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Combining Unsupervised Muscle Co-Contraction Estimation with Bio-Feedback allows Augmented Kinesthetic Teaching

Roberto Meattini¹, Davide Chiaravalli¹, Luigi Biagiotti², Gianluca Palli¹ and Claudio Melchiorri¹

Abstract—Nowadays, an increasingly diversification of products and production lines would largely benefit from intuitive and multimodal robot teaching strategies. The present article proposes an augmented kinesthetic teaching system, which is based on surface electromyographic (sEMG) measurements from the operator forearm. Specifically, sEMG signals are used for minimal-training unsupervised estimation of forearm’s muscles co-contraction level. In this way, also exploiting a vibrotactile bio-feedback, we evaluate the ability of operators in stiffening their hand – during kinesthetic teaching – in order to modulate the estimated level of muscle co-contraction to (i) match target levels and (ii) command the opening/closing of a gripper, i.e. in exploiting their sEMG signals for effective augmented robot kinesthetic teaching tasks. Experiments were carried out involving ten subjects in two different kind of experimental sessions, in order to test both co-contraction modulation abilities, and actual usage of the co-contraction for programming robot functionalities during kinesthetic teaching. The obtained results provide positive outcomes on the intuitiveness and effectiveness of the proposed system and approach, paving the way to a new generation of advanced teaching by demonstration interfaces.

Index Terms—Physical Human-Robot Interaction, Learning from Demonstration, Human-Centered Automation.

I. INTRODUCTION

Collaborative robots are recently gaining a central role in an increasing number of scenarios, ranging from industrial to service robotics. One of the most diffused goals with collaborative robots, consists in demonstrating the required behaviour for the execution of a given task by means of kinesthetic teaching. Indeed, since in *kinesthetic demonstration* the robot’s links are physically guided by the operator, the problem of having kinematic dissimilarities between teacher and robot is greatly mitigated with respect to the other class of programming by demonstration approaches known with the name of *observational demonstration*, in which the operator teaches motions to the robot by directly performing the motions herself [1], [2], [3], [4]. For this reason, kinesthetic teaching is often a desirable approach in numerous industrial use cases. However, while extensive investigation has been dedicated to robot demonstration paradigms, kinesthetic teaching shows limitations related to its usability for robot pro-

gramming with respect to the wide spectrum of functionalities offered by modern collaborative robots [2]. With increasing diversification of industrial production lines, there is a growing necessity for alternative, wearable human-robot interfaces that can be exploited during physical robot demonstration. The goal is to have an *augmented kinesthetic teaching*, in such a way to provide with the capacity of bidirectional information exchange with the robot during the manual trajectory guidance.

In literature, several works have investigated a variety of interaction strategies and interface modalities to communicate information from operators to robots. A possible approach regards the tracking of human kinematic parameters by means of motion capture systems. The usage of vision systems has been explored for gestures [5], postures [6] and gaze [7] recognition based interaction modalities. Other works investigated human-robot communication channels using interfaces based on haptic devices [8], such as handles equipped with force sensors placed on the robot for the measurement of human grips [9]. However, these types of interaction methods require external/obtrusive setups. Additionally, some of them do not allow free-hand operations, which instead is essential to the aim of realizing an augmented kinesthetic teaching systems. In recent years, human-robot interaction has largely benefited from wearable devices for the measurements of human biological signals. In particular, voluntary human motor intentions have been shown to be detectable from surface electromyography (sEMG) [10]. For these reason, we claim that online extraction of information from sEMG signals represents a valuable interaction modality for allowing augmented kinesthetic teaching, which is the aspect at the core of the present work. Other works in literature have already explored the usage of sEMG measurements as an advanced human-robot interaction modality. In [11], operator’s hand gestures are recognized from sEMG signals. Other relevant studies have used real-time sEMG to estimate human arm impedance and transfer it to a remote robot [12]. Several works used sEMG for rehabilitative and assistive robotic applications —e.g. see [13], [14]. Differently from previous studies, with the contribution of this work we want to exploit sEMG *during* robot’s end-effector physical guidance, focusing both on system integration and interpretation of sEMG signals leveraging on unsupervised learning. Importantly, we consider the human ability of simultaneously activating antagonistic forearm’s muscles by stiffening the hand during the execution of both static postures and dynamic motions [15]. This aspect is particularly suitable to realize augmented kinesthetic teaching, since the increase of co-contraction (i.e. stiffening the hand) can be generated without changes in the forces/motions of the human limbs. Therefore, this means that the operator – within the specific considered task of physically teaching a robot end-effector trajectory – can fully exploit the generation of human

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net forces/motions for the physical robot guidance, while the augmented teaching information is produced by means of sEMG-measured muscle co-contraction. This is not possible, for example, if the augmented teaching information is provided just by means of a button on the robot, since it would require a specific pressure level by the operator, which can be difficult (or even impossible) to be produced while performing kinesthetic teaching. Furthermore, the usage of a button would require the operator to constantly keep her hand exactly on a predefined location, which can result incompatible with some human forces/motions necessary to physically guide the robot.

