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EMG-based Variable Impedance Control with Passivity Guarantees for Collaborative Robotics

Maciej Bednarczyk¹, Hassan Omran¹ and Bernard Bayle¹

Abstract—In this paper, a new methodology is developed for safely changing the interaction dynamics of a collaborative robot. A strategy based on electromyography is proposed to distinguish operator forces from those resulting from interactions with the environment. This allows to obtain information about the operator intentions and include it into the robot control strategy for an enhanced physical human–robot interaction. The safety of the resulting variable impedance control is guaranteed by imposing the passivity of the interaction. Experimental validation shows a good performance of the proposed method and illustrates the advantages of such a strategy in cases where human, robot and environment interact with each other.

Index Terms—Human-Robot Collaboration, Physical Human-Robot Interaction, Compliance and Impedance Control

I. INTRODUCTION

THE evolution of robotics and recent advances in the field of physical Human-Robot Interaction (pHRI) tend toward human oriented design of robotic mechanisms and control strategies. In this framework, characterizing the behavior of the human operator comes into the center of attention, especially in the case of human-robot collaborative systems. Even if a fully automated robotic system shows greater performance in precision, repeatability and load capacity than a human operator when operating in a well defined environment, many tasks require the human ability of fast judgment and adaptation in case of unpredicted events. In this context, collaborative systems are designed to combine both the robot force and precision, and the operator judgment and flexibility.

With the development of collaborative robots (called cobots), human-robot collaboration has become a research topic of paramount importance in multiple fields of application such as manufacturing [1], or robot-assisted medical interventions such as rehabilitation robotics [2], [3], to mention just a few. In collaborative scenarios, the question of handling physical contact with an unmodeled environment in the best possible way is a crucial issue. This can be obtained typically by controlling the compliance of the interaction between the robot and its environment, resulting in the classical impedance

control (IC) scheme [4], [5]. In the case of complex interactions, the desired response of the robotic system needs to be regulated by properly modifying the impedance parameters. This can be achieved by means of a variable impedance controller (VIC) [6]. One of the main challenges in interaction management using VIC lies in the proper selection of the impedance parameters, not only according to the task but also to ensure stability for all possible parameters variations [7]. This issue has been addressed by several approaches such as the energy tanks [8].

Once the integrity of the human operator can be guaranteed, the challenge for effective collaboration between the human and the robot can be addressed. This challenge lies in the ability to establish efficient communication between both sides and especially in the prediction of the operator intentions [9]. This is of particular interest in robot-assistive tasks in which the robot needs to acquire a perception of the operator activities during task execution and adapt the level of assistance when needed. Human activity can typically be estimated by measuring the force applied by the operator on the robotic system using mechanical force-torque sensors. Due to its simplicity, this strategy is commonly used in many collaborative applications such as object manipulation [10], [11], [12]. The major drawback of such a method consists in the fact that sensor measurements include some undesired components. Indeed, besides measuring the human-robot interaction, it will also measure gravity, friction forces and other interaction forces resulting from the contact with an uncertain environment [9]. Alternatively, measurable bio-signals such as surface electromyography (EMG) could also be used to measure the forces applied by the human operator [13]. EMG signals are the result of muscle bio-electrical activity and are often used in the control strategies of assistive robotic systems. They reflect the operator’s muscle voluntary contractions, providing an insight on his intentions. In many applications involving EMG-controlled robots, EMG signal magnitude is used as a trigger to enable some level of assistance of the robotic system [14]. An alternative to that is to integrate bio-signals directly into the robot control strategy using a model of the operator activity for better assistance.

Recent implementations of collaborative control strategies based on VIC also include information about muscle activity using EMG. In [15] the operator muscle activity is used to switch the robot damping between predefined values. The work presented in [16] uses the concept of tele-impedance where the robot is controlled using both motion commands and impedance profiles which are generated by the operator interacting with some environment. In [17], the concept of

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tele-impedance was used in an approach where the robot is taught by the user how to perform the desired task. This method however turned out to require a complex setup and an experienced operator. As a response to these issues, the work of [18] introduces a framework based on EMG and manipulability assessment of the human arm to provide information about the human behavior and task requirements. However, the previously mentioned works share the common shortcoming of not guaranteeing the passivity of the interaction while adapting the impedance.

