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Experimental Evaluation Of Intuitive Programming Of Robot Interaction Behaviour During Kinesthetic Teaching Using sEMG And Cutaneous Feedback ⋆

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Abstract: Modern applications related to service or production can nowadays benefit from the introduction of collaborative robots already available on the market and endowed with several advanced features such as precise torque control or safe physical interaction with operators. More importantly, collaborative robots allow operators to teach end-effector trajectories by means of physical interaction – known as kinesthetic teaching – which is one of the most intuitive programming-by-demonstration techniques. However, important functionalities provided by modern collaborative robots, like the possibility of performing smooth interactions, cannot be programmed intuitively with the available framework of kinesthetic teaching. In the present study, we propose and experimentally evaluate a robot programming framework for the simultaneous teaching of both trajectories by means of kinesthetic teaching, and robot interaction behavior by means of impedance shaping along the trajectory exploiting a wearable interface. Specifically, the wearable interface is designed to not affect the free motion of the operator, necessary to perform kinesthetic teaching, and it is based on the usage of surface electromyography (sEMG) and vibrotactile stimulation. In this way, we propose an intuitive robot programming framework for an offline robot trajectory and interaction behavior programming, according to which the operator will be able to plan interactions with the environment and humans. In this article, we report a preliminary experimental evaluation of the proposed system, in which an operator will teach a 7-degrees-of-freedom manipulator the execution of a task on a robotic wiring test-bed. In the experiment, the programming of requested compliance levels during the kinesthetic teaching of a trajectory is performed, and the reported results show that the provided wearable interface is successfully exploited by the operator. Finally, the experiment also demonstrates that the offline intuitive programming of trajectories and impedance levels can be exploited online for human-robot co-work.

Keywords: Human-centered automation, human-robot interaction, programming by demonstration.

1. INTRODUCTION

Teaching a robot different complex tasks, by means of intuitive human-robot interfaces, is a topic of major interest in robotics research. In particular, the affirmation of modern collaborative robots in a wide rage of applications, both in industrial and services scenarios, is pushing even more the need of an intuitive robot programming techniques. In this relation, nowadays collaborative manipulators available in the market are able to co-work with humans, thanks to the capability of performing physical interaction with an adequate level of safety. Furthermore, advanced sensing and functionalities such as force control and measurements of joint torques are provided, concurring to the regulation of the compliant interaction capabilities of the robot (Lee and Ott, 2011). This context has paved, the emerging of novel programming frameworks for robots that can be grouped under the name of Programming-by-Demonstration (Lee, 2017) (PbD.) Accordingly to PbD, the plan of the tasks of a collaborative robot can be carried out by operators, even non-expert users, by exploiting human-robot interfaces and interactions (HRI). Among the multiple possible realizations of the PbD approach, one of the solutions that results as more attractive for both research laboratories and industrial partners is the so-called kinesthetic teaching (Calinon, 2009; Villani et al., 2018; Kormushev et al., 2011). In kinesthetic teaching, the programming of the robot end-effector trajectory is performed through direct physical interaction between humans and robot (i.e. physical HRI), with the former guiding the latter by using

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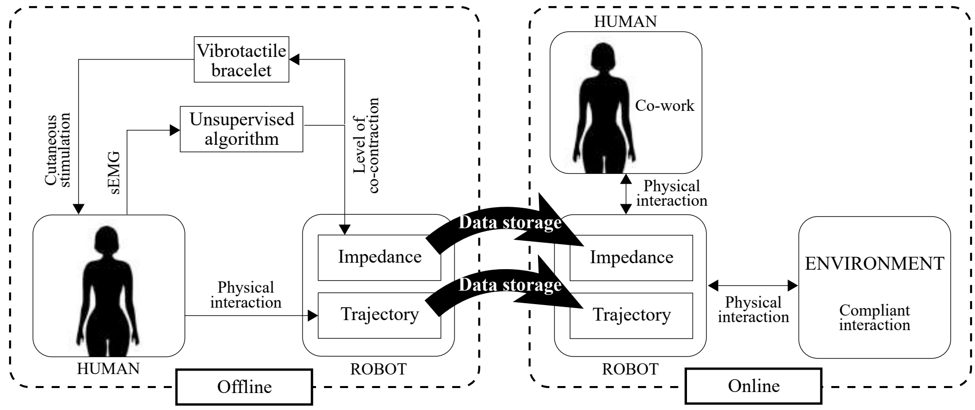