In this work we propose an augmented kinesthetic teaching system that uses – in addition with respect to traditional kinesthetic teaching – information extracted from forearm sEMG signals. The latter are used to estimate the operator’s voluntarily modulation of hand muscles co-contraction during physical robot guidance. Specifically, our estimation is based on a fast unsupervised calibration session, that requires a small amount of sEMG data without any labelling operation (Sec. II-C.) Furthermore, we provide the operator with a bio-feedback of the actual modulated level of co-contraction. More specifically, in this study, the ability of operators to modulate the estimated level of co-contraction to (i) provide target levels and (ii) control the opening/closing of a gripper is tested. In literature, several feedback modalities have been studied —e.g. visual or auditory stimuli [16], haptic displays [17]. Other types of feedback are based on wearable devices, among which the vibrotactile feedback sees a wide spectrum of uses. Applications can be found in studies related to remote robot control or collision awareness [18]. In the present work, we use a vibrotactile kind of bio-feedback because (i) it requires minimal attention from the operator with respect to auditory or visual channels, (ii) is unobtrusive and (iii) can be implemented with very small vibrotactile motors wearable on the human body. We tested the proposed system on a simplified setup reproducing the scenario of robotic teaching for wiring of industrial switchgear equipments. Ten subjects were involved in the experiments, and asked to teach the end-effector trajectory of a 7-DoF collaborative robot, while simultaneously modulating the sEMG-estimated co-contraction exploiting different vibrotactile bio-feedback modalities. In such a way, the trajectory is memorized by the robotic manipulator and then repeated for the execution of: (i) grasping of cable extremities, (ii) connecting of cable connectors into switchgear components and (iii) routing of the cable through a cable channel. The reported results show that the proposed system enables intuitive and effective augmented kinesthetic teaching (Sec. III-B), and paves the way for further developments in the field of advanced programming of collaborative robots.

II. MATERIALS AND METHODS

A. General Framework Overview

The *Kinesthetic Robot Teaching* area is the human-robot interface zone in which the physical interaction takes place. This is highlighted in Fig. 1 by a discontinued arrow between the human and robot, denoting the physical guidance of the collaborative manipulator. In the *Augmenting Robot Teaching* area, an interface with the operator’s neuro-motor information is realized by means of biological measurements. Specifically,

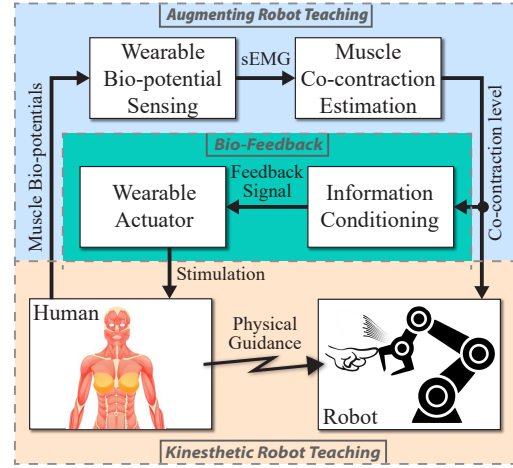


Fig. 1. Conceptual scheme of the proposed augmented kinesthetic teaching.

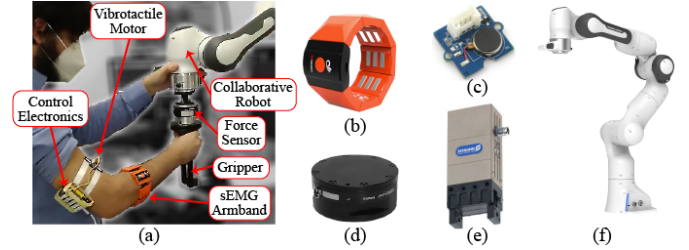


Fig. 2. (a) The augmented kinesthetic teaching setup of the present work. (b) gForcePRO sEMG armband. (c) Grove vibration motor. (d) ATI 6-axis force sensor. (e) SCHUNK parallel gripper. (f) Franka Emika Panda collaborative robot.

in our framework we consider a wearable sensing device measuring the sEMG activity from the operator’s forearm. The sEMG signals are then exploited to estimate the muscles co-contraction level. Such estimation is a continuous and real-time interaction modality at the operator’s disposal for augmenting the kinesthetic robot teaching. In our framework we make the operator aware of the current co-contraction level. This is realized as conceptually illustrated in the *Bio-Feedback* area of Fig. 1, which is a part of the *Augmenting Robot Teaching* area.

B. Augmented Kinesthetic Teaching Setup

1) *Wearable sEMG Sensing and Signal Processing*: In this work, eight sEMG channels were acquired from the operator’s forearm muscles. The signal acquisition was performed by means of the gForcePro commercial wearable sEMG armband (see Fig. 2(b)), by OYMotion¹. The armband was placed in proximity of the *Flexor Digitorum Superficialis* and *Extensor Digitorum Communis* muscles, because these are the predominant muscles producing antagonistic flexion and extension actions in the hand [19]. Raw sEMG data were acquired from the armband at 1 kHz and streamed to a PC exploiting the embedded Bluetooth interface. A processing chain is implemented for each sEMG channels, composed by [13] (i) a 50 Hz notch filter for powerline interference cancellation, (ii) a 20 Hz highpass filter for baseline noise reduction, and (iii) the root mean square (RMS) value of the signal was computed over a 200ms running window.

2) *Wearable Vibrotactile Bracelet*: The operator was provided with a skin stimulation produced by means of a vibration

¹<http://www.oymotion.com/>

motor. In particular, a Grove vibration motor – by Seeed Technology Co.² – was embedded within a wearable bracelet applicable on the upper arm (see Fig. 2(a)-(c).) The vibration motor was controlled via a Seeeduino V4.2 board², (Fig. 2(a).) The motor vibration intensity could be modulated according to a range of integer values from 100 to 255.