In this work, we propose a control strategy for the adaptation of the impedance of collaborative robots, based on operator's intentions and movements. These intentions are estimated using a real-time EMG to force model. Moreover, we show how to implement passivity filters in order to make the physical human-robot interaction safe. The passivity filters have been presented in details in our previous work [19] where we have addressed the issue of ensuring stability for VIC. The proposed method is based on the design of a filter that allows the tracking of impedance profiles while guaranteeing the passivity of the interaction dynamics. In this paper, we focus more on the utility of these filters for an adaptive interaction between the human and the robot. For more generality, the experimental validation of the proposed method will be done using a 7-DoF collaborative robotic manipulator.

The rest of the paper is organized as follows. In Section II, some basic concepts of robot dynamics, variable impedance control and passivity filters are presented. Section III introduces our control strategy combining EMG-based human arm modeling with VIC, with some experimental results presented in Section IV. The paper is concluded in Section V

II. VARIABLE IMPEDANCE CONTROL AND PASSIVITY FILTERS

A. Rigid body dynamics and robot model

Let's consider the model of an n -joint serial robotic manipulator operating in an m -dimensional task space

$$H(q)\ddot{q} + c(\dot{q}, q) + g(q) = \tau_c - J(q)^T f_{ext} \quad (1)$$

with \ddot{q} , \dot{q} , $q \in \mathbb{R}^n$ the joint acceleration, velocity and position respectively. $\tau_c \in \mathbb{R}^n$ is the commanded joint torque, $f_{ext} \in \mathbb{R}^m$ the total external wrench exerted at the robot end-effector, $J(q) \in \mathbb{R}^{m \times n}$ denotes the robot Jacobian matrix and $H(q) \in \mathbb{R}^{n \times n}$, $c(\dot{q}, q) \in \mathbb{R}^n$ and $g(q) \in \mathbb{R}^n$ are the inertia matrix, Coriolis and gravity terms, respectively. The robot dynamics (1) can be simplified by means of a computed torque control law and some usual model manipulations [20].

B. Variable Impedance Control

In order to dynamically link the system positions, velocities and accelerations with the external forces, the input of the system is computed in order to obtain

$$M\ddot{e}_p + D(t)\dot{e}_p + K(t)e_p = f_{ext} \quad (2)$$

with $e_p = p_r - p \in \mathbb{R}^m$, where p is the robot end effector pose and p_r a reference motion. The interaction is then characterized by the impedance resulting from the apparent virtual mass

$M \in \mathbb{R}^{m \times m}$, the desired damping $D(t) \in \mathbb{R}^{m \times m}$ and the desired stiffness $K(t) \in \mathbb{R}^{m \times m}$. Note that M , $D(t)$ and $K(t)$ are symmetric positive definite user-defined matrices. In the proposed controller we consider, $D(t)$ and $K(t)$ time-varying, while M is assumed to be constant. In this work, we assume that the impedance model matrices are all diagonal and that it can be decoupled according to its DoFs $i \in [1, \dots, m]$. The change in the system impedance varies between some stiffness (respectively damping) values K_0 and K_1 (respectively D_0 and D_1) such that

$$K(t) = K_0 + \Gamma(t)\delta K \quad (3)$$

$$D(t) = D_0 + \Gamma(t)\delta D \quad (4)$$

with $\delta K = K_1 - K_0$, $\delta D = D_1 - D_0$ and Γ a diagonal matrix where all diagonal terms γ_i are differentiable gains such that $0 \leq \gamma_i \leq 1$. In order to simplify the notation, time dependence of Γ , K and D will be omitted in the further development.

C. Passivity Filter

As arbitrary variations of impedance parameters can lead to instability, a passivity filter can be used to guaranty system stability, as explained and shown with more details in our previous work [19]. In fact, we showed that if the varying impedance parameters satisfy the following passivity conditions:

$$0 \leq K - \dot{D} \quad (5)$$

$$0 \leq 2DM^{-1}(K - \dot{D}) - \dot{K} + \ddot{D} \quad (6)$$

then system passivity can be guaranteed. We also showed that as M , K , D are chosen to be diagonal, the impedance behavior can be decoupled, leading to a set of scalar passivity conditions on the switching variable γ_i . We define the diagonal terms of M , K , D , δK and δD as respectively m_i , k_i , d_i , δk_i and δd_i .

