

Comparison Of Weakly Supervised Regression Of sEMG Signals With State-Of-the-Art Unsupervised Methods For Robot Hand Control: A Pilot Study [★]

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Abstract: The development of control strategies for multi-articulated robotic hands remains a key challenge in robotics. A promising approach leverages machine learning applied to surface electromyography (sEMG) for detecting human grasping intentions and controlling robotic devices. Most current methods rely on supervised learning to regress sEMG signals into robotic hand commands. However, unsupervised approaches are increasingly favored as they bypass the need for labor-intensive or imprecise instant-by-instant labeling of sEMG signals.

This study explores three sEMG regression methods: unsupervised Nonnegative Matrix Factorization (NMF) and autoencoder (AE), and a recently developed novel weakly supervised technique leveraging the soft-Dynamic Time Warping (soft-DTW) divergence. Unlike standard unsupervised methods, soft-DTW supports nonlinear fitting, crucial for capturing the complex dynamics of human grasping intentions. By smoothing the traditional DTW metric, soft-DTW measures similarity between sequences while handling temporal misalignments, making it particularly effective for weakly supervised regression tasks avoiding for the necessity of instant-by-instant labeling of sEMG data. Preliminary experiments indicate that the soft-DTW-based approach surpasses NMF and AE in regressing grasp closure profiles for power, ulnar, and tripod motions, offering a significant step forward in intuitive robotic hand control.

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1. INTRODUCTION

The estimation of human grasping intentions offers an effective way to incorporate a user's cognitive skills into the control of multi-articulated robotic grasping devices. This approach benefits robotics applications such as telemanipulation and prosthetics by enabling human-in-the-loop control of robotic hands based on the operator's intentions (Melchiorri (2013)).

In this context, we focus on surface electromyographic (sEMG) signals for robotic hand control (Micera et al. (2010)). These interfaces use sEMG signals from the forearm, processed by machine learning algorithms, to generate commands for artificial hands (Meattini et al. (2018)). Current state-of-the-art methods for decoding sEMG signals online primarily use supervised or unsupervised machine learning techniques. Supervised learning can classify signals into discrete grasp actions or regress continuous grasping motions, such as the modulation of grasp closure

levels. However, classification approaches become increasingly complex with more grasping actions due to the need for transition logics (e.g., finite-state machines), which do not guarantee high reliability in the presence of misclassifications (Ingraham et al. (2015)). As a result, supervised regression has become more prevalent, enabling users to continuously and proportionally control grasping actions using forearm sEMG signals (Meattini et al. (2018)), a paradigm referred to as *simultaneous and proportional* (s/p) control. Despite its potential, supervised regression struggles with unreliability in real-life, non-laboratory settings (Nowak et al. (2017)). Challenges include (i) imprecise instant-by-instant labeling of sEMG signals and (ii) the need for long, tedious training dataset acquisition procedures. These limitations lead to performance degradation in unstructured environments and user frustration, which undermines overall control effectiveness.

To address these issues, unsupervised approaches have been investigated for linear or nonlinear regression of sEMG signals without labeled training data (Jiang et al. (2014)). Two prominent unsupervised techniques are Non-negative Matrix Factorization (NMF) (Lin et al. (2018)) and autoencoders (AE) (Vujaklija et al. (2018)), which offer linear and nonlinear information extraction, respectively.

Unsupervised regression methods achieve s/p control by

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leveraging intrinsic data structures in sEMG signals but cannot directly perform nonlinear data *fitting*. To overcome this limitation, we have recently propose a novel paradigm combining nonlinear fitting with the elimination of instant-by-instant labeling (Meattini et al., 2022). This approach employs a flexible neural network architecture and a differentiable version of Dynamic Time Warping (DTW) – the soft-DTW divergence – as a loss function for minimally supervised training (Müller (2007)). DTW has been widely used for classification and clustering of time-series data, including inertial measurements, muscular signals, and videos (Meattini et al. (2019), Atzori et al. (2013), AbdelMaseeh et al. (2015), Akl and Valaee (2010), Schultz and Jain (2018)).

This pilot study compares regression models for sEMG-based robotic hand control without requiring instant-by-instant labeling. We tested three techniques on sEMG data collected from five subjects performing three grasping motions (power, ulnar, and tripod grasping): (i) the soft-DTW-based weakly supervised approach and the unsupervised methods (ii) NMF and (iii) AE. Results show that the soft-DTW-based approach performs better than NMF and AE in regression performance, highlighting its potential for sEMG-driven human-robot interfaces. This finding suggests promising applications for prosthetic control, particularly for transradial amputees, and warrants further investigation in this direction.