3) *Collaborative Robot System and Control*: As robotic manipulator we used the Panda robot, a 7-DoF manipulator recently commercialized by Franka Emika GmbH³ (Fig. 2(f).) The Panda robot was equipped with a parallel gripper end-effector from SCHUNK GmbH & Co.⁴, see Fig. 2(e). Furthermore, a 6-axis force sensor (ATI Industrial Automation⁵, see Fig. 2(d)) was placed at the base on the end-effector by means of a custom 3D-printed intermediate flange.

The kinesthetic teaching required for the manipulator to provide a low impedance interface between the user and the controlled arm. To this purpose a force control loop was implemented. Let's consider the Franka Emika Panda dynamic model, described by [20]

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + g(q) = \tau + J^T(q)\vec{F}_h \quad (1)$$

where $M(q) \in \mathbb{R}^{n \times n}$ is the inertia matrix, $C(q, \dot{q}) \in \mathbb{R}^{n \times n}$ the Coriolis matrix, $g(q) \in \mathbb{R}^n$ the gravitational term. $J^T(q)$ represent the manipulator Jacobian and $q \in \mathbb{R}^n$ is the joint vector. The response of the system is determined by the external action imposed by the user \vec{F}_h and the control vector τ characterized by three actions: the Coriolis and gravity compensation $\hat{C}(q, \dot{q}) + \hat{g}(q) \in \mathbb{R}^n$, the orientation control τ_o and the friction compensation τ_r

$$\tau = \hat{C}(q, \dot{q}) + \hat{g}(q) + \tau_o + \tau_r \quad (2)$$

The non-linear dynamics compensation allowed for easy reconfiguration and guidance of the arm according to the user specific task. Its estimation is provided in real-time from the Franka Emika Panda internal controller.

The orientation control action imposed a fixed orientation to the robot tool for the task. In particular the end effector approach direction was kept perpendicular to the horizontal plane. This choice allowed a simplified control scenario aimed at abstracting the user from the motion control of the arm with respect to the task under execution. An impedance dynamics, controlled in real-time and adjusted according to the user sensibility, was considered:

$$\tau_o = J_r^T(-K_s e_o - K_d J_r \dot{q}). \quad (3)$$

The matrices K_s and K_d represent the stiffness and damping gain matrix respectively, e_o the orientation error and J_r the rotational Jacobian.

The friction compensation implemented a correction to unmodelled friction effects exploiting the filtered measurements of the 6-axis force sensor mounted on the end effector.

$$\tau_r = J^T(F_t T_{res}) \quad (4)$$

The low pass filter F_t allowed to reject high frequency vibrations induced by the motors and by the elasticity of the

gripper structure whereas the measured torque T_{res} provided a real-time estimation of the occurring frictional effects.

C. sEMG-driven Co-Contraction Estimation and Vibrotactile Bio-Feedback

1) Generative Model of Antagonistic Muscle Activations:

We are interested in exploiting the sEMG measurements from the gForcePRO armband described in the previous subsection, in order to estimate the level of hand muscles co-contraction. Let us consider the RMS value of the online 8-channel sEMG acquisition $E(t) \in \mathbb{R}^{8 \times 1}$. This multidimensional biological signal can be seen, at each time instant, as the product of a *muscular synergy matrix* $M \in \mathbb{R}^{8 \times n}$ and the neural drives $U(t) \in \mathbb{R}^{n \times 1}$ [21], where $n = 2$ denotes the number of muscular antagonistic activations that generate the hand stiffening. Then, the sEMG activity $E(t)$ can be expressed as:

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

in which M and $U(t)$ are unknown, whereas $E(t)$ is available from the gForcePRO sEMG armband. In other words, in considering eq. (5) we use the concept of muscle synergies to model the sEMG activity as the modulation of supraspinal neural drives – i.e. the matrix $U(t)$ in eq. (5) – through the muscular synergistic weights – i.e. the matrix M in eq. (5) (refer to [21] for details.) Recalling that we are interested in extracting the level of co-contraction related to the stiffening of the hand, we exploit the concept of human antagonistic actuation [22], according to which the stiffening of human joints is realized by two antagonistic muscle activations. Following this concept, it is then possible to consider two hand flexion and extension antagonistic actions, corresponding to two groups of antagonistic muscles that generate the sEMG activity. In this relation, we also consider two neural drives for each antagonistic action. We can therefore write the the unknown matrices M and $U(t)$ in eq. (5) as

$$M = [s_{\text{ext}} \ s_{\text{flex}}], \quad U(t) = \begin{bmatrix} u_{\text{ext}}(t) \\ u_{\text{flex}}(t) \end{bmatrix}, \quad (6)$$

where $s_{\text{ext}}, s_{\text{flex}} \in \mathbb{R}^{8 \times 1}$ are the extension and flexion components of the muscular synergy matrix and $u_{\text{ext}}(t), u_{\text{flex}}(t) \in \mathbb{R}$ are the extension and flexion components of the neural drives. Equations (6) and (5) represent the sEMG generative model of the hand antagonistic muscle activations. Since U in eq. (6) represents the neural drives that activate the hand extension and flexion groups of antagonistic muscles, its components can be considered for the estimation of the level of co-contraction (i.e. the simultaneous activation of muscular antagonistic actions), as reported in the following.

