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Muscle Synergy-driven Motor Unit Clustering for Human-Machine Interfacing *

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Abstract—**Electromyographic signals (EMGs) can provide information on the overall activity of the innervating motor neuros in any given muscle but also globally reflect the underlying neuromechanics of human movement (e.g., muscle synergies). motor unit(MU) decomposition is a technique based on the deconvolution of high-density EMGs (HD-EMG) in order to derive the activities of the corresponding motor neurons. This powerful yet very sensitive tool has seen some traction in human-machine interfacing (HMI) for rehabilitation. Here, we propose combining the synergy-inspired channel clustering in order to isolate the most prominent regions of EMG activation in each targeted degree of freedom (DoF) and thus cater to decomposition's sensitivity demands. Our assumption is that this will lead to a higher number of extracted MUs and consequently better motion estimation in HMIs. Indeed, in four subjects, we have shown a 69% average increase in the number of MUs when decomposition was done using muscle-synergy channel clustering. Consequently, all three of our kinematic estimators benefited from an increased pool of units, with the linear regressor showing the greatest improvement once compared to, the artificial neural network and the gated recurrent unit, which had the overall best performance.**

Clinical Relevance— **The results demonstrated in this work provide a new perspective on the online EMG-driven HMI systems that can be greatly beneficial in the rehabilitation of motor disorders.**

I. Introduction

Electromyographic signals (EMGs) have been widely adopted as control inputs for human-machine interfaces (HMI) due to their ease of application and rich information content. Commonly, such systems rely on observing EMG amplitudes from an agonist-antagonist muscle pair in order to control a desired degree of freedom (DoF) of the interface [1]. The extension of this approach to multiple DoF has proven to be challenging. Hence, to further improve the functionality of EMG-based HMIs, machine learning (ML) algorithms have been developed specifically [2]. For instance, the pattern recognition-based control schemes learn emerging EMG patterns from physiologically appropriate muscle contractions and then further classify them into corresponding functions [3]. While providing direct access to multiple DoFs, such classification schemes are still delivering only discrete-motion control and can steer one joint or motion class at a time. Thus, EMG-based HMIs have been shifting towards continuous (proportional or regression) control approaches, which rely on similar features to create and provide a continuous mapping from the muscle space (EMGs) to the output kinematics [4], [5]. These methods can coordinate control of multiple joints/actions at a time instead of classifying them into a discrete number of classes. However, an increase in the number of actions is a reliability challenge for these systems [6].

In order to further improve the capabilities of HMIs, particularly in terms of precision, features based on individual motor unit (MU) activities have been considered [5], [7], [8]. These decomposed neural features from high-density EMGs (HD-EMG) indirectly represent the underlying physiological processes of EMG's generation and identify the activities of the motor neurons innervating the muscle [9], [10]. Here, the EMG signals can be reflected as a convolutive mixture of the series of discharge timings (motor unit spike train, MUST) of the motor neurons innervating the muscle with motor unit action potentials (MUAP) [9]. MUST is regarded as a source or neural command/drive sent to muscles by the motor neurons within the spinal cord [9]. The identified MUST can then, theoretically, be used as a feature as a myocontrol signal [11].

Still, the reliable extraction of MUs for HMI applications can pose a challenge due to the high computational complexity and sensitivity of the decomposition approach [12]. To address these shortcomings, attempts have been made to constrain the decomposition sensor space and target specific muscles to extract MUs [13]. However, in order to venture away from heuristic, anatomy-targeted approaches, a concept of muscle synergies can be employed [6]. This minimally supervised dimensionality-reduction technique driven by EMG amplitudes can indicate the region of relevance for each specific motion by looking at the spatial distribution of each synergy [6]. These regions (clusters) can then further guide a focused decomposition effort and potentially provide a higher number of Mus in a reliable fashion. We hypothesize that units extracted in such a way have a beneficial impact on motion estimation accuracy and decrease computational paradigm.

Here, we propose a minimally supervised way of region selection based on biological constraints to get optimal motor unit extraction at lower cost. We further compare three

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continuous myoelectric control methods tasked to estimate the three DoF wrist kinematics from the MUST level: (1) linear regression (LR), (2) artificial neural network (ANN), and (3) gated recurrent unit (GRU) network. Finally, the performance of these three algorithms has been benchmarked using neural features extracted by clustered and non-clustered approaches.

II. Methods

A. Participants

In this study, four righthanded able-bodied subjects (all male, age 30 ± 3 years) with no known neurological or musculoskeletal disorders have been recruited. The Ethics Committee of Aalto University granted ethical approval for this study, and all participants read, understood, and signed an informed consent form before starting any experiment.