Fig. 1. Conceptual scheme of the proposed intuitive robot programming framework.

her/his own arms and hands. A different approach, known with the name of observational demonstration (Yamane and Hodgins, 2009; Mu et al., 2019), is based on the direct demonstration of the task by the operator. The system records the teacher motions through a set of external sensors, usually characterized at least by a vision system (Geibel et al., 2019; Cakmak et al., 2011; Häring et al., 2012) and exploits learning strategies to correctly identify the operator actions to be imitated (Ott et al., 2008; Dariush et al., 2008; Nakaoka et al., 2005). However, this approach results to be more complex to implement because of the kinematic dissimilarities between the operator and the robot. For these reasons, in many industrial scenarios, kinesthetic teaching is considered as a more viable approach.

In this work, a novel programming framework in which kinesthetic teaching is enhanced by a wearable human-robot interface is presented. The usage of wearable interfaces has been proven to be an effective alternative to, for example, haptic handles for force rendering (Walker et al., 2010) or vision systems for tracking of the gaze (Geibel et al., 2019), hand gestures (Geibel et al., 2019) or body postures (Cakmak et al., 2011). Indeed, wearable interfaces allow (i) freehand motions of the operator and (ii) do not require the placement of grounded setups in the working environment, minimizing the encumbrance (Ruffaldi et al., 2017). In our approach, we propose the exploitation of a wearable interface, composed by surface electromyography (sEMG) signals and vibrotactile stimulation, to allow the operator program the manipulator's level of compliance while performing kinesthetic teaching. In particular, we rely on the ability of a human operator to tense antagonistic muscles during static or dynamic movements (Patel et al., 2014) to produce a specific level of muscular co-activation (Burdet et al., 2013). In this way, the operator will be able to modulate the muscle co-contraction level to a desired value while guiding the robotic manipulator for kinesthetic teaching purposes. In particular, the desired behavior is obtained by linearly modifying the manipulator impedance in relation to the co-contraction modulation. The proposed approach enables a new programming paradigm, in which an offline teaching phase can be performed to produce an online interaction behavior of the robot. In other words, it allows to intuitively program a mechanically compliant trajectory. In order to preliminarily test the proposed solution, an experimental evaluation was carried out in the context of a robotic wiring task on a switchgear test-bed. In particular, we demonstrate the actual suitability of our approach in enabling an operator to perform the kinesthetic teaching of a trajectory for wiring purposes, while also modulating the level of compliance of the robot for smooth and safe interactions with humans and environment during the online task execution.

2. MATERIAL AND METHODS

2.1 Intuitive Robot Programming Framework

According to the proposed programming framework, illustrated in the general scheme reported in Fig. 1, two different modalities of intuitive programming are made available for the user. The first one is devoted to the programming of the trajectories that the operator wants to be reproduced by the robot end-effector.It is realized by physical interaction between the user and the robot manipulator, with the latter being guided by the user through the desired configurations by means of kinesthetic teaching. The second programming modality, provided to the operator, is devoted to the shaping of the robot impedance dynamics along the taught trajectory, that is realized by a wearable human-robot interface system that measures the forearm's sEMG (see Sec. 2.2) to provide the user the ability to modulate the motion in real-time by means of stiffening of her/his hand (see Sec. 2.4), while a cutaneous vibrotactile feedback (see Sec. 2.2) lets the operator be aware of the current hand stiffening level, allowing a closed-human-in-the-loop shaping of robot impedance (see Sec. 2.3). As illustrated in Fig. 1, subsequently the *offline* teaching phase of the robot, the trajectory and impedance information programmed by the operator are stored for subsequent *online* usage during the actual execution of the task by the robot. According to this framework, human-robot co-working and, in general, safe and compliant physical interaction of the robot with the environment can be intuitively pre-programmed simultaneously thanks to the kinesthetic programming of the robot trajectory.