2) *Offline Muscular Synergy Matrix Estimation*: In order to online compute the operator's co-contraction level during kinesthetic teaching tasks, first of all it is necessary to estimate the muscular synergy matrix introduced in the generative model of the previous subsection. This is addressed offline by performing a fast calibration session as explained in the following. The operator is asked to execute a simple motion, consisting in closing and opening her hand (i.e. flexion and extension finger motions) two times with minimal hand stiffening, followed by two additional closing and opening

²<https://www.seeedstudio.com/>

³<https://www.franka.de/>

⁴<https://schunk.com/>

⁵<https://www.ati-ia.com/>

motions while stiffening the hand as much as possible –i.e. at a subjective maximum acceptable level (see Fig. 3.) During the execution of these four closing and opening hand motions, the sEMG signals are recorded and collected in a matrix $E_{\text{offline}} \in \mathbb{R}^{8 \times d}$, corresponding to the d data samples of muscle activity during the calibration session. In this way a recoding containing sEMG information produced by antagonistic flexion/extension activation is obtained for minimal and maximal hand stiffening in different opening/closing configurations. A block scheme of the calibration session is shown in the top part of Fig. 3.

Therefore, recalling eqs. (6) and (5), E_{offline} can be considered as given by the expression

$$E_{\text{offline}} = MU_{\text{offline}}, \quad (7)$$

with

$$M = [s_{\text{ext}} \ s_{\text{flex}}], \quad U_{\text{offline}} = \begin{bmatrix} u_{\text{ext}}^T \\ u_{\text{flex}}^T \end{bmatrix}, \quad (8)$$

where $U_{\text{offline}} \in \mathbb{R}^{2 \times d}$ is the matrix of the offline neural drives. Note that the extension and flexion components $u_{\text{ext}}, u_{\text{flex}} \in \mathbb{R}^{d \times 1}$ are not a function of time in this case. Taking into account (7), M and U_{offline} are computed by applying to E_{offline} the unsupervised factorization algorithm Non-negative Matrix Factorization (NMF)⁶. In this way, M is now available for being used during the online co-contraction estimation as explained in the next subsection. Note that the usage of NMF allows to weight the sEMG channels without the necessity of a precise positioning of the sensors on the forearm, and to avoid empirical procedures. Differently, U_{offline} is used only offline in order to compute the scaling parameters k_{ext} and k_{flex} for the online neural drives $u_{\text{ext}}(t)$ and $u_{\text{flex}}(t)$, respectively, according to

$$k_{\text{ext}} = \frac{\sum_{i \in S} u_{\text{ext}_i}}{d_S}, \quad k_{\text{flex}} = \frac{\sum_{i \in S} u_{\text{flex}_i}}{d_S}, \quad (9)$$

where u_{ext_i} and u_{flex_i} are the i -th sample of u_{ext} and u_{flex} , and S is the set denoting the d_S samples only related to the part of the hand opening/closing calibration motion executed by stiffening the hand (refer also to Fig. 3.) Incidentally, note that maximum and minimum co-contraction levels are not related necessarily to the open and close hand configurations only.

3) *Online Co-Contraction Estimation and Bio-Feedback:* Once the calibration session is concluded, the muscular synergy matrix is available for the online co-contraction level estimation (see the bottom part of Fig. 3.) It is therefore possible to compute its pseudo-inverse M^+ to online estimate the neural drives as

$$U(t) = M^+ E(t). \quad (10)$$

Subsequently, using the scaling parameters obtained in the calibration session as described in (9), the antagonistic activations are derived as:

$$a_{\text{ext}}(t) = u_{\text{ext}}(t)/k_{\text{ext}}, \quad a_{\text{flex}}(t) = u_{\text{flex}}(t)/k_{\text{flex}}, \quad (11)$$

⁶Given a nonnegative matrix $A \in \mathbb{R}^{m \times n}$ (a matrix whose elements are all non negative), the product WH is called nonnegative matrix factorization of A if nonnegative 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 [23].

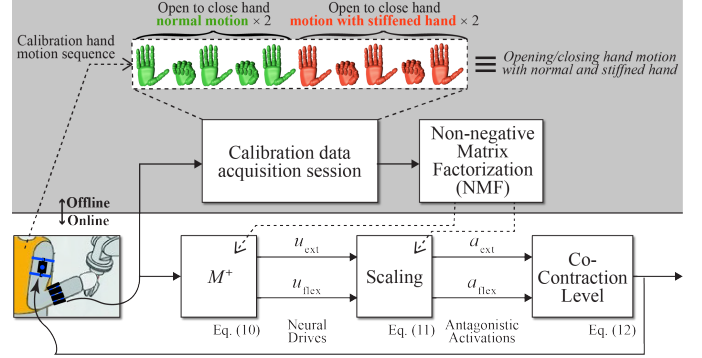


Fig. 3. sEMG-driven co-contraction estimation and bio-feedback.

and, finally, the online co-contraction level $\gamma(t)$ is computed according to

$$\gamma(t) = \min(a_{\text{ext}}(t), a_{\text{flex}}(t)). \quad (12)$$

Then, in order to provide the bio-feedback to the user, the co-contraction level needs to be mapped in the input range of values of the wearable vibrotactile motor. This specific step is described in detail in the next section.

III. EXPERIMENT

A. Experimental Task and Protocol Description

1) *Subjects:* For the evaluation of the co-contraction augmented teaching, we engaged 10 healthy participants (1 female, age: 25, and 9 males, age: 30.5 ± 4 – right handed: 8 sbjs., left handed: 2 sbjs.) They will be here referred to as S1, S2, ..., S10. The subjects had no previous experience with the setup and sEMG-measured co-contraction before the experiment. The experiment was performed in accordance with the Declaration of Helsinki and all participants were thoroughly informed about the experimental protocol and were asked to sign an informed consent form.