In fact, in the case where $\delta d_i \neq 0$, equation (5) gives a passivity condition for $\dot{\gamma}_i$ such that

$$\dot{\gamma}_i \leq \frac{\delta k_i}{\delta d_i} \gamma_i + \frac{k_{0i}}{\delta d_i} \triangleq h_{1i}(\gamma_i) \quad (7)$$

We also showed that passivity condition (6) is satisfied as long as γ_i satisfies

$$\dot{\gamma}_i \leq \frac{a_{3i}\gamma_i + a_{4i}\gamma_i^2 + a_{5i}}{a_{1i} + a_{2i}\gamma_i} \triangleq h_{2i}(\gamma_i) \quad (8)$$

with

$$\begin{aligned} a_{1i} &= \delta k_i + \frac{2}{m_i} d_{0i} \delta d_i & a_{3i} &= \frac{2}{m_i} (d_{0i} \delta k_i + k_{0i} \delta d_i) \\ a_{2i} &= \frac{2}{m_i} \delta d_i^2 & a_{4i} &= \frac{2}{m_i} \delta k_i \delta d_i & a_{5i} &= \frac{2}{m_i} k_{0i} d_{0i} \end{aligned}$$

Combining the two passivity conditions, given by equations (7) and (8), with a low-pass filter, in order to ensure smoothness of γ_i , a passivity filter can be designed in such a way that it takes as input the desired switching profile $\bar{\gamma}_i$ and generates an output profile γ_i that guarantees the system passivity. The filter can then be defined by

$$\dot{\gamma}_i = \min(h_{1i}(\gamma_i), h_{2i}(\gamma_i), \beta(\bar{\gamma}_i - \gamma_i)) \quad (9)$$

where β is the gain of a low-pass filter that allows to ensure the smoothness of γ_i . Integrating (9) yields γ_i that tracks $\bar{\gamma}_i$ in such a way that passivity conditions are respected.

III. EMG-BASED VARIABLE IMPEDANCE CONTROL

In many robotic applications with human-robot interactions, the human and the robot interact not only with each other, but also with the external unmodeled environment. In this case, distinguishing between the forces that are applied by the operator from those applied by the environment and adapting the robot behavior accordingly becomes essential.

A. Varying Interaction Dynamics based on Human Intentions

In this context, the following scenario is considered: when no human input is detected by the system, the robot follows some reference position p_r under impedance control and thus can react to environmental contact wrench f_e as shown in Figure 1a. However, when the operator participates to the interaction by generating some wrench f_h on the system, the impedance model used by the controller is modified as shown in Figure 1b. The desired behavior of system in

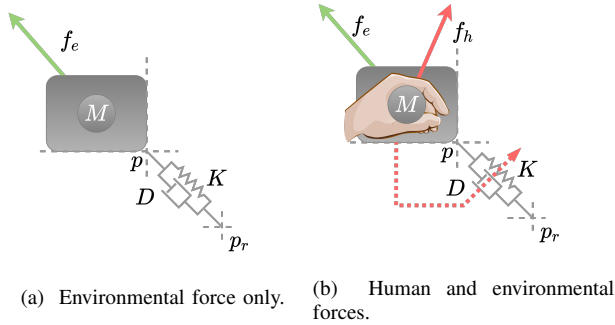


Fig. 1. System under VIC.

contact with the environment and without any human input, is given by the impedance model characterized by its stiffness K_e and damping D_e . On the other hand, when only the human operator is exerting wrench on the end-effector, the impedance model is given by the stiffness K_h and damping D_h . When human and environment interact simultaneously with the robot, the impedance parameters change accordingly to the ratio of both wrenches. In this way, it is possible to have different interaction dynamics with the human from those with the environment. For instance, the robot could be having a stiff behavior while interacting with the environment, while being very compliant when it interacts with the human operator.

The change in the system impedance is considered to be affine and vary between the stiffness (respectively damping) values K_e and K_h (respectively D_e and D_h) such that

$$K(t) = K_e + \Gamma(t)\delta K \quad (10)$$

$$D(t) = D_e + \Gamma(t)\delta D \quad (11)$$

with $\delta K = K_h - K_e$, $\delta D = D_h - D_e$ and Γ is the diagonal switching variable matrix such that for each eigenvalue of Γ , $0 \leq \gamma_i \leq 1$ and $\Gamma = g(f_h, f_e)$, where g is some function of the forces generated by the environment f_e and forces generated

by the user f_h . In the case when the environment wrench f_e is zero, the switching variable matrix Γ is set to be the null matrix.