2.2 Wearable Interface Setup

sEMG Sensing The gForcePro armband (OYMotion [1]) was used as the wearable device for the acquisition of the

[1] http://www.oymotion.com/

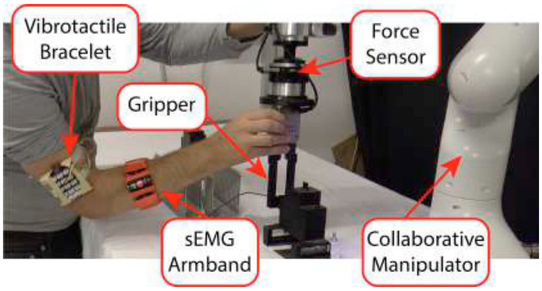

Fig. 2. Setup for the evaluation of the proposed intuitive programming framework.

sEMG from the operator's forearm (see Fig. 2), providing an 8-dimensional signal. More specifically, the location of the bellies of the *Flexor Digitorium Superficialis* and *Extensor Digitorium Communis* muscles were identified by means of standard empirical procedures as outlined in (Perotto, 2011), to place the armband in proximity of the muscles that predominantly co-contract during the voluntary stiffening of the hand (fingers and wrist.) The armband has an embedded Bluetooth interface that allows to stream raw sEMG data at 1kHz to a nearby PC. In order to extract meaningful features from the raw sEMG, a filtering procedure was applied to each sEMG channel, composed by (Meattini et al., 2018; De Luca et al., 2010): *(i)* 50Hz notch filter (powerline interference cancellation), *(ii)* 20Hz highpass filter (baseline noise reduction), *(iii)* the root-mean-square (RMS) value over a 200ms running window (Hogan and Mann, 1980).

Cutaneous Vibrotactile Stimulation A specifically designed wearable vibrotactile bracelet was provided to the user to convey cutaneous vibration feedback related to sEMG signals during the hand stiffening. This enables the user to be aware of the shaping of the robot impedance along the taught trajectory. In detail, a Seeed Technology Co. [2] vibration motor was embedded in a bracelet made by fabric and fastening straps. In this way, the feedback signal (i.e. the actual level of co-contraction, see Sec. 2.4) was modulated in accordance to a proper range of integer values by means of the control electronics embedded in the bracelet (see Fig. 2.) The bracelet was worn by the user on her/his upper arm.

2.3 Collaborative Robotic Setup and Control

The Franka Emika Panda robot was used as collaborative manipulator. The manipulator, characterized by seven DoF, was also equipped with a 6-axis force sensor by ATI Industrial Automation and a SCHUNK GmbH & Co gripper was used as end-effector (see Fig. 2.)

The control of the robot during the kinesthetic teaching was implemented according to an impedance control strategy. The dynamic model of a manipulator in the workspace can be expressed as:

$$M(x)\ddot{x} + C(x,\dot{x})\dot{x} + g(x) = F_{\text{input}} + F_h, \qquad (1)$$

with $M(x) \in \mathbb{R}^{n\times n}$, $C(x,\dot{x}) \in \mathbb{R}^{n\times n}$ and $g(x) \in \mathbb{R}^n$ the inertia, Coriolis-Centrifugal and gravity term respectively, defined in the workspace as a function of the robot end-effector pose x. The behavior of the robot is given according to the external wrench F_h, applied by the operator and a control input F_{input} equal to:

$$F_{\text{input}} = \hat{C}(x,\dot{x}) + \hat{g}(x) + F_c + F_r, \qquad (2)$$

in which three different control actions are specified: the Corialis-Centrifugal matrix and gravity term $\hat{C}(x,\dot{x}) + \hat{g}(x)$, the desired impedance dynamics through a PD controller F_c and a compensation of frictional effects F_r. Moreover, the PD controller term is defined as:

$$F_c = K_p(x_d - x) - K_d\dot{x}, \qquad (3)$$

where the positive definite matrices $K_p, K_d \in \mathbb{R}^{6\times 6}$ impose the desired behavior, while x and x_d respectively represent the end effector actual and desired position in the workspace. By selectively set to zero the gain of the diagonal of matrix K_p, it is possible to specify the direction where motion is allowed for the operator during the kinesthetic teaching. A similar control strategy is also exploited during the online replica of the motion. In particular, since the robot is expected to move autonomously and to modify its compliance according to the offline user programming, the elements of the main diagonal of the matrix K_p are modified as:

$$k_{\text{online}} = (k_{\max} - k_{\min})\gamma(t) + k_{\min}, \qquad (4)$$

where the control input $\gamma(t) \in [0, 1]$ specifies the level of compliance of the robot, set between a maximum $k_{\max}$ and a minimum $k_{\min}$. The term γ can be programmed by the operator during kinesthetic teaching by exploiting the sEMG and vibrotactile interface introduced in the previous section and according to the concepts described in the following Sec. 2.4.

2.4 Muscle Co-Contraction Estimation and Vibrotactile Stimulation Modulation

In order to be able of estimating the hand stiffening level voluntarily modulated by the operator, we estimate the hand muscles co-contraction level obtained from forearm's sEMG signals measured by the gForcePRO armband described in Sec. 2.2.1. To this purpose, let $E(t) \in \mathbb{R}^{8\times 1}$ be the online 8-dimensional RMS value of the sEMG acquisition. According to the sEMG generative model proposed by (Jiang et al., 2008), the multidimensional sEMG signal can be expressed as:

$$E(t) = MU(t), \qquad (5)$$

where $M \in \mathbb{R}^{8\times n}$ is the muscular synergy matrix, $U(t) \in \mathbb{R}^{n\times 1}$ is the neural drives matrix. In this relation, in accordance with the concept of muscle synergies (Jiang et al., 2008) and human antagonistic actuation (Burdet et al., 2013), the hand stiffening can be seen as generated by the action of two antagonistic muscular activations, by means of that $n = 2$. Please notice that in eq. (5), the sEMG armband provides $E(t)$, whereas the matrices M and $U(t)$ are unknown. In this way, since the regulation of the activation of the two hand's antagonistic muscle groups is represented by the neural drives $U(t)$, it is therefore possible to consider the components of $U(t)$ for the co-contraction level estimation.

To this purpose, the estimation of the muscular synergy matrix M, which can be made by an offline recording procedure as described in the following, is required. Thereafter, it will be then possible to exploit the obtained muscular synergy matrix to compute online the muscles

[2] https://www.seeedstudio.com/

co-contraction due to the stiffening of the operator's hand. The offline procedure for the estimation of the muscular synergy matrix requires the operator to perform a motion consisting in the repetition of the closing and opening of the hand for two times, requiring a flexion and extension motions of the fingers. Subsequently, this motion has to be repeated two additional times, but with the maximum level of hand stiffening. Specifically, the maximum level is freely decided by the operator, who simply stiffens her/his hand during the motion up to a subjective maximum acceptable level. During the execution of this offline procedure, the recording of the sEMG signals is stored. Given d data samples of muscle activity, the corresponding sEMG data collection will be $E_{\text{offline}} \in \mathbb{R}^{8\times d}$. In light of the generative model previously introduced in eq. (5), the following expression can be used to describe the matrix E_{offline}:

$$E_{\text{offline}} = MU_{\text{offline}}, \quad (6)$$

where it is possible to consider $M = [s_{\text{ext}}\ s_{\text{flex}}]$, and $U_{\text{offline}} = \left[u_{\text{ext}}^{\text{T}} u_{\text{flex}}^{\text{T}}\right]^{\text{T}}$ the matrix of the offline neural drives. In this context, we compute the matrices U_{offline} and M using the Non-negative Matrix Factorization (NMF) [3] algorithm to E_{offline}, i.e. an unsupervised factorization techniques that have been already successfully implemented for the extraction of human motor intentions from sEMG and more importantly, it allows avoiding the necessity of empirical procedures to obtain the same positioning of the sEMG electrodes over different session/re-uses, since it is able to automatically compute the weights of the matrix M. Note that, the matrix U_{offline} – which is also obtained from the application of the NMF to the matrix E_{offline} – is just exploited for the computation of the scaling factors for the online neural drives:

$$k_{\text{ext}} = \frac{\sum_{i\in S} u_{\text{ext}_i}}{d_S} \quad , \quad k_{\text{flex}} = \frac{\sum_{i\in S} u_{\text{flex}_i}}{d_S}, \quad (7)$$

where d_S denotes the number of samples of the offline neural drives related to the part of the hand opening/closing calibration motion executed by stiffening the hand – as previously described in this section – and forming the set S. Once the matrix M and the scaling parameters k_{ext} and k_{flex} are obtained as described above, the offline calibration procedure can be considered concluded.

Considering now the online procedure for the estimation of the co-contraction level from the sEMG signals, we can exploit the muscular synergy matrix M obtained from the calibration procedure. Specifically, we are interested in computing the pseudo inverse of the muscular synergy matrix, i.e. M^+. In this way, it is possible to derive the online neural drives according to:

$$U(t) = M^+E(t). \quad (8)$$

It follows that we can now exploit the online neural drives to compute the hand's muscular antagonistic activations $a_{\text{ext}}(t)$ and $a_{\text{flex}}(t)$. To this purpose, we exploit the scaling factors obtained from eq. (7), in accordance to the following expressions:

[3] Given a nonnegative matrix $A \in \mathbb{R}^{m\times n}$ (a matrix whose elements are all non-negative), the product WH is called non-negative matrix factorization of A if non-negative matrices $W \in \mathbb{R}^{m\times k}$ and $H \in \mathbb{R}^{k\times n}$, with $k < \min(m, n)$, are found such that the functional $f(W, H) = \frac{1}{2}\|A - WH\|_F^2$ is minimized (Berry et al., 2007).

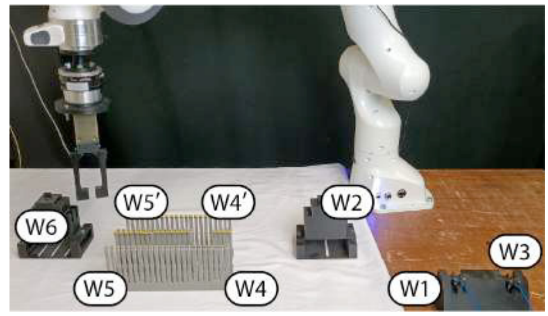

Fig. 3. Robotic wiring task test-bed.

$$a_{\text{ext}}(t) = u_{\text{ext}}(t)/k_{\text{ext}} \quad (9)$$
$$a_{\text{flex}}(t) = u_{\text{flex}}(t)/k_{\text{flex}}. \quad (10)$$

Once the muscular antagonistic activations are obtained, it is possible to finally compute the online hand muscles co-contraction level $\gamma(t)$ as:

$$\gamma(t) = \min(a_{\text{ext}}(t), a_{\text{flex}}(t)). \quad (11)$$

Thereafter, the estimated hand muscles co-contraction level is mapped into the wearable vibrotactile motor input range to convey to the operator the feedback about the current level of muscle co-contraction and enabling, in this way, a closed-human-in-the-loop control of $\gamma(t)$ by means of voluntary stiffening of the operator's hand. Considering ρ_{max} and ρ_{min} as the maximum and minimum values of the vibrotactile motor input range, the vibration intensity $\eta(t)$ provided by the vibrotactile bracelet is modulated as:

$$\eta(t) = (\rho_{\text{max}} - \rho_{\text{min}})(1 - \gamma(t)) + \rho_{\text{min}}, \quad (12)$$

according to which, the stimulation conveyed to the operator is proportional to the error between 1 and the co-contraction level $\gamma(t)$.