2) *Cable Routing and Connection Baseline Task:* The experimental protocol was designed exploiting a specific cable routing and connection task, using a simplified switchgear setup visible in Fig. 4 and described at the beginning of this section. Looking at the Fig. 4(c), the subjects were required to: (i) pick up the first cable extremity from the cable storage location T1; (ii) carry the cable in order to insert the cable connector into the connection T2; (iii) move to T3 in order to pick up the second cable extremity; (iv) carry the cable realizing a routing through the cable channel situated between the locations T4 and T5; and, finally, (v) move to T6 in order to perform the final insertion of the connector into the switchgear component.

On this basis, each subject was asked to perform specific co-contraction modulations with vibrotactile bio-feedback. This was performed according to two different sessions of augmented kinesthetic teaching evaluation (each one performed one time by each subjects): (i) modulation of the co-contraction according to target reference bands, receiving a continuous bio-feedback, and (ii) modulation of the co-contraction in order to activate the gripper opening, receiving a threshold-enabled bio-feedback. During the augmented kinesthetic teaching, the subjects were specifically instructed to use the hand with sEMG sensors for guiding the robot (they were also allowed to use both hands.) After that the calibration

phase was completed and before of each experimental session, the subjects performed a practice session of 10 minutes in order to freely familiarize with the system, without instructions provided by the experimenter.

3) *Reference Band Co-Contraction Modulation*: In this first session, the subjects had to modulate the co-contraction in order to match predefined reference bands. In particular, the co-contraction level had to be modulated within target reference bands at instructed locations and/or during specific actions while physical guiding of the robot end-effector, according to the previously described cable routing and connection baseline task. In detail, two reference bands were defined: (i) a lower reference band, between the values 0.5 and 0.6 of the (normalized) co-contraction level, and (ii) a higher reference band, between the values 0.8 and 0.9 of the (normalized) co-contraction level. Specifically, the subject where required to match the higher reference band during the cable picking at T1, cable insertion at T2, cable picking at T3 and cable insertion at T6 (i.e. during six actions/locations of the baseline task.) Differently, the lower reference band was asked to be matched during the cable routing between T4 and T5 inside the cable channel. For the remaining operations during the baseline task (i.e. moving from T1 to T2, from T3 to T4 and from T5 to T6), the subjects were asked to generate the minimum possible co-contraction. Importantly, the vibrotactile bio-feedback signal $\beta(t)$ provided to the subjects a stimulation intensity proportional to the error between the current co-contraction value and the target reference band, that is:

$$\beta(t) = \begin{cases} (r_{\max} - r_{\min}) \frac{e_{\inf}(t)}{b_{\inf}} + r_{\min}, & \text{if } \gamma(t) < b_{\inf} \\ 0, & \text{if } b_{\inf} \leq \gamma(t) \leq b_{\sup} \\ (r_{\max} - r_{\min}) \frac{e_{\sup}(t)}{b_{\sup}} + r_{\min}, & \text{if } \gamma(t) > b_{\sup} \end{cases} \quad (13)$$

where r_{\max} and r_{\min} are the maximum and minimum values of the vibrotactile motor input range, $\gamma(t)$ is the co-contraction level introduced in (12), $e_{\inf} = |\gamma(t) - b_{\inf}|$, $e_{\sup} = |\gamma(t) - b_{\sup}|$ and b_{\inf} , b_{\sup} are the lower and upper limit of the reference bands. In particular, the latter were set as $b_{\inf} = 0.5$, $b_{\sup} = 0.6$ for the lower reference band, and $b_{\inf} = 0.8$, $b_{\sup} = 0.9$ for the higher reference band by the experimenter during the experimental sessions (the subscripts \inf and \sup stay for “inferior” and “superior”). According to (13), the subjects felt a bio-feedback vibration proportional to the error between the actual co-contraction and the target reference band. Therefore, they were asked to bring the vibrotactile stimulation to zero during the kinesthetic teaching of the cable routing and connection task, when instructed by the experimental protocol described above. The opening and closing of the parallel gripper were instructed by the subjects using a simple vocal command.

4) *Gripper Activation Co-Contraction Modulation*: In this second session, the subjects were asked to use the co-contraction to activate the opening of the parallel gripper. In particular, if the (normalized) co-contraction level was modulated above an activation threshold of 0.5, the gripper open, otherwise it remained closed (i.e. a normally closed gripper functioning was adopted.) Consequently, the subjects had to activated the gripper opening during the cable picking

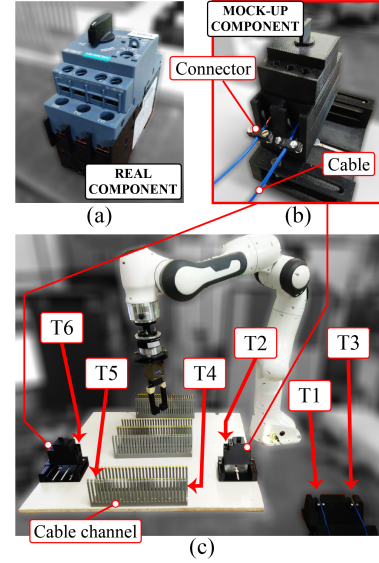


Fig. 4. Simplified switchgear setup.