In practice, the robotic system is not able to differentiate the wrench applied by the environment and from the one applied by the operator and can only measure the total external wrench applied on the end-effector being the sum of all applied wrenches such that $f_{ext} = f_h + f_e$. For this reason, in order to distinguish the wrench f_h , the operator is equipped with EMG sensors that can measure his muscular activity. During interaction only between the robot and the operator, the human arm dynamics produce EMG signals μ and a wrench applied on the robot end-effector $f_{ext} = f^h$. These signals can be used to derive an EMG to force model of the human arm.

B. Human arm dynamics model estimation

When modeling the EMG-force relationship, it is of particular interest to take into account the subject and time variability of the EMG-based human arm dynamics. In order to cope with this time dependency, a Linear Parameter-Varying model has been considered in [21] where the scheduling parameter is considered to be the elbow angle. However, this requires measuring all the necessary variables related to the body kinematics. Moreover, this method comes with the burden of more complicated calculations that are not feasible in real-time. In this work we consider a linear time-varying parameters model, which is more adapted for real-time applications. The EMG-force relationship, expressed as a linear, discrete time, input/output model is supposed here to have the form

$$f_{hk} = - \sum_{i=1}^{n_a} A_{i,k} f_{hk-i} + \sum_{i=1}^{n_b} B_{i,k} \mu_{k-i-n_k+1} \quad (12)$$

where f_{hk} and μ_k are the human force and EMG signal at time step k , respectively and $A_{i,k}$ and $B_{i,k}$ the time varying model parameter matrices. The number of past inputs and outputs used in the model are given by n_a and n_b , n_k is an input to output delay. The parameters are estimated using a classical Recursive Least Squares (RLS). See [22] (pages 52 and 57) for a full description of the used method. The idea is to minimize the difference between the measured outputs and the prediction of the outputs based on past and current inputs as well as past outputs.

During the phases where only the human is interacting with the robot, the force sensor measures the force applied by the human. In this case, we activate the identification process described previously. Then, we stop the identification process at time j , and we consider the most recent set of parameters to find an estimation of the human force \hat{f}_k based on the measured EMG signals using the estimator:

$$\hat{f}_{hk} = - \sum_{i=1}^{n_a} A_{i,j} \hat{f}_{hk-i} + \sum_{i=1}^{n_b} B_{i,j} \mu_{k-i-n_k+1} \quad (13)$$

C. Control Architecture

The human EMG to force relationship given by the recursive model (13) produces estimates of the human wrench \hat{f}_h . When contact with the environment is detected, by the means

of a dedicated sensor, the estimation is interrupted and the previously estimated model parameters are used to compute the human wrench \hat{f}_h from the EMG signal μ . The overall control architecture is shown in Figure 2a. Inside the controller

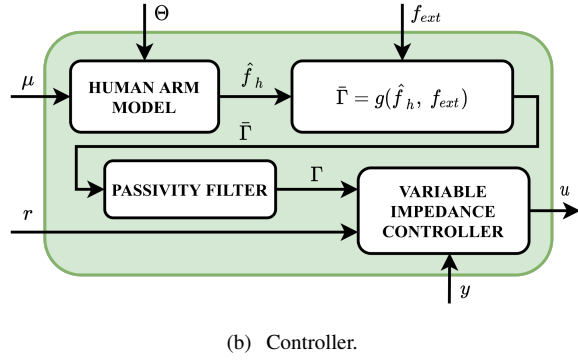
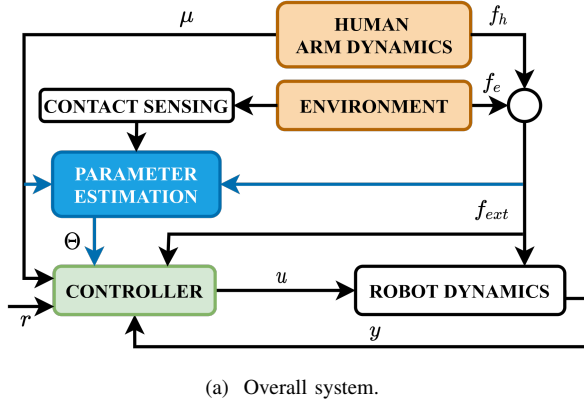