3. EXPERIMENT

3.1 Robotic Wiring Task

In order to evaluate the proposed intuitive programming framework, a robotic wiring task was carried out, consisting in teaching a robot manipulator the execution of a cable routing and connection operations. In particular, to carry out the wiring experiment, a specific test-bed was realized (see Fig. 3), consisting in the reproduction of a mock-up switchgear. In this context, an operator was asked to perform a robot programming session as described in the following. Firstly, a kinesthetic teaching task was required, in accordance with Fig. 3:

i) at location W1: pick up of one cable extremity;
ii) at location W2: insertion of the cable extremity into the connector of the switchgear component;
iii) at location W3: pick up of the second cable extremity;
iv) between locations W4 and W5: cable routing inside the cable channel;
v) at location W6: insertion of the second cable extremity in the switchgear component (conclusion of the wiring task.)

In addition to these kinesthetic teaching operations, the operator was also asked to simultaneously program different levels of robot compliance along the taught trajectory, by modulating the muscles co-contraction through the voluntary stiffening of his hand (i.e. of wrist and

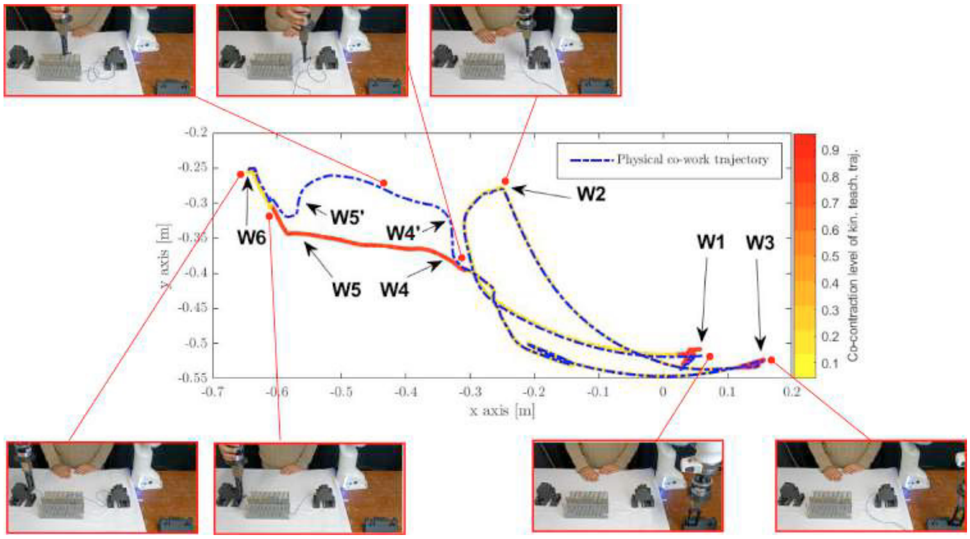

Fig. 4. Robotic wiring task experiment. Continuous line: trajectory programmed using kinesthetic teaching with the relative co-contraction level. Blue dotted line: trajectory obtained during online human-robot co-work (with frame sequence of the online wiring task execution.)

fingers.) More specifically, the modulation of a maximum level of co-contraction (i.e. $\gamma(t) \approx 1$, corresponding to a maximum level of robot compliance) was required during the cable extremity picking (locations W1, W3, see Fig. 3) and insertion operations (locations W2, W6.) Additionally, the modulation of a medium level of co-contraction (i.e. $\gamma(t) \approx 0.5$, corresponding to a medium level of robot compliance) was required during the cable routing operation (locations W4-W5). Finally, for the remaining parts of the wiring task trajectory – that include the motions between locations W1 and W2, W3 and W4, W5 and W6 – the modulation of a level of co-contraction as lower as possible was required from the operator (i.e. a minimum level of co-contraction, corresponding to a minimum level of robot compliance.) The grasping operations of the parallel gripper (i.e. opening and closing of the two parallel fingers) were programmed by the operators by means of simple vocal commands.