B. Signal Acquisition and Experiment Setup

Two types of data were recorded from each participant's dominant arm. Three 8 × 8 electrode arrays (ELSCH064NM3, OT Bioelettronica, IT) were used to obtain 192 HD-EMG signals. The electrodes were placed so as to cover the entire circumference of the upper half of the forearm. The signals were sampled at 2048Hz, digitized with a $16 -$ bit analog to digital converter by a benchtop bio-amplifier (Quattrocento, OT Bioelettronica, IT), and in-hardware band-pass filtered using a third-order Butterworth with a cut of frequency of 3–900Hz. In addition, joint kinematic signals were simultaneously recorded by three wireless inertial measurement units (IMUs) (Xsens Technologies BV, NL) placed along the posterior sides of the upper arm, lower forearm, and hand. These were synchronized with the HD-EMG system and sampled at 80Hz. Each subject was instructed to perform three repetitions of six wrist motor tasks, encompassing three DOFs: wrist flexion/extension (DOF1), wrist radial/ulnar deviation (DOF2), and forearm pronation/supination (DOF3). Each motion was visually prompted using trapezoidal contraction profiles (trapezoidal cue: two seconds rest, two seconds rising and falling edges, ten seconds steady contraction at the comfortable level corresponding to the full range of the respective DoF).

C. Muscle synergy inspired EMG clustering method

Non-negative matrix factorization (NMF) is one of the common ways to extract underlying neuromechanics of human movement [14], [15]. It assumes that the source matrix and the factorized matrix are all non-negative. As shown in equation (1), the NMF decomposes muscle activation patterns of EMG signals (their root mean square (RMS) values) into a few (k) muscle synergies (motor modules) w_{ji} and temporal activation coefficient (neural or descending commands) C_i. Muscle synergies specify the relative activation level across muscles (the weights of each muscle). The activation coefficient represents how much the corresponding synergy was activated or used to generate force.

$$m_i(t) = \sum_{j=1}^{k} C_i(t) w_{ji} + e_i(t) \qquad (1)$$

where m represents EMGs, i is channel number, k is the number of synergies, and e is reconstruction error. While extracting muscle synergies using NMF, we assumed six synergies for the whole EMG dataset (one for each targeted DoF). From each synergy, based on the amplitude of activation (threshold of 50% (empirically determined) of maximum activity in each synergy), a subset of channels (clusters) was selected and further used for a focused MU decomposition.

D. Neural Feature Extraction

Multi-channel EMG signals can be approached as a convolution between the discharge timings of motor units (a series of delta functions) and the action potentials of muscle units (with finite duration) [9], [10]:

$$x_i(k) = \sum_{l=0}^{L-1} \sum_{j=1}^{n} h_{ij}(l) S_j(k-l) + n_i(t) \ ; i = 1{:}m \qquad (2)$$

where $x_i(k)$ is the discrete-time representation of the i_{th} EMG channels, with k spanning from 0 to D_R (recording duration in samples), and i, ranging from 1 to m. n and m are the number of active motor units and channels (observations), respectively, and L is the duration of the action potentials. h_{ij} is the action potential of the j_{th} motor unit (MUAP) as recorded at channel i. S_j is the spike train of the j_{th} motor unit (MUST), and $n_i(t)$ is the additive noise at channel i. In all decomposition algorithms, the goal is to reconstruct MUSTs, while the only accessible measurement is EMG signals. This study used offline and pseudo-online methods for neural feature extraction through blind source separation (BSS) EMGs decomposition [7]–[10], [16]. The offline phase performs the computationally demanding tasks of BSS. It retrieves system parameters such as the mean value of each observation (μ), the whitening matrix (W), a bank of matched filters, signal cluster centroid (scc) and noise cluster centroids (ncc) of peaks required by the online step to extract MUSTs activities in real-time [7]. To simulate a real-time application, the data was processed in windows, where the length of the sliding window was set to $160\ ms$ with no overlap [5], [8].

E. User intention estimation

To evaluate the performance of the decomposed neural features using clustered and non-clustered methods, we compared three regression methods for estimating their kinematic intentions: linear regressor (LR), artificial neural network (ANN), and gated recurrent unit (GRU) network [17]. These estimators were trained in the calibration phase by extracted neural features using clustered and non-clustered approaches. In the testing/evaluation phase, the neural features were extracted using a pseudo-online decomposition algorithm to estimate kinematic output (three DoF, six motions). Moreover, a 3-fold cross-validation was applied to the dataset to test the estimator's ability to predict new (testing) data which was not used during estimator training [4]. The success of each regression model in the estimation of intended kinematics was quantified using a R^2 score [4].

$$R^2 = 1 - \frac{\sum_{d=1}^{D}\sum_{i=1}^{N}\left(x_{d,i}^{real} - x_{d,i}^{est}\right)^2}{\sum_{d=1}^{D}\sum_{i=1}^{N}\left(x_{d,i}^{real} - \overline{x_{d,i}^{real}}\right)^2} \qquad (3)$$

where D is the number of DoFs involved (D = 3 in this study), N is the sample size. $x_{d,i}^{real}$ and $\overline{x_{d,i}^{real}}$ are the actual value of the target and its mean value. $x_{d,i}^{est}$ is the estimated value of the target obtained by the regression algorithms. Moreover, a moving average filter was used to smooth the estimation outputs.