2. MATERIALS AND METHODS

Regression approaches for myocontrol of robotic devices are based on the idea that independent neural drives, shared by different muscles can be observed in the sEMG signal recorded during user’s hand motions. This provides the user with a s/p grasp control over multiple DoFs. In this section, we introduce two state-of-the-art unsupervised regression techniques (NMFa and AE) and a novel weakly supervised method (soft-DTW neural network).

2.1 Regression Models

Denoting by $E(t) = [e_1(t) \dots e_8(t)]^T \in \mathbb{R}^{8 \times 1}$ the RMS value of the 8-channel sEMG signal, different linear and nonlinear regression models can be employed to find the mapping between myoelectric signals and neural commands.

NMF As explained in the generative model presented in (Jiang et al., 2008), the RMS value of the sEMG signal can be obtained by modulating supraspinal neural drives through appropriate synergistic weights. As a consequence, we can write the sEMG signal at each instant of time as the product between a *muscular synergy matrix* $S_M \in \mathbb{R}^{8 \times 2n}$ and *neural drives vector* $U(t) \in \mathbb{R}^{2n \times 1}$:

$$E(t) = S_M U(t) \quad (1)$$

where n is the number of DoFs activated during hand movements. In our case, the opening and closing motion of the human hand can be seen as a single DoF ($n = 1$) controlled by two groups of flexor and extensor muscles. Therefore, in accordance with the concept of human antagonistic actuation model (Burdet et al., 2013), we can

rewrite eq. (1) considering two non-negative neural drives that activate such antagonistic actions:

$$E(t) = [s_{Me} \ s_{Mf}] \begin{bmatrix} u_e(t) \\ u_f(t) \end{bmatrix}, \quad (2)$$

where $s_{Me}, s_{Mf} \in \mathbb{R}^{8 \times 1}$ are the extension and flexion components of the muscular synergy matrix, while $u_e, u_f \in \mathbb{R}$ are the corresponding neural commands. This linear mixture model can be effectively solved for S_M and U by using NMF algorithm. Finally, we can exploit the pseudo-inverse of the muscular synergy matrix S_M to online estimate the robot hand control commands from sEMG signals (Meattini et al., 2018).

Autoencoder Regression models such as the one based on NMF simplify the mapping problem assuming a linear function between neural commands and myoelectric signals. Conversely, autoencoders enhance the representation power of linear regression techniques by catching nonlinear relations within the data.

Leveraging again on the antagonistic actuation model concept, an AE with two neurons in the hidden layer is used in considered to map the 8-channel sEMG signal into itself, while collecting the features representing neural control information in the latent space. Given the RMS value of the sEMG signal $E(t) \in \mathbb{R}^{8 \times 1}$, the encoder part extracts neural commands for extensor and flexors muscles $A(t) = [a_e(t) \ a_f(t)]^T \in \mathbb{R}^{2 \times 1}$ as:

$$A(t) = h(W_I E(t) + B_I) \quad (3)$$

where $W_I \in \mathbb{R}^{2 \times 8}$ is the input weight matrix, $B_I \in \mathbb{R}^{2 \times 1}$ is the input bias vector and h denotes a logarithmic sigmoid activation function. The decoder reconstructs back the input signal $\widehat{E}(t) \in \mathbb{R}^{8 \times 1}$ with a linear activation function:

$$\widehat{E}(t) = W_O A(t) + B_O \quad (4)$$

where $W_O \in \mathbb{R}^{8 \times 2}$ is the output weight matrix and $B_O \in \mathbb{R}^{8 \times 1}$ is the bias vector from the hidden layer to the output. The autoencoder was trained using a scaled conjugate gradient descent algorithm and the training procedure was repeated 10 times in order to select the optimal set of network parameters. Therefore, the encoder part can be then used to online extract control inputs for a root hand from sEMG signals (Vujaklija et al., 2018).

Soft-DTW Neural Network The regression model in this context is implemented as a neural network with a flexible feed-forward architecture. The distinctiveness of this neural network lies in its training process, which is based on a loss function defined by the soft-DTW divergence. This approach eliminates the need for instant-by-instant labeling of the training dataset, as elaborated below (Meattini et al., 2022).