at T1, cable releasing after the insertion at T2, cable picking at T3 and, finally, cable releasing after the insertion at T6 (i.e. during four actions/locations of the baseline task.) At the same time, it was important that the gripper remained closed during the cable routing/transportation phases, that is when moving between the locations T1 to T2, T2 to T3 and T3 to T6. In this augmented kinesthetic teaching scenario, the vibrotactile bio-feedback signal $\beta(t)$ was also modulated according to the same activation threshold, described by

$$\beta(t) = \begin{cases} (r_{\max} - r_{\min}) \frac{e_{\text{thr}}(t)}{b_{\text{thr}}} + r_{\min}, & \text{if } \gamma(t) > b_{\text{thr}} \\ 0, & \text{if } \gamma(t) \leq b_{\text{thr}} \end{cases} \quad (14)$$

where $e_{\text{thr}} = |\gamma(t) - b_{\text{thr}}|$, b_{thr} is the threshold value for the activation of the gripper opening and the remaining notation has been already introduced in (13). In particular, the threshold was set as $b_{\text{thr}} = 0.5$, in accordance to the experimental protocol specified above.

B. Results

1) *Reference Band Co-Contraction Modulation*: First of all, we report in Fig. 5 the end-effector trajectories taught to the robot by the different subjects, projected in the $x - y$ plane for clarity of visualization. In particular, in Fig. 5, the task locations T1—T6 previously introduced are highlighted with red circles. As expected, it is possible to observe that all subjects performed similar trajectory teachings. We then report the results specifically concerning the modulation of the co-contraction level according to the reference bands. In particular, the results for a single subjects are reported in Fig. 6, whereas aggregated results over the ten subjects are given in in Fig. 7. Fig. 6 shows the behaviour presented by the subject S1. Specifically, it is possible to observe that the subject successfully modulated the co-contraction level during the kinesthetic teaching of the robot. In particular, the higher reference band (red dashed lines in Fig. 6) was matched in the gray-coloured zones related to the task locations T1, T2, T3, T4-to-T5 and T6 as requested by the instructed experimental protocol (see in Fig. 4), presenting only small oscillations around the requested target. Also the lower reference band

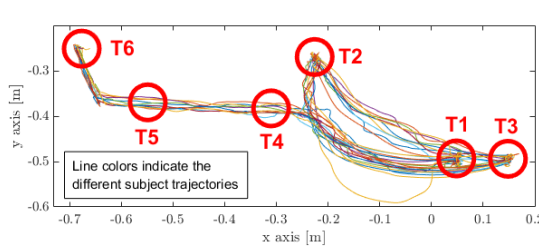


Fig. 5. Robot trajectories for the reference band experiment.

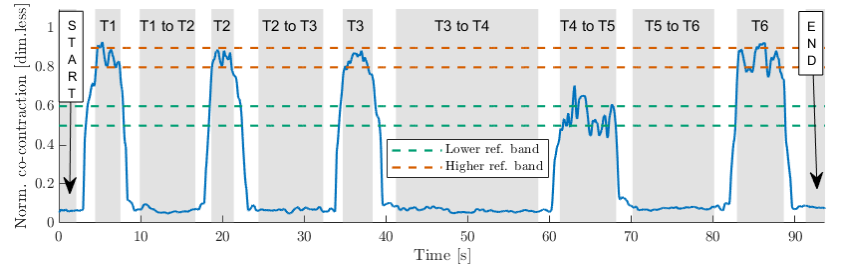


Fig. 6. Co-contraction modulation for the subject S1 during the reference bands experiment.

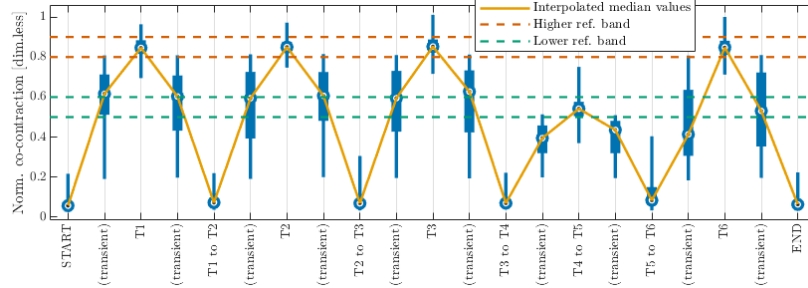


Fig. 7. Aggregated results over the subjects for the reference bands experiment.

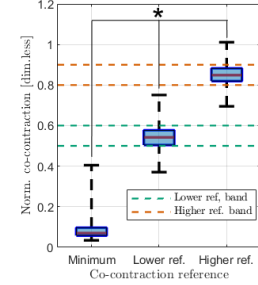


Fig. 8. Boxplot for the reference bands experiment. “*” indicates statistical significance.

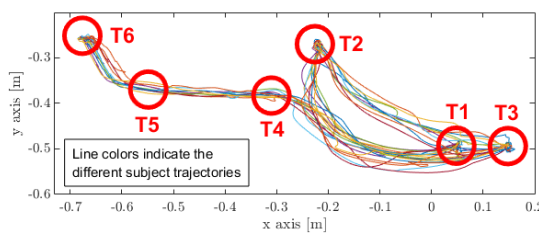


Fig. 9. Robot trajectories for the gripper activation experiment.