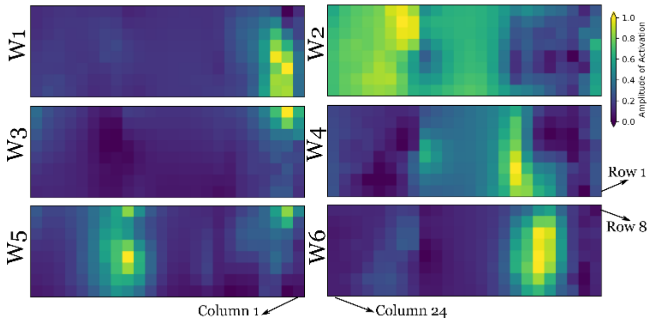

Figure 1. The spatial distribution of the six synergies extracted using NMF from Subject 1. Each map depicts RMS values across the three HD-EMG recording matrices (8 x 24 channels). From here, clusters of activities have been identified by considering the threshold of 50% of maximum activity in each synergy. Then each cluster has further been used for focused EMG decomposition.

III. Results

Figure 1. shows the spatial distribution of each muscle synergy extracted using NMF for subject 1. From each synergy (W_i), a subset of channels (clusters) was selected based on the activation amplitude and further used for a focused MU decomposition.

TABLE I shows the average number of extracted MUs in the clustered and non-clustered conditions for all subjects. Data were averaged across all participants for each motion and rounded to the nearest integer. An average of 51 and 86 MUs were extracted for all motions through the non-clustered and clustered method, respectively. Among six motions, wrist extension and ulnar deviation yielded a higher number of extracted MUs than the other motions, regardless of the clustering method. Figure 2. shows subject 2 performance for one-fold of data. Figure 3. shows the pseudo-online myoelectric control performance of LR, ANN, and GRU network trained with clustered and non-clustered neural features. The LR method consistently has 10% higher average performance when operating on clustered neural features.