3.2 Online Wiring Task and Results

The results of the offline programming of the robotic wiring task are reported in the following, showing the online outcome of the task programmed by the operator. Consistently to the presented experimental protocol, the programming of maximum levels of robot compliance were requested during cable picking and connection. The reason was to produce a safe and smooth interaction with the switchgear components, with the aim of avoiding damages and failures thanks to the possibility of the robot to compensate small misalignment due to slightly different grasping of the connector located at the cable extremity. Differently, the programming of the medium level of robot compliance during the cable routing through the channel (locations W4-W5) was required in view of an online human-robot co-working along the related part of the trajectory. Indeed, during the execution of the online robotic wiring task, the operator was required to perform a modification at run-time, consisting in a physical interaction with the robot to modify the routing path to a different cable channel corresponding to the locations W4*-W5* (see Fig. 3) instead of W4-W5. Practically, the robot cyclically performed the baseline wiring task according to the trajectory programmed offline with the kinesthetic teaching, while the human-robot co-work had to be performed by the operator upon request of the experimenter.

According to the online execution of the wiring task experiment, the robot resulted to be able to perform the programmed operation of cable picking, connection, transportation and routing with a success rate of 100% along 10 cyclic repetitions of the wiring task. Additionally, the operator successfully carried out the human-robot co-work related to the deviation, at run-time, of the robotic cable routing trajectory through the cable channel W4*-W5*, which was randomly instructed by the experimenter during the cyclic repetitions. Fig. 4 reports the trajectory executed by the robot during the autonomous online wiring task according to the baseline kinesthetic teaching (continuous color-coded line) and the trajectory that resulted from changes applied at run-time by the operator by means of human-robot co-work (dotted line). In particular, the color-coded line in Fig. 4 allows to observe the level of co-contraction modulated by the user during the offline teaching, which has been regulated in order to have higher mechanical compliance at the requested locations W1, W2 and W4–W5 (red color of the color-coded line in Fig. 4.) The positive outcomes of the experiment demonstrate the effectiveness of the proposed intuitive programming framework and preliminary provides future perspective for the development of a new generation of advanced multimodal teaching by demonstration approaches.

4. CONCLUSIONS

In this article, a novel programming framework for collaborative manipulators based on the integration of kinesthetic teaching with wearable sEMG-driven and vibrotactile human-robot interfaces has been presented. The proposed system allowed an operator to program both desired trajectories, through physical guiding of the manipulator end effector and interaction behavior of the robot. The muscles' co-contraction level related to the voluntary stiffening of the hand was estimated by means of an unsupervised technique applied to forearm's sEMG signals and provided to the user an additional programming degree for the shaping of the robot impedance along the trajectory during kinesthetic teaching. This enabled the offline programming of robot compliance levels to perform, subsequently, online smooth interaction with both environment and operators (human-robot safe interaction for co-working.). Furthermore, according to the offline programming of the robot interaction behavior by means of the provided wearable interface, the robot successfully interacted with both the switchgear components and the operator for co-working operators at run-time. The reported outcomes provide promising perspective for future investigations and for applications in real industrial scenarios. Improvements of the system for more complex scenarios will be the object of future development and experimentation. The introduction of additional interfacing modalities provided to the operator will be investigated, with the aim of obtaining multiple programming channels to be exploited in parallel to the kinesthetic programming approach.

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