

Robot Kinesthetic Teaching Enhanced by sEMG-based Estimation of Muscle Co-Contraction and Bio-Feedback

Roberto Meattini, Davide Chiaravalli, Gianluca Palli and Claudio Melchiorri

Abstract—sEMG signals are exploited for unsupervised estimation of the co-contraction level of forearm’s muscles. In this way, by also exploiting a feedback based on a vibrotactile bracelet, the ability of operators in stiffening their hand was evaluated during kinesthetic teaching, in order to regulate the estimated co-contraction level to (i) match reference levels and (ii) activate the opening/closing of a gripper, i.e. in using their myoelectric signals enhance robot kinesthetic teaching operations. Experiments were carried out. The results provide positive outcomes on the intuitiveness and effectiveness of the proposed system and approach.

Index Terms—Human-Centered Automation.

I. INTRODUCTION

In this work an enhanced kinesthetic teaching system that uses information obtained from sEMG signals is proposed. The sEMG signals are exploited to estimate the operator’s hand muscles co-contraction during physical guidance of the robot trajectory. In particular, the estimation is based on an unsupervised calibration, that requires a small amount of sEMG data without labelling operation. Furthermore, we give to the operator a vibrotactile bio-feedback modulated in accordance to the actual modulated level of muscle co-contraction.

II. METHODS AND EXPERIMENTS

A. Generative Model of Antagonistic Muscle Activations

We are interested in exploiting the sEMG measurements from a gForcePRO armband (Fig. 1) 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 $U(t) \in \mathbb{R}^{n \times 1}$ [1], 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:

$$E(t) = MU(t), \quad (1)$$

in which M and $U(t)$ are unknown, whereas $E(t)$ is available from the gForcePRO sEMG armband.

This work was partially supported by the European Commission’s Horizon 2020 Framework Programme with the project REMODEL under grant agreement No. 870133.

The authors are with the Dept. of Electrical, Electronic and Information Engineering (DEI) of the Univ. of Bologna, Bologna, Italy. E-mails: roberto.meattini2@unibo.it, davide.chiaravalli2@unibo.it, gianluca.palli@unibo.it, claudio.melchiorri@unibo.it.

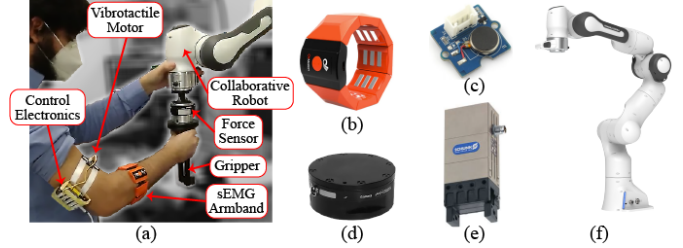


Fig. 1. (a) The augmented kinesthetic teaching setup of the present work. (b) gForcePRO sEMG armband. (c) Groove vibration motor. (d) ATI 6-axis force sensor. (e) SCHUNK parallel gripper. (f) Franka Emika Panda collaborative robot.

B. Offline Muscular Synergy Matrix Estimation

Recalling eq. (1), E_{offline} can be considered as given by the expression

$$E_{\text{offline}} = MU_{\text{offline}}, \quad (2)$$

where, M and U_{offline} are computed by applying to E_{offline} the unsupervised factorization algorithm Non-negative Matrix Factorization (NMF)¹. 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

$$k_{\text{ext}} = \frac{\sum_{i \in S} u_{\text{ext}_i}}{d_S}, \quad k_{\text{flex}} = \frac{\sum_{i \in S} u_{\text{flex}_i}}{d_S}, \quad (3)$$

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 a hand opening/closing calibration motion executed by stiffening the hand.

C. Cable Routing and Connection Baseline Task

The experimental protocol was designed exploiting a specific cable routing and connection task. The subjects were required to: (i) pick up the first cable extremity from the cable

¹Given 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 [2].

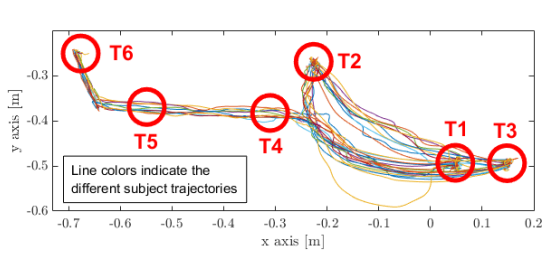


Fig. 2. Robot trajectories for the reference band experiment.

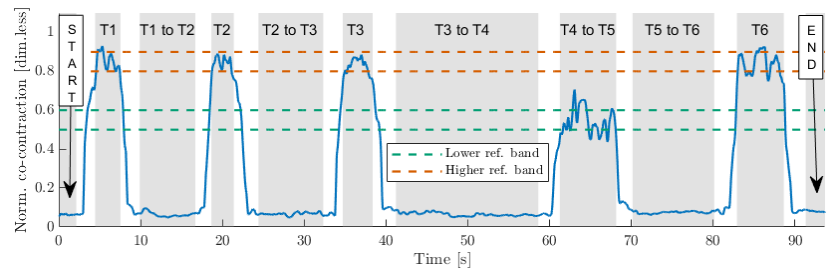


Fig. 3. Co-contraction modulation for the subject S1 during the reference bands experiment.

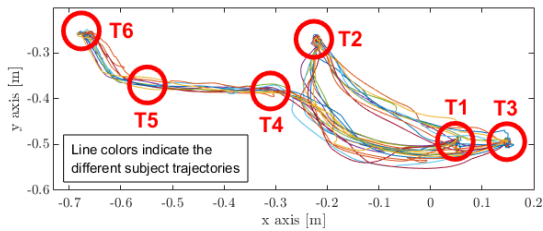


Fig. 4. Robot trajectories for the gripper activation experiment.

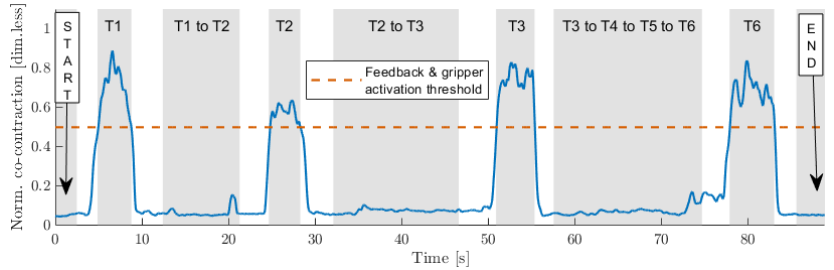


Fig. 5. Co-contraction modulation for the subject S1 during the gripper activation experiment.

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.

D. Results

1) *Reference Band Co-Contraction Modulation*: First of all, we report in Fig. 2 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. 2, 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. 3. It is possible to observe that the subject successfully modulated the co-contraction level during the kinesthetic teaching of the robot.

2) *Gripper Activation Co-Contraction Modulation*: Fig. 5 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. 5) 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. 5 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.

III. CONCLUSIONS

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.

REFERENCES

- [1] N. Jiang, K. B. Englehart, and P. A. Parker, "Extracting simultaneous and proportional neural control information for multiple-dof prostheses from the surface electromyographic signal," *IEEE transactions on Biomedical Engineering*, vol. 56, no. 4, pp. 1070–1080, 2008.
- [2] M. W. Berry, M. Browne, A. N. Langville, V. P. Pauca, and R. J. Plemmons, "Algorithms and applications for approximate nonnegative matrix factorization," *Computational statistics & data analysis*, vol. 52, no. 1, pp. 155–173, 2007.