \le -\varrho\|\sigma\| - \tilde{\rho}\|\sigma\|\lambda_{\max}\{C_2M^{-1}\} + \tilde{\rho}\lambda_{\max}\{C_2M^{-1}\}\|\sigma\| \\ \le -\varrho\|\sigma\|.$$

While if $\|\sigma\| < \varepsilon_\sigma$, $\mathrm{sign}\,(\|\sigma\|-\varepsilon_\sigma) = -1$, and thus one has

$$\dot{\mathcal{L}} \le -\varrho\|\sigma\| + 2\tilde{\rho}\|\sigma\|\lambda_{\max}\{C_2M^{-1}\},$$

meaning that nothing can be said about the behaviour of σ when $\|\sigma\| < \varepsilon_\sigma$. The two conditions imply that σ is ultimately bounded in the set $\Omega_\sigma \coloneqq \{\sigma \in \mathbb{R}^n : \|\sigma\| \le \varepsilon_\sigma\}$, thus implying the enforcement of a practical sliding mode. ■

VI. Experiments and Results

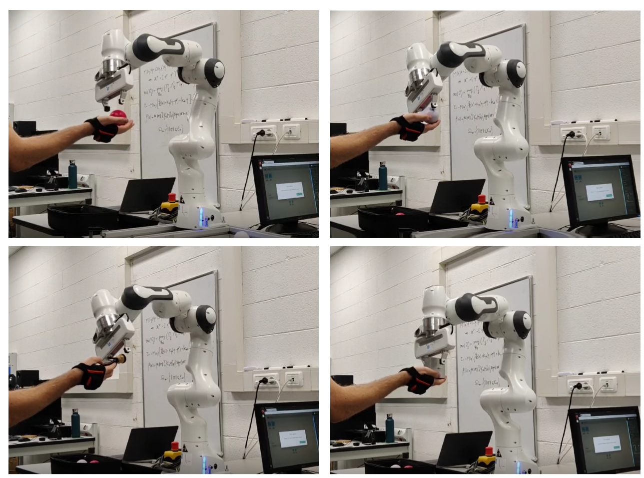

Fig. 3: The instants in which the handover operation is performed. The robot adapts the pose of its end-effector so that it follows the orientation of the IMU sensor.

The proposed ergonomic handover approach has been validated experimentally[1] relying on the Franka Emika Panda, a collaborative robot with $n = 7$ degrees of freedom, along with a MTw Awinda IMU, both visible in Fig. 3. In the experiment, the human operator is required to perform the handover of four different object with different shape and mass, unknown to the controller. In particular, the objects have been chosen so that the mass varies between few grams up to 1.5 kilograms.

[1]Video available at https://youtu.be/dF2I-OOw1DY

The DNN employed to compensate the partially unknown dynamics is structured so that $L_0 = 14$, $L_1 = L_2 = 16$, $L_3 = 7$. Hence, it is characterized by $k = 2$ hidden layers, each composed by 16 neurons, all activated using the hyperbolic tangent function, which is Lipschitz continuous. The weights of the DNN weights are adjusted according to (23), with Γ_j, for $j = 0, 1, 2$, being defined as the identity matrix with suitable dimensions. As for the controller, the gain matrices in (22) are selected as $K_p = K_d = 5 \cdot I_{7\times 7}$, the coefficients used to compute the conventional sliding variable are σ_0 are $C_1 = C_2 = I_{7\times 7}$, while the discontinuous control gain $\hat{\rho}$ is updated according to (25), with $\mu = 0.85$ and $\varepsilon_\sigma = 0.3$. Finally, the reference $q^\star$ has been generated considering $p_h = \begin{bmatrix} 0.47 & 0.18 & 0.47 \end{bmatrix}^\top$, and choosing $\nu = 0.6$ in (20).

The results of the experiment are presented in Fig. 4 and in Fig. 5. In particular, the former shows that the proposed DNN-AISM controller is able to drive the pose error inside a boundary layer around zero, hence performing the ergonomic handover task. Moreover, Fig. 5 depicts the norm of the integral sliding variable σ and the discontinuous control gain ρ, showing that, apart from the phases in which the robot picks or places an object, changing τ_h, $\|\sigma\|$ is successfully driven inside the set Ω_σ, ensuring a practical sliding mode, always maintaining a reasonably small discontinuous gain.

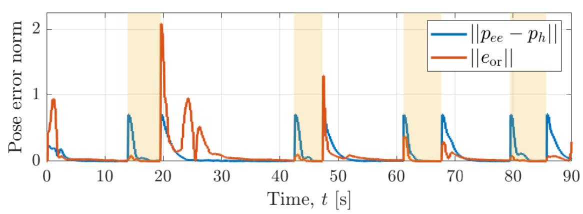

Fig. 4: Time behavior of the pose error. The yellow areas denote the time transients in which an object is grasped by the robot.

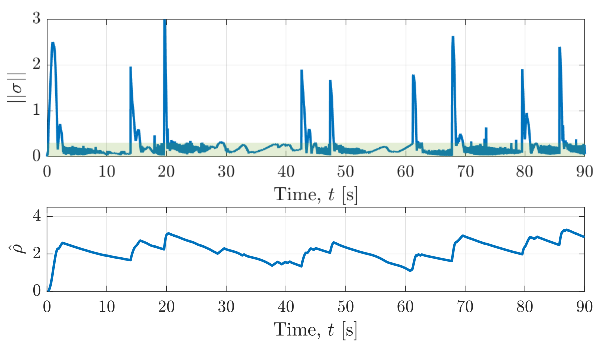

Fig. 5: Time behaviour of the norm of the integral sliding variable (above) and the discontinuous control gain (below). The green area indicates the set Ω_σ.

VII. Conclusions

In this paper, we proposed a strategy for performing the handover task ensuring a high degree of ergonomics for the human operator. To cope with the dynamics uncertainties introduced by the manipulated objects, a DNN based ISM controller with adaptive discontinuous gain is proposed. In particular the weights of the DNN are adjusted according to adaptation laws obtained thorough Lyapunov analysis. The proposal has been experimentally assessed performing the handover task with a Franka Emika Panda robot, measuring the hand orientation with an MTw Awinda IMU, obtaining satisfactory results.

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