Fig. 2. Block-diagram illustrating the overall system architecture during human-robot interaction. Θ is the vector of the estimated parameters.

block, as shown on Figure 2b, the estimated human wrench \hat{f}_h is used to compute the impedance model switching variables such that

$$\bar{\Gamma} = g(\hat{f}_h, f_{ext}) \quad (14)$$

In this case, we measure the wrench applied by the environment $f_e = f_{ext} - \hat{f}_h$. This wrench also contains modeling errors of the estimation of f_h . As applying $\bar{\Gamma}$ directly to VIC parameters $K(t)$, $D(t)$ could lead to the loss of passivity and thus to instability issues, the switching variable is first filtered by the means of the passivity filter (9), resulting in Γ that guarantees passivity. This new switching variable is then used in VIC to compute $K(t)$ and $D(t)$ from equations (10) and (11). Finally, the controller produces the input u that is fed to the robotic system.

IV. ENHANCED HUMAN-ROBOT INTERACTION

A. Experimental Setup

In order to validate the proposed strategy, an experiment is designed as shown in Figure 3. A handle is mounted on the end effector of a KUKA *iiwa* 14 collaborative robot and has been equipped with an ATI Mini40 force-torque sensor. A stretch band of about 180N/m stiffness can be attached to the handle. Its goal is to emulate an unmodded external forces applied to the system. The operator is equipped with 8 EMG

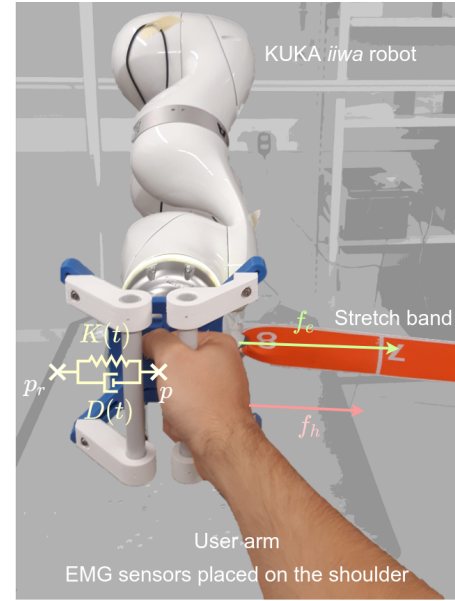


Fig. 3. Experimental setup.

sensors. The placement is done accordingly to the SENIAM recommendations [23] and depicted in Figure 4. The EMG

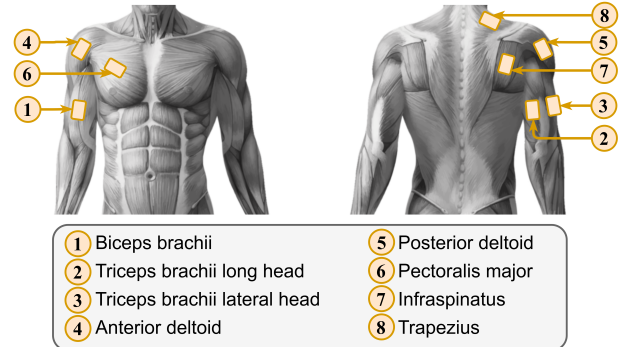


Fig. 4. EMG sensors placement.

signals, which represent the input of the estimator, are acquired using the Delsys Trigno Wireless System (Delsys Inc) with a sampling rate of 1kHz. The muscular activation signal is derived from the raw EMG data accordingly to the following processing steps. The acquisition system applies a first band-pass filter between 20 and 450 Hz, in order to filter out offsets and baseline drifts as well as to avoid aliasing. Then, during the processing, the bandwidth of the signal is further reduced using a Butterworth filter that selects the frequencies between 20 and 350 Hz, implemented by means of the series of a fifth order high-pass and a second order low-pass filter. Full-Wave Rectification is applied to the resulting signal by taking its absolute value. The envelope extraction, is performed using a second order Butterworth low-pass filter with a cut-off frequency of 1.775 Hz. The robot is controlled using the KUKA FRI communication interface. For simplicity, only one Cartesian DoF is considered and chosen horizontal and normal to the human and robot, that is in the direction of the stretch band. The impedance profile reference switching variable is

