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Effects of Decomposition Parameters and Estimator Type on Pseudo-Online Motor Unit Based Wrist Joint Angle Prediction

Dennis Yeung, Francesco Negro, and Ivan Vujaklija

Abstract—**The decomposition of HD-EMG into motor unit (MU) discharge timings permit a detailed window into the motoneuronal manifestation of motor intent. Recently, the feasibility of MU-driven wrist joint angle estimation was preliminarily demonstrated although the influences of certain parameter selections have yet to be fully investigated. Here, a decomposition algorithm was used to predict wrist joint kinematics over three DoFs in a pseudo-online manner. Three separate estimator types were tested and the effects of two key parameters on their prediction accuracies were studied: the decomposition extension factor and process window length. Pre-recorded EMG from four able-bodied subjects was decomposed in a simulated real-time manner as to permit parameter scanning, with the tested estimators being linear regression (LR), linear discriminant analysis (LDA), and LDA with LR for proportionality control (LDA-LR). Results showed the best performing combination of parameters were an extension factor of 8 with window length of 50ms which allowed the LDA-LR estimator to yield an average R^2 value of 0.86±0.05. Under the most computationally demanding set of parameters, the median processing time of the algorithm on a desktop computer was 47ms which was within the update rate of the proposed system. Such results also indicate that parameters optimal for online control applications deviate from those ideal for offline physiological studies.**

I. Introduction

MOTOR unit (MU) discharge timings constitute the encoding for muscle activation and various techniques to extract such information via decomposition of electromyography recordings (EMG) have been proposed [1], [2]. Recently, Kapelner et al. demonstrated that the prediction of wrist kinematics can be improved using neural features extracted from high-density EMG measurements [3], however such decomposition was performed in an offline manner. Indeed, traditional decomposition methods have high computation overheads that restrict their application to mainly offline studies, though efforts have been made to address this issue [4]. In particular, Barsakcioglu & Farina proposed a system capable of extracting activity from five MUs in the forearm for real-time control of a hand prosthesis with on/off control of 4 device functions [5].

In this study, a similar approach for online decomposition was implemented for the continuous estimation of wrist kinematics. The estimation was done in pseudo-real time as the extraction of neural information was processed in a windowed manner to simulate a real-time application. We compared the performance of three estimators: linear regression (LR), linear discriminate analysis (LDA) with cumulative spike counts used for proportionality control, and LDA with class-specific LR for proportionality (LDA-LR). LR acts as a simple regressor, LDA is a well-established myocontrol classifier, whereas LDA-LR aims to combine the intrinsic proportional capabilities of LR and the clear motion distinction of LDA. The effects of the decomposition extension factor (R) and the window length (WL) across the three estimators were also analyzed by scanning a range of settings. R influences the quantity of sources that are identified while WL affects system responsiveness with both parameters contributing to process computation overhead.

II. Methods

A. Experiment Setup and Protocol

Four healthy right-handed males, aged 28-33, participated in the study approved by local ethical board of Aalto University. They all provided written informed consent. HD-EMG was recorded from each subject's dominant side with three 8x8 electrode matrices spaced evenly around the bulk of the forearm, sampled at 2048Hz by a benchtop bioamplifier (OT Bioelettronica, IT). Wrist joint angles were recorded by three wireless Inertial Measurement Units (IMUs) (Xsens Technologies B.V, NL) attached to the posterior sides of the upper-arm, lower forearm and hand.

Subjects performed three repetitions of six wrist motor tasks following trapezoidal activation profiles with 2s up/down ramps and 10s plateaus: flexion/extension (DoF1+/DoF1-), radial/ulnar deviation (DoF2+/DoF2-) and pronation/supination (DoF3+/DoF3-) with the data being segmented into three folds of train/test sets. A framework developed by Negro et al. [6] was employed for batch decomposition of the train set EMG and the resultant decomposed spike count (DSC) features were used to train the estimators. The online decomposition algorithm was then used to extract DSC features from the test set for kinematics estimation. To simulate a real-time application, test set data was processed in windows which advanced in steps of 50ms. For WL values beyond 50ms, this resulted in overlaps of 50-450ms between consecutive windows.

B. Pseudo-Online Decomposition and Estimation

The proposed online algorithm alleviates the

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computational requirements of blind source extraction by relying on properties obtained from prior decomposition of the training set. From the batch method, underlying sources of the EMG were identified through the optimization of a set of separation vectors:

$$\mathbf{S}(t) = \mathbf{B}^{\top}\,\underline{\mathbf{W}}\,\underline{\mathbf{X}}(t) \tag{1}$$

Where $\mathbf{S}(t)$ is the set of sources, $\mathbf{B}$, the bank of matched filters, $\underline{\mathbf{W}}$, the whitening matrix and $\underline{\mathbf{X}}$, the extended zero-meaned EMG. Here, $\mathbf{B}$ and $\underline{\mathbf{W}}$ matrices for each motor task were first obtained from their respective training sets via the batch method. These were then applied by the online algorithm to extract source signals from the test data. Peaks detected in these source signals were then accepted as spikes if they fell within their respective cluster limits from the original decomposition of the train set.