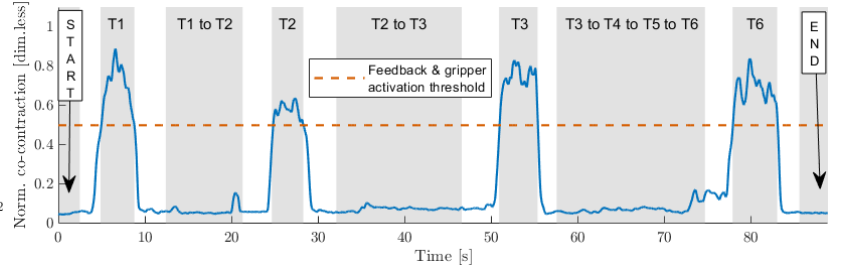


Fig. 10. Co-contraction modulation for the subject S1 during the gripper activation experiment.

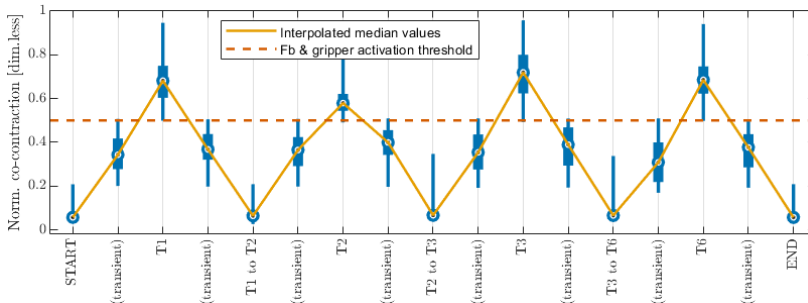


Fig. 11. Aggregated results over the subjects for the gripper activation experiment.

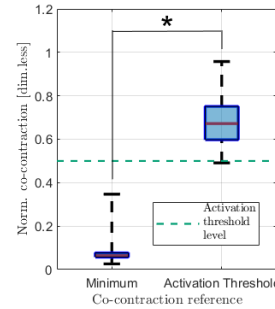


Fig. 12. Boxplot for the gripper activation experiment. “*” indicates statistical significance.

(green dashed lines in Fig. 6) was successfully achieved by the co-contraction modulation during the cable routing through the cable channel (gray-coloured zone related to the task locations T4-to-T5.) Additionally, the co-contraction level was correctly limited above the lower reference band (at possible minimum level) during the movements between task locations (gray-coloured zones T1-to-T2, T2-to-T3, T3-to-T4 and T5-to-T6.) Differently, the white-coloured zones in Fig. 6 indicate the *transient* part of the co-contraction modulation, that is the parts in which the subject was approaching the task zones where different reference bands were requested. We therefore

considered this parts differently, in order to evaluate subjects' rise times in achieving the target bands, as reported in the following of this section. In Fig. 7, the aggregated results over the ten subjects for the reference bands experiment are reported. The different data have been grouped by means of boxplots related to the same zones highlighted in Fig. 6. From the boxplots it is possible to see that all subjects matched the co-contraction reference bands as instructed. Only small errors can be observed around the targets. In particular, in Fig. 7, by looking at the yellow line interpolating the median values of the ten subjects' co-contraction, it is clear that all subjects

showed a behaviour totally similar to the one reported from the subject S1 in Fig. 6. A maximum error of 0.12 and 0.18 was reported for the higher and lower reference bands, respectively (without considering the transient zones.) A statistical analysis has been performed on the data reported in Fig. 8, in which the co-contraction modulations were further grouped according to the different requested reference levels to be matched – i.e., minimum, lower band, higher band. In particular, a one-way repeated measures Analysis of Variance (ANOVA) was conducted. The statistical significance was set to $p < .001$. The Shapiro-Wilk test for normality check and Mauchly's test for sphericity check were performed, reporting that the ANOVA assumptions were not violated. The result of the ANOVA revealed that the level of co-contraction modulated by the subjects in case of minimum, lower band and higher reference bands were all statistically significantly different, $F(2, 6) = 63.15$ and $p < .001$. This means that all subjects were actually able of producing significantly different levels of the provided augmented teaching signal, as instructed.

2) *Gripper Activation Co-Contraction Modulation*: Fig. 10 reports the single subject results for this evaluation session (subject S1.) In detail, the co-contraction level was brought over the gripper activation threshold (red dashed lines in Fig. 10) in the gray-coloured zones related to the task locations T1, T2, T3 and T6. This successfully allowed to teach to the robot the required cable grasping and releasing actions. At the same time, during gray-coloured zones in Fig. 10 related to the movements between the task locations T1-to-T2, T2-to-T3 and T3-to-T4-to-T5-to-T6, the co-contraction level was correctly maintained under the gripper activation threshold (at possible minimum level) preserving the cable from falling during the routing and transportation phases. Also in Fig. 10, the white-coloured zones indicate the *transients*, in which the subject was approaching or leaving a task zones.

Also the aggregated results show a behaviour that is very similar to the one reported for subject S1. This can be clearly observed looking at the boxplot reported in Fig. 11. In Fig. 12, the co-contraction data were grouped in relation to the request of a minimum co-contraction level or an activation of the gripper. A one-way repeated measures ANOVA was conducted. The statistical significance was set to $p < .001$. ANOVA assumptions were verified by Shapiro-Wilk test for normality and Mauchly's test for sphericity. The result of the ANOVA revealed that the co-contraction modulations in case of a minimum level or a gripper activation level were all statistically significantly different, $F(1, 9) = 24.62$ and $p < .001$. The subjects were therefore able of modulating significantly different levels of co-contraction in order to teach the gripper opening/closing during the robot end-effector physical guidance.