Given the RMS sEMG signal $E(t) \in \mathbb{R}^{8 \times 1}$, it is used as the input to a feed-forward neural network architecture consisting of n hidden layers followed by an output layer. The output of a generic $(j-1)$ -th hidden layer is expressed as

$$a^{(j)}(t) = \mathcal{F}(W^{(j)}a^{(j-1)}(t) + b^{(j)}), \quad (5)$$

where $\mathcal{F}(\cdot)$ represents the hyperbolic tangent sigmoid transfer function of the N_j neurons in the hidden layer, $b^{(j)} \in \mathbb{R}^{N_j}$ is the bias vector, $a^{(j-1)}(t) \in \mathbb{R}^{N_{j-1}}$ is the input vector, and $W^{(j)} \in \mathbb{R}^{N_j \times N_{j-1}}$ is the weight matrix. For the network's output layer, the following expression holds:

$$a^{(n+1)}(t) = \mathcal{H}(W^{(n+1)}a^{(n)}(t) + b^{(n+1)}), \quad (6)$$

where $\mathcal{H}(\cdot)$ is the linear transfer function, and $a^{(n)}(t) \in \mathbb{R}^{N_n}$, $W^{(n+1)} \in \mathbb{R}^{N_{n+1} \times N_n}$, and $b^{(n+1)} \in \mathbb{R}^{N_{n+1}}$ represent the input vector, weight matrix, and bias vector of the output layer, respectively.

To utilize the output $a^{(n+1)}(t)$ for controlling the grasping motion of a robotic hand, the neural network is trained using backpropagation to optimize its parameters (i.e., weights and biases). Specifically, we consider a target output $T \in \mathbb{R}^{1 \times d}$ with d samples and an 8-dimensional sEMG training dataset $E_T \in \mathbb{R}^{8 \times d}$ as input to the network, which produces an output $A_T \in \mathbb{R}^{2 \times d}$. The loss function is then computed using the soft-DTW divergence as (Blondel et al., 2021)

$$D(A_T, T) = S(A_T, T) - \frac{1}{2}S(A_T, A_T) - \frac{1}{2}S(T, T), \quad (7)$$

where $S(A_T, T)$ is the soft-DTW operator (Cuturi and Blondel, 2017), defined as

$$S(A_T, T) = \min_{\pi \in \mathcal{A}(A_T, T)}^\lambda \sum_{i, j \in \pi} d(a_{T_i}, t_j)^2, \quad (8)$$

where $a_{T_i}, t_j \in \mathbb{R}^2$ are elements of A_T and T , respectively, $d(a_{T_i}, t_j)^2$ is the squared Euclidean distance, and \min^λ is the *soft-min* operator defined as (Cuturi and Blondel, 2017)

$$\min_x^\lambda f(x) = -\lambda \log \sum_x \exp\left(\frac{-f(x)}{\lambda}\right), \quad (9)$$

where $\lambda > 0$ ensures that, as $\lambda \rightarrow 0^+$, the soft-DTW $S(\cdot, \cdot)$ converges to the standard non-differentiable DTW. In this work, we set $\lambda = 0.1$. In Eq. (8), $\mathcal{A}(A_T, T)$ denotes the set of all admissible alignment paths (Sakoe and Chiba, 1978) between A_T and T . Crucially, the target output T is provided *a posteriori* with respect to the recording of the sEMG training dataset. This approach eliminates the need for instant-by-instant labeling or synchronism/phase alignment between sEMG and labels, leveraging the invariance properties of the soft-DTW similarity measure with respect to temporal misalignments and nonlinear distortions (Cuturi and Blondel, 2017).

3. EXPERIMENTAL SESSION AND RESULTS

3.1 Subjects and Experimental Protocol

To evaluate and compare the regression models for forearm sEMG signals described earlier, we conducted a pilot

study involving five healthy, right-handed male participants, aged 30 ± 4 years. These individuals were specifically selected to ensure consistency in the study parameters. Each participant took part in an sEMG data acquisition protocol, which entailed recording signals from their right forearm during specific hand motions that were carefully designed to replicate real-world scenarios. The sEMG bracelet utilized in this study is elaborated in Sec. 3.2. Each subject was instructed to perform continuous opening and closing grasping motions corresponding to three distinct types of grasps: power, ulnar, and tripod. For each grasp type, participants executed five continuous open-close cycles while