MOTOR UNIT SUBSET SELECTION FOR SCALABLE REAL-TIME INTERFACING

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ABSTRACT

Current methods for motor unit (MU) based human-machine interfacing do not scale well with the expansion of output functionality. This is due to the high computational demands of the initial MU parameter extraction via decomposition of high-density surface electromyography recordings. We propose an alternative approach that relies on task-specific batch decomposition processes along with a MU subset selection step to address feature redundancy. Offline analyses were conducted using EMG and kinematics pertaining to 18 wrist/forearm motor tasks recorded from 11 able-bodied subjects. The mutual information-based minimal Redundancy Maximal Relevancy (mRMR) feature selection framework was tested and compared to Maximal Relevancy (MR) and two arbitrary selection methods. Subset MUs were then used for joint kinematics estimation corresponding to those 18 motor tasks by three different regressors. The mRMR selection scheme was found to retain MUs with the highest predictive power. When the portion of tracked MUs was reduced to 25%, regression accuracy decreased by only 3.5%.

INTRODUCTION

The firing times of motor neurons are the most basic unit of neural drive responsible for instigating muscle force generation. Such information could be leveraged to facilitate more intuitive and dextrous human-machine interfacing (HMI). The application of blind source separation techniques on high-density surface electromyography (EMG) recordings has been previously used to estimate the motor unit (MU) firing times embedded within the surface signal [1], [2]. Such methods have been extended to online applications which permit real-time interfacing driven by the direct firing activity of MUs. So far, this has been demonstrated in control of up to 2 Degrees of Freedom (DoFs) [3], [4].

Current methods for MU-based interfacing do not scale efficiently with the expansion of supported functionality due to the high computational demands of the initial decomposition phase. In particular, the gradient-based and fixed-point iteration methods used to optimize separation vectors scale poorly with the significant increase in data that accompanies each supported function. We propose conducting this initial extraction of MUs in a task-wise manner with separate batch processes to leverage distributed computing resources and to reduce the overall initialization time of the interface. To address the resultant redundancy in extracted sources, a MU subset selection step is implemented using feature selection techniques.

The feasibility of the proposed interfacing pipeline was analysed in cross-validation format using EMG from 18 motor tasks pertaining to the single and pair-wise combined activations of three wrist/forearm DoFs. From the train data set, MUs were identified via task-wise batch decomposition and MU subset selection was performed. The minimal Redundancy Maximal Relevancy (mRMR) feature selection scheme proposed in [5] was tested along with Maximal Relevancy (MR) and two arbitrary schemes based on randomness and MU activity. From the test data set, the activities of subset MUs were extracted with an online decomposition algorithm and used for kinematics estimation. Results using three regression algorithms: linear regression (LR), multilayer perceptron (MLP) and kernel ridge regression (KRR) were obtained. Assessment of the selection criteria was made based on the changes to open-loop estimation accuracy as subset sizes were reduced.

METHODS

Subjects

Eleven healthy subjects, seven male and four female, all right-handed, aged 26-34, participated in the experiment. The study was approved by the local ethical board of Aalto University and all participants gave their written informed consent in accordance with the Declaration of Helsinki.

Experimental Protocol

High density EMG was recorded from each subject's dominant side with three 8x8 electrode matrices spaced evenly around the bulk of the forearm. The channels were sampled at 2048 Hz by a benchtop bioamplifier (OT Bioelettronica, IT). Wrist joint angles and rotation were recorded at a rate of 80 Hz with three wireless Inertial Measurement Units (IMUs) (Xsens Technologies B.V, NL) attached to the posterior sides of the upper-arm, mid-forearm and hand. Subjects were seated upright with their recorded limb relaxed by their side. Three repetitions of single and pair-wise combinations of motions pertaining to wrist flexion/extension (FL/EX), radial/ulnar deviation (RD/UD) and forearm pronation/supination (PR/SU) were recorded with trapezoidal activation profiles of 2 s ramp time and 10 s plateau time resulting in a dataset of 18 motor tasks. Recordings and analyses were carried out using an in-house developed Matlab (MathWorks Inc, MA, USA) framework. Offline analyses were conducted in cross-validation format where the training set comprised of two repetitions of each motor task while the test data was formed from the remaining repetitions. Initial MU extraction, subset selection, and estimator training were conducted with the train set while the pseudo-online decomposition algorithm was applied to the test set to simulate the real-time interfacing.