Lastly, Tab. I reports the results of a questionnaire qualitatively evaluating the outcomes Perceived Ease of Use (PE), Perceived Usefulness (PU), Emotions (E) and Comfort (C). The subjects rated seven statements (Tab. I) with regard to the “reference band” and “gripper activation” experimental sessions, on a Likert scale from 1 (entirely disagree) to 7 (entirely agree.) All the average scores computed over the subjects were greater than 6, except for the statement C2

in which the score was no lower than 5 (see Tab. I). This shows a preliminary, qualitative positive evaluation on the overall system and aspects such as ease of modulating co-contraction, general experience with this specific augmented kinesthetic teaching, preference of co-contraction modulation with respect to voice commands for the control of the gripper and interpretability of the vibrotactile feedback (also in relation to the location on the upper arm.) The lower score for statement C1 likely highlights that the ease of co-contraction modulation change with duration, and future work will be dedicated to deeper study the behaviour of muscle signals and co-contraction modulation during longer muscle activations.

IV. DISCUSSION AND CONCLUSIONS

The major benefit of the proposed augmented kinesthetic teaching paradigm is related to the fact that the augmented teaching information can be provided by the operator independently from the generation of human net forces/motions. Conversely, a different method of providing augmented teaching information such as using a button located on the robot (as it is also provided by default in the Franka Panda robot) would require specific force/pressure to the operator, with the hand constrained in a predefined location.

Furthermore, the proposed approach also open the possibility for future developments in which the muscle co-contraction can be interpreted by the robotic system from a human intent detection point of view, since humans modulate co-contraction also in relation to the accuracy and velocity of their limb motions.

In relation to the commands that the users can provide to the robot, we would like to highlight that, with the proposed approach, the augmented teaching information can be used for communicating to the robot both continuous commands (e.g. in order to teach the modulation of dynamic parameters such as impedance, or geometric parameters such as for optimization of trajectories), or discrete commands by applying thresholds to the co-contraction signal (as for the experiment of controlling the activation of the gripper in this study.) On the other hand, further studies need to be performed to investigate the ability of the users in freely providing commands, that is without the request of matching a target reference. To evaluate this aspect, future experimentations will be dedicated to test how accurately the users are able to autonomously distinguish between different bio-feedback vibration levels, and specific experimentation will be dedicated to this aspect in future work.

Finally, future work will also investigate the class of kinesthetic teaching tasks for which the modulation of co-contraction results as statistically significantly more challenging. If we are able to identify such “difficult” tasks, it can be possible to limit the use of our method only to the part of the kinesthetic teaching where the co-contraction is easier or, alternatively, use the vibrotactile feedback itself to make the user aware of the possibility of increased difficulty, such that her can decide whether to perform the kinesthetic teaching in a different manner, or with additional attention/mental effort. Another possibility would also be to limit the co-contraction modulation to a discrete set of commands (e.g. on-off commands by means of low contraction vs. high co-

TABLE I
QUALITATIVE EVALUATION OF USER EXPERIENCE. SCORES: LIKERT SCALE FROM 1 (ENTIRELY DISAGREE) TO 7 (ENTIRELY AGREE.)

Outcome type		Questionnaire	"Reference Band" Average Score (\pm Std. deviation)	"Gripper Activation" Average Score (\pm Std. deviation)
Perceived ease of use	PE1	<i>It was easy to modulate the co-contraction during the kinesthetic teaching.</i>	6 \pm 0.94	6 \pm 0.47
	PE2	<i>The provided vibrotactile feedback was easy to interpret to the aim of co-contraction modulation.</i>	6.4 \pm 0.52	6.6 \pm 0.63
	PU1	<i>I think the system allows to modulate co-contraction for augmented kinesthetic teaching tasks.</i>	6.2 \pm 0.63	6 \pm 0.81
Perceived usefulness	PU2	<i>I preferred controlling the gripper with co-contraction modulation than voice commands.</i>	n.a.	6 \pm 0.52
Emotions	E1	<i>I liked to modulate the co-contraction using the system during kinesthetic teaching.</i>	6.2 \pm 0.63	6.4 \pm 0.52
	C1	<i>It was appropriate to have the vibrotactile feedback on the upper arm instead of the forearm.</i>	6 \pm 0.52	6.2 \pm 0.63
Comfort	C2	<i>It was easy to modulate the co-contraction regardless of the duration of the required regulation.</i>	5.4 \pm 0.7	5.6 \pm 0.51

contraction levels) for the tasks in which a fine, continuous modulation would be too challenging.

In conclusion, in this work, a human-robot interaction system has been presented, with the aim of realizing an augmented kinesthetic teaching for robot programming. In particular, the proposed approach was based on an estimation of the forearm muscles co-contraction using sEMG measurements, and a vibrotactile bio-feedback. Ten subjects were involved in an experiment consisting in physical demonstrating the end-effector trajectory of a 7-DoF collaborative manipulator, for executing a cable routing and connection task on a simplified switchgear setup. In this experimental scenario, two different evaluation sessions were performed, in order to assess both the ability of modulating the co-contraction according to target references, and the ability of modulating the co-contraction for programming the opening/closing of the robot gripper while executing kinesthetic teaching. The results show that all subjects were able to successfully modulate the co-contraction matching target references, and intuitively teach robot grasping actions. The results are supported by statistical significance. The reported positive outcomes allow for future work and developments. First of all, we will improve the co-contraction estimation using multiple sEMG sensors in different arm locations, and we will deepen the study about the actual role of the vibrotactile feedback. Also deeper investigations about the effect of physical robot guidance and muscle fatigue on co-contraction estimation/modulation will be carried out. The results obtained in the present pilot work provide positive perspectives and can pave the way for a new generation of advanced robot programming.

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