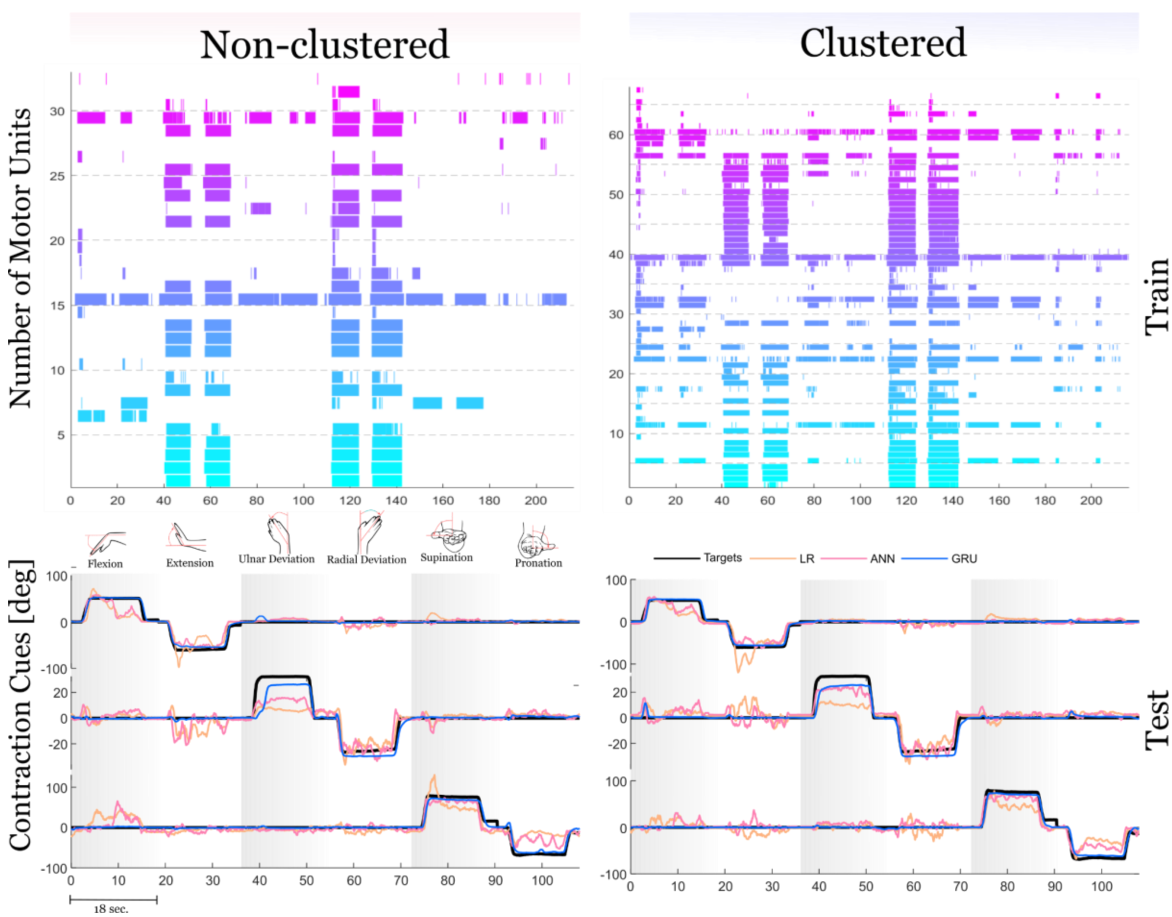

Figure 2. Myoelectric control assessment of subject 2. The top panel shows the extracted neural features using two repetitions of each motion by clustered and non-clustered methods. The bottom panel shows the performance of three regression methods using one repetition of each motion. Orange, pink, and blue colors represent estimated kinematics outputs using LR, ANN, and GRU with respect to the target cue shown in black color. While the R^2 score using the non-clustered method are 62%, 65%, and 96% using LR, ANN, and GRU, respectively, the clustered method values are 73%, 77%, and 97% using the same regressors.

TABLE I. THE NUMBER OF EXTRACTED MOTOR UNITS

DOF	Task	Number of Motor Units	
		Non-Clustered	*Clustered*
1	*Flexion*	17 ± 7	40 ± 20
	Extension	35 ± 7	57 ± 22
2	*Radial Deviation*	14 ± 10	26 ± 17
	Ulnar Deviation	28 ± 16	55 ± 11
3	*Supination*	17 ± 12	30 ± 18
	Pronation	20 ± 16	42 ± 26
Total Number of MUs		51 ± 11	86 ± 25

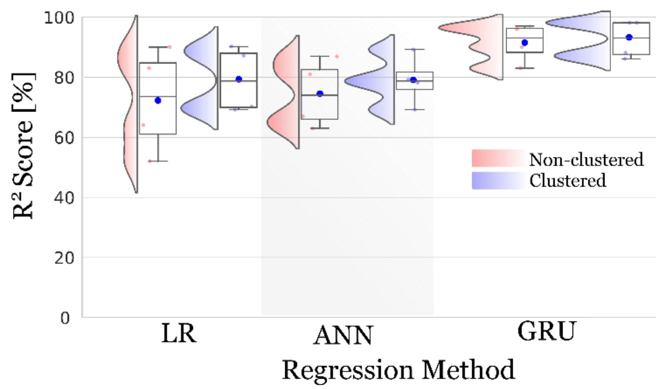

Figure 3. The overall R^2score for LR, ANN, and GRU regression methods trained with neural features extracted by non-clustered and clustered methods.

IV. DISCUSSION

For the purpose of optimal motor unit decomposition, we proposed a minimally supervised way of EMG channel clustering based on muscle-synergy-inspired constraints. The average number of extracted MUs across all four subjects increased from 51 to 86 during the blind-source-separation decomposition using the clustering approach for all motions. A possible explanation for this increase may be that the amplitude-driven spatial constraints help with the convergence to the more reliable sources [18] that are in turn having a higher likelihood of getting identified as MUs by the decomposition algorithm. Furthermore, in both clustered and non-clustered approaches, it was observed that across three DoFs, the decomposition algorithm yielded a larger number of MUs during wrist extension and ulnar deviation motions. This finding is in line with the earlier results [19], and it is presumably due to the strong involvement of surface muscles in these motions, which allow for an easier decomposition.

In conclusion, as was to be expected, the results indicate that a higher number of MUs present during the regressor training allows for a more reliable estimation. This holds true regardless of the applied algorithm; however, the linear method seems to benefit more from the clustering approach in relative terms. Moreover, the estimation performance of the deep networks (GRU) outperforms that of the LR and ANN, which all indicates that the model's complexity tends to yield higher performance while requiring less computational cost enabled by clustering method [4]. In the future, the aim is to expand the subject pool and perform similar comparisons in a fully real-time scenario.

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