Batch and Online Decomposition

The batch decomposition methodology employed in this work follows that of [1] while the online decomposition algorithm is based on the methods proposed in [3], [6]. In brief, the batch algorithm sequentially estimates a set of separation vectors, $\mathbf{B}$, that compensates for the action potentials of their respective MUs and de-mixes the source activities, $\mathbf{S}$, from an extended EMG, $\tilde{\mathbf{Z}}$, that has been centered and then whitened with $\mathbf{W}$:

$$\mathbf{S}_c = \mathbf{B}_c' \mathbf{W}_c \left(\tilde{\mathbf{Z}}_c - \mathrm{E}[\tilde{\mathbf{z}}_c(k)] \mathbf{1} \right) \tag{1}$$

where $\mathbf{1}$ is a vector of ones of appropriate size, subscript $c \in \{1, \dots, C\}$ denotes the enumerated coding of a motor task and $C = 18$ in this work. Peak detection on each source signal, then k-means++ binary clustering of the peaks gives a set of spike cluster limits, $\Psi = \{(hi_n, lo_n), n = 1, .., N\}$. Following a refinement step, sources are vetted by their silhouette (SIL) score which is analogous to a pulse-to-noise ratio and lagged versions of extracted sources are discarded. The pseudo-online decomposition algorithm thus applies the pre-conditioning and separation vectors to unseen data for source extraction while stored clusters inform the estimation of spike times. The schematic for this process is given in Fig 1B which also shows the computation of the *decomposed spike count* feature vector, $\mathbf{x}(t)$, from windowed EMG, $\mathbf{Z}(t)$.

MU Subset Selection

A full feature matrix is first constructed by extracting the activities of all identified MUs over the full training data set. This is achieved by applying the online decomposition algorithm to extract the activities of MUs initially identified from individual motor tasks over the entire repertoire of training movements (Fig. 1A). To formulate the selection methods, it is convenient to define the activity of each MU as a random variable within set $F = \{x_n, n = 1, .., N\}$. The subset selection step now identifies a subset, S, based on some optimality criterion and future deployment of the online decomposition algorithm would only need to extract the activities of MUs within S.

Under the MR selection scheme, the MUs whose activities share the highest mutual information with the motor task annotation, ℓ, are prioritized:

$$\max_{S \subseteq F} \sum_{x_n \in S} \mathrm{I}(x_n; \ell). \tag{2}$$

where $\mathrm{I}(;)$ returns the mutual information between its argument variables.

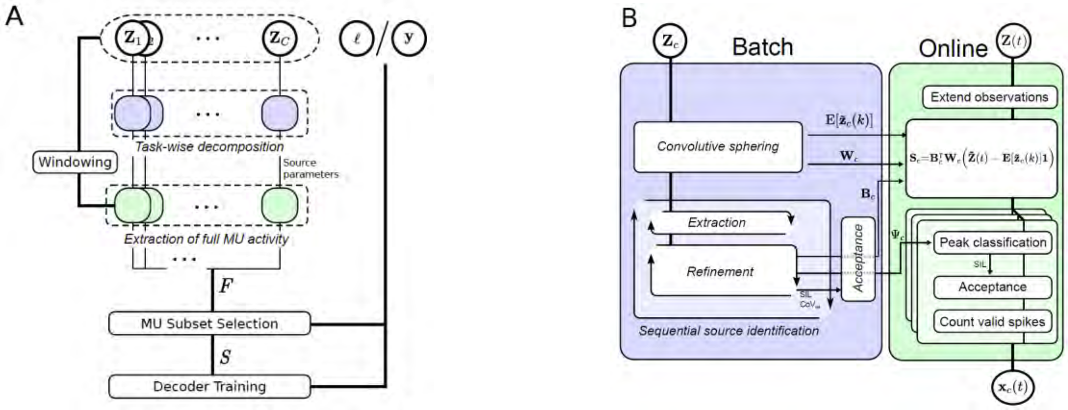

Figure 1: (A) Initialization process of the proposed MU-based interfacing. (B) Schematic for batch and online decomposition techniques showing the parameters that are transferred.

The mRMR scheme sequentially compiles S where, in each step, candidate MUs are also penalized by the mutual information they share with MUs that have already been selected. The criterion to satisfy at each step now writes as

$$\max_{x_n \in F-S} \frac{\mathrm{I}(x_n; \ell)}{\frac{1}{|S|}\sum_{s \in S} \mathrm{I}(x_n; s)}. \tag{3}$$

For comparative purposes, two naive selection schemes were also tested. The first is to select MUs by random while the second method prioritized MUs that were most active during the training movements.

Regression Algorithms

In LR, a linear mapping between S and kinematic labels ($\mathbf{y}$) is established by the Penrose-Moore pseudoinverse method. For MLP-based estimation, single hidden-layer feedforward networks using the tanh activation function are trained via the Levenberg-Marquardt backpropagation algorithm with each DoF estimated by a dedicated network while the optimal hidden-layer node counts are obtained via grid search. With KRR, a mapping is formed by the inner products between samples projected to a higher dimensional kernel feature space. The radial basis function is employed. Two hyperparameters, the ridge regularization scale and the kernel spread, are optimized via grid search.