III. Results

The number of MUs extracted from each motor task, averaged across all subjects, is shown in Fig.1. As R was increased, the number of identified MUs also increased although this trend levelled off beyond R=9. Estimation with LDA-LR performed the best overall with the highest R^2 value of 0.86±0.05 from R=8 and WL=50ms. For LR, the best value was 0.83±0.6 from R=9 and WL=150ms while, for LDA, this was 0.81±0.06 from R=8 and WL=50ms. It can be seen from Fig. 2 that the parameters R and WL affected each estimator type differently. While a significant improvement was seen in all estimators by increasing R from 1 to 3, less improvement was seen from further increase of R. This may be that the additional MUs obtained with higher R values offer minimal extra information towards the joint kinematics state for this set of simple motor tasks. This also suggests that, for proportional myocontrol applications, lower R values may be used than those recommended for physiological studies [6].

WL had little effect on LR performance as large values may only contribute to the smoothness of the estimations. LDA performed poorly with larger WLs which indicates higher misclassification rates as larger spans of time were used to calculate DSC. This trend was also repeated for

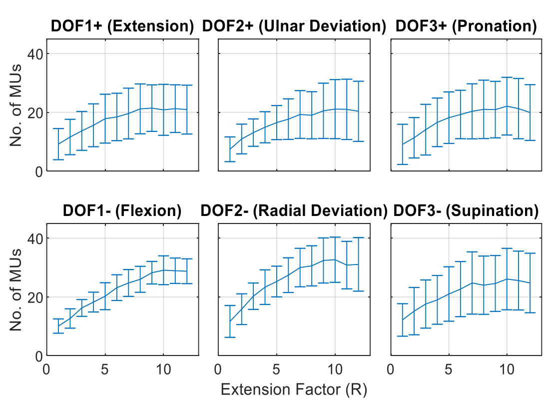

Fig. 1. Average number of MUs extracted from each motor task across all subjects.

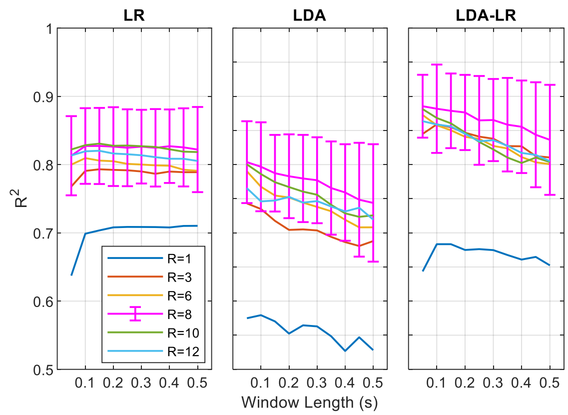

Fig. 2. Effects of R and WL on the estimation accuracies of the LR, LDA and LDA-LR estimators.

LDA-LR which improved on the naïve method for proportionality estimation used by LDA. As such LDA-LR, yielded higher and more consistent goodness-of-fit values.

The processing time of the online algorithm performed on a PC (Intel Xeon 3.60GHz 32GB RAM & MATLAB 2019a, Mathworks, USA) at the highest loads (R=13, WL=500ms) was measured and a median time of 47ms was obtained which was below the estimation update rate. It should be noted however, that further focus on code optimization would lead to even shorter process times.

IV. Conclusion

This work analyzed the effects of two key parameters for online decomposition of EMG on the estimation accuracy of wrist joint angles. While a higher decomposition extension factor led to the extraction of more MUs, the contribution of additional sources to estimation accuracy diminishes. Similarly, larger values of window length did not yield the optimal performance. The results therefore indicate that a less computationally demanding set of online decomposition parameters may be used in the case of neural data-driven control applications.

References

[1] A. Holobar and D. Farina, “Blind source identification from the multichannel surface electromyogram,” *Physiol. Meas.*, vol. 35, no. 7, pp. R143–R165, Jul. 2014.

[2] D. Farina *et al.*, “Man/machine interface based on the discharge timings of spinal motor neurons after targeted muscle reinnervation,” *Nat. Biomed. Eng.*, vol. 1, p. 25, 2017.

[3] T. Kapelner *et al.*, “Predicting wrist kinematics from motor unit discharge timings for the control of active prostheses,” *J. Neuroeng. Rehabil.*, vol. 16, no. 1, p. 47, Dec. 2019.

[4] V. Glaser, A. Holobar, and D. Zazula, “Real-Time Motor Unit Identification From High-Density Surface EMG,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 21, no. 6, pp. 949–958, Nov. 2013.

[5] D. Y. Barsakcioglu and D. Farina, “A real-time surface EMG decomposition system for non-invasive human-machine interfaces,” in *2018 IEEE Biomedical Circuits and Systems Conference (BioCAS)*, 2018, pp. 1–4.

[6] F. Negro, S. Muceli, A. M. Castronovo, A. Holobar, and D. Farina, “Multi-channel intramuscular and surface EMG decomposition by convolutive blind source separation,” *J. Neural Eng.*, vol. 13, no. 2, p. 026027, Apr. 2016.