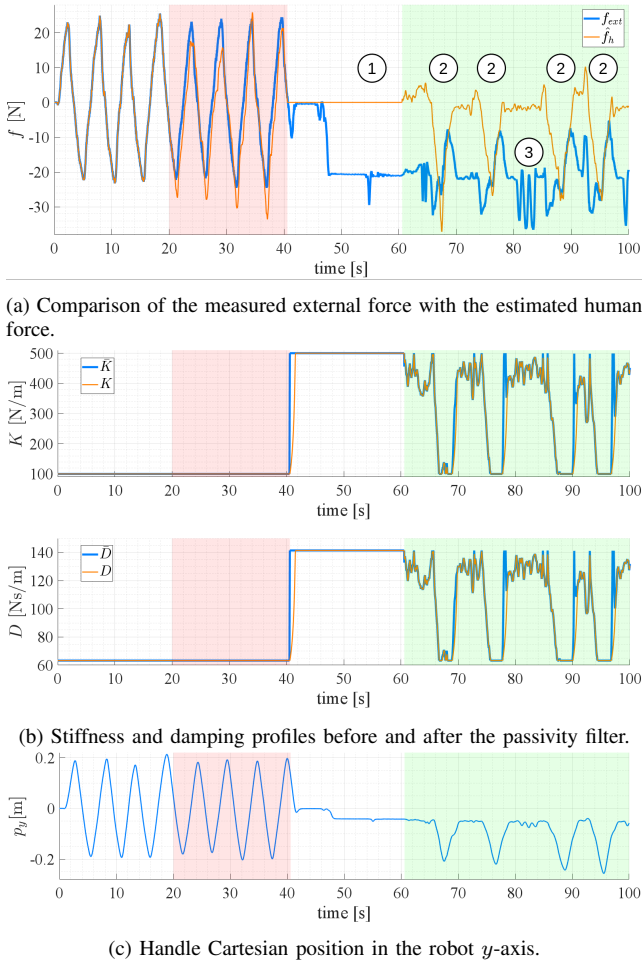


Fig. 5. Experimental data of EMG-based VIC.

chosen such that

$$\bar{\Gamma} = 1 - \frac{\alpha |\hat{f}_h|}{\alpha |\hat{f}_h| + |f_{ext} - \hat{f}_h|} \quad (15)$$

and $\bar{\Gamma} = 1$ if $f_{ext} = \hat{f}_h = 0$, with $\alpha = 2$ a gain that increases the influence of the operator input and also reduces the sensitivity to the estimation error. In fact, as α is chosen high, the weight of $|f_{ext} - \hat{f}_h|$ becomes negligible. Equation (15) gives $\bar{\Gamma} = 0$ if only the operator force is applied, resulting in an impedance profile $K = K_h$ and $D = D_h$ from equations (10) and (11). Meanwhile, if only the environment exerts a force on the system, $\bar{\Gamma} = 1$ and $K = K_e$ and $D = D_e$. Finally, when forces come from both sources, the resulting switching variable is a ratio of the force amplitudes that can be modulated by means of the gain α , as needed for the application.

B. Results

The four phases of the experimentation are illustrated in Figure 5 with the colored areas. First, the user applies some forces on the handle so that the model estimation can be performed (first white area on figures). In the second phase, the user continues to push-pull the handle, this time however, the force is predicted by the model (red area on figures).

Meanwhile, the stretch band is not attached to the handle, so that the only forces measured by the force sensor are the ones applied by the operator. During these two phases the VIC is given a constant low stiffness of $K_h = 100\text{N/m}$ and a damping $D_h = 63.25\text{Ns/m}$ resulting in a damping ratio of 1. In the third phase (second white area on figures), the user force prediction is disconnected and the stiffness is set to $K_e = 500\text{N/m}$ and the damping to $D_e = 141.42\text{Ns/m}$. In this phase the stretch band is attached to the system. Finally, in the fourth phase (green area of figures), the proposed multi force source interaction strategy is activated. The different forces applied to the system are illustrated in Figure 6 and come from the stretch band (Interaction 1), the operator right arm with EMG sensors (Interaction 2) and his left arm without sensors (Interaction 3).

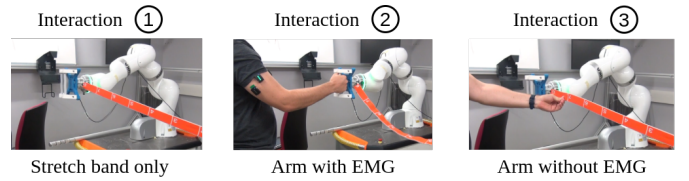


Fig. 6. Visualization of interactions during the experimentation phases. The numbers on top of the figures correspond to the ones of Figure 5a.

The first remark that can be made is about the second (red) phase, where the estimated model is used to predict the force (Figure 5a). As shown in the previous section, the predicted output fits the force intention of the user with $FIT = 67.8$ and $VAF = 96.6$, even though the estimated amplitude is not always exact. One can also notice that in the third phase, the attached band creates a constant force of -20N on the handle that simulates an external interaction force with an unmodeled environment, which can be observed in Figure 6 as Interaction 1. In order for the environmental force not to be only static, in phase four (green), the user also applies some additional pulls on the stretch band with his left arm that has no EMG sensors placed on it. This can be observed in Figure 6 as Interaction 3. Finally, when the operator uses his right arm with attached EMG sensors, as shown in Figure 6 as Interaction 2, the controller estimates the intentions of moving the handle what results in a decrease of stiffness and damping (Figure 5c). The decrease of the impedance profiles can be observed in Figure 5b. When the user applies some force with the EMG equipped arm, the impedance profiles decrease to K_h and D_h , whereas in the other cases the profiles remain close to K_e and D_e . The fact that the profiles are not strictly equal to K_e and D_e results from the fact that even at rest, the estimation produces some force output due to the gravity compensation activity of the human arm. This difference remains, however, rather low and can further be decreased by using the gain α if more precise tuning of the profiles is required for a certain application. In fact, if α is chosen smaller, it decreases the sensitivity of the controller to small forces made by the user. Finally, one can notice that the effective stiffness and damping profiles that are applied by the robot, in Figure 5b, are modified by the passivity filter in order to guarantee a stable interaction.

V. CONCLUSION

With the possibility of safely changing the interaction dynamics, the understanding of the operator intentions and including this information into the robot control strategy for enhanced pHRI comes to the fore. A strategy based on EMG is proposed to distinguish operator forces from interactions with the environment and modify the robot interaction dynamics accordingly. Because of their fair trade-off between accuracy and complexity, as well as their capacity of adaptation to changing conditions, linear time-varying models that are recursively identified are explored to map the relationship between EMG and the force produced by the human arm. This information is used in the robot control strategy to perform a modification of the interaction dynamics by means of a VIC. In order to face the requirements of different potential applications, the switching variable $\bar{\Gamma}$ is adapted as needed. The use of the passivity filter, which should not be compared with a classical filter, guarantees stable and thus safe execution of the impedance changes. Experimental validation shows a good performance of the proposed EMG-force models and illustrates the advantages of such a strategy when human, robot and environment interact with each other. Also, the implemented impedance profile changes are only influenced by the forces applied by the EMG equipped arm even in case of variations of the environmental forces.

It should be noted that while the proposed filters provide passivity guarantees, they could be conservative. The conservatism means that the filter would limit the desired variations of the impedance in favor of the passivity property. This could lead to a degradation in the performance. One solution would be to investigate less conservative passivity conditions, and consider them for the filter design. Another limitation is related to the choice of variation model of the impedance parameters in equations (10) and (11). The proposed method could possibly be adapted for a more general form of variations. Finally, there is also a limitation related to the EMG-force model, which is considered to be linear time-varying in this study. While this model is sufficient for simple movements, an enhanced modeling of the human arm dynamics and the EMG-force relationship should be necessary for more complicated movements. The previous limitations open the way to future research in the field.

REFERENCES

- [1] V. Villani, F. Pini, F. Leali, and C. Secchi, "Survey on human-robot collaboration in industrial settings: Safety, intuitive interfaces and applications," *Mechatronics*, vol. 55, pp. 248–266, Nov 2018.
- [2] R. Bogue, "Rehabilitation robots," *Industrial Robot: An International Journal*, vol. 45, no. 3, pp. 301–306, May 2018.
- [3] L. M. Weber and J. Stein, "The use of robots in stroke rehabilitation: A narrative review," *NeuroRehabilitation*, vol. 43, no. 1, pp. 99–110, Jul 2018.
- [4] M. Schumacher, J. Wojtusich, P. Beckerle, and O. von Stryk, "An introductory review of active compliant control," *Robotics and Autonomous Systems*, vol. 119, pp. 185–200, 2019.
- [5] N. Hogan, "Impedance control: An approach to manipulation," *Journal of Dynamical Systems, Measurement, and Control*, vol. 107, pp. 1–7, Mar 1985.
- [6] M. Sharifi, A. Zakerimanesh, J. Mehr, A. Torabi, V. Mushahwar, and M. Tavakoli, "Impedance Variation and Learning Strategies in Human-Robot Interaction," *IEEE Transactions on Cybernetics*, pp. 1–14, 2021.
- [7] K. Kronander and A. Billard, "Stability Considerations for Variable Impedance Control," *IEEE Transactions on Robotics*, vol. 32, no. 5, pp. 1298–1305, 2016.
- [8] F. Ferraguti, N. Preda, A. Manurung, M. Bonfe, O. Lambercy, R. Gassert, R. Muradore, P. Fiorini, and C. Secchi, "An energy tank-based interactive control architecture for autonomous and teleoperated robotic surgery," *IEEE Transactions on Robotics*, vol. 31, no. 5, pp. 1073–1088, Oct 2015.
- [9] A. Ajoudani, A. M. Zanchettin, S. Ivaldi, A. Albu-Schäffer, K. Kosuge, and O. Khatib, "Progress and prospects of the human-robot collaboration," *Autonomous Robots*, vol. 42, no. 5, pp. 957–975, Jun 2018.
- [10] R. Ikeura and H. Inooka, "Variable impedance control of a robot for cooperation with a human," in *Proceedings of 1995 IEEE International Conference on Robotics and Automation*, vol. 3. IEEE, 1995, pp. 3097–3102.
- [11] T. Tsumugiwa, R. Yokogawa, and K. Hara, "Variable impedance control based on estimation of human arm stiffness for human-robot cooperative calligraphic task," in *Proceedings 2002 IEEE International Conference on Robotics and Automation (Cat. No.02CH37292)*, vol. 1. IEEE, 2002, pp. 644–650.
- [12] V. Duchaine and C. Gosselin, "Investigation of human-robot interaction stability using Lyapunov theory," in *Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on*. IEEE, 2008, pp. 2189–2194.
- [13] L. Bi, A. G. Feleke, and C. Guan, "A review on emg-based motor intention prediction of continuous human upper limb motion for human-robot collaboration," *Biomedical Signal Processing and Control*, vol. 51, pp. 113–127, May 2019.
- [14] H. Krebs, J. Palazzolo, L. Dipietro, M. Ferraro, J. Krol, K. Rannekleiv, B. Volpe, and N. Hogan, "Rehabilitation robotics: Performance-based progressive robot-assisted therapy," *Autonomous Robots*, vol. 15, no. 1, pp. 7–20, Jul 2003.
- [15] S. Grafakos, F. Dimeas, and N. Aspragathos, "Variable admittance control in phri using EMG-based arm muscles co-activation," in *2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. IEEE, Oct 2016, pp. 1900–1905.
- [16] A. Ajoudani, N. 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, Nov 2012.
- [17] L. Peternel, T. Petrič, E. Oztop, and J. Babič, "Teaching robots to cooperate with humans in dynamic manipulation tasks based on modal human-in-the-loop approach," *Autonomous Robots*, vol. 36, no. 1, pp. 123–136, Jan 2014.
- [18] L. Peternel, N. Tsagarakis, and A. Ajoudani, "A human-robot co-manipulation approach based on human sensorimotor information," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 7, pp. 811–822, Jul 2017.
- [19] M. Bednarczyk, H. Omran, and B. Bayle, "Passivity filter for variable impedance control," in *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Oct 2020, pp. 7159–7164.
- [20] B. Siciliano and O. Khatib, *Springer Handbook of Robotics*. Springer International Publishing, 2016.
- [21] M. Pesenti, Z. Alkhoury, M. Bednarczyk, H. Omran, and B. Bayle, "Linear parameter-varying identification of the EMG-force relationship of the human arm," in *2019 28th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*, Oct 2019, pp. 1–6.
- [22] K. J. Åström and B. Wittenmark, *Adaptive Control: Second Edition*. Courier Corporation, Apr 2013.
- [23] H. J. Hermens, B. Freriks, C. Disselhorst-Klug, and G. Rau, "Development of recommendations for semg sensors and sensor placement procedures," *Journal of Electromyography and Kinesiology*, vol. 10, no. 5, pp. 361–374, Oct 2000.