Statistical Analysis

Decoding accuracy was gauged by the coefficient of determination (R^2) between estimated kinematics and ground truth. Repeated-measures ANOVA followed by Bonferroni-corrected pairwise comparisons were used to detect statistically significant differences between the different selection scheme and subset size combinations tested for each regressor.

RESULTS

On average, 20.3 ± 8.8 viable MUs were extracted via batch decomposition from the two training repetitions of each motor task.

Decoding performances from the different subset selection scheme and subset size combinations are shown in Fig. 2. Statistically significant differences were detected amongst the subset selection-size combinations for all decoding algorithms. Apart from the LR results, mutual information-based selection schemes (MR/mRMR) prevented significant performance drops when the number of MUs extracted for estimation were reduced by 50%.

Table I shows the average R^2 values yielded with subset sizes reduced to 25%. Overall, mRMR-selected MUs retained the highest predictive power and resulted in the lowest performance drops (-3.5%) while randomized selection performed the worst (-14.8%).

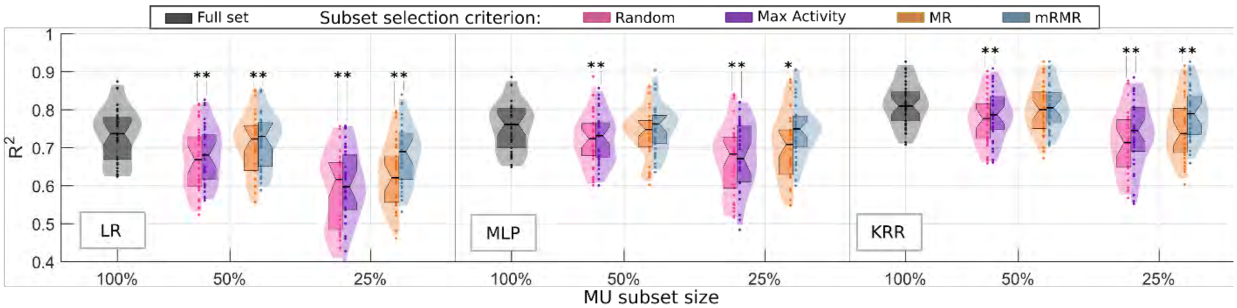

Figure 2: Violin plots of estimation performance of different regressors, MU subset selection methods, and MU subset sizes. Light shaded areas represent probability density functions estimated by kernel density estimation, while darker shaded blocks show the 1st-3rd quartile range. Corresponding medians are indicated by black notches. Statistically significant differences with corresponding full MU set are indicated by asterisks.

Table 1: Regression-based decoding performance (R^2) at MU subset size = 25%

	LR	**MLP**	**KRR**	**Average**
Full set	0.73±0.07	0.76±0.06	0.82±0.06	0.77±0.07
Random	0.58±0.11 -20.6%	0.67±0.09 -11.7%	0.71±0.08 -12.6%	0.65±0.11 -14.8%
Max Activity	0.6±0.10 -18.5%	0.68±0.09 -10.1%	0.74±0.08 -9.7%	0.67±0.11 -12.6%
MR	0.63±0.09 -14.6%	0.70±0.09 -7.1%	0.75±0.08 -7.8%	0.69±0.10 -9.7%
mRMR	0.69±0.08 -6.8%	0.75±0.08 -0.08%	0.79±0.07 -3.0%	0.74±0.09 -3.5%

REFERENCES

[1] 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.

[2] A. Holobar and D. Zazula, "Gradient Convolution Kernel Compensation Applied to Surface Electromyograms," in *Independent Component Analysis and Signal Separation*, Berlin, Heidelberg: Springer Berlin Heidelberg, 2007, pp. 617–624.

[3] D. Y. Barsakcioglu and D. Farina, "A real-time surface EMG decomposition system for non-invasive human-machine interfaces," *2018 IEEE Biomed. Circuits Syst. Conf. BioCAS 2018 - Proc.*, Dec. 2018.

[4] C. Chen, Y. Yu, X. Sheng, D. Farina, and X. Zhu, "Simultaneous and proportional control of wrist and hand movements by decoding motor unit discharges in real time," *J. Neural Eng.*, vol. 18, no. 5, p. 56010, Oct. 2021.

[5] Hanchuan Peng, Fuhui Long, and C. Ding, "Feature selection based on mutual information criteria of max-dependency, max-relevance, and min-redundancy," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 27, no. 8, pp. 1226–1238, Aug. 2005.

[6] D. Y. Barsakcioglu, M. Bracklein, A. Holobar, and D. Farina, "Control of Spinal Motoneurons by Feedback from a Non-invasive Real-Time Interface," *IEEE Trans. Biomed. Eng.*, pp. 1–1, Jun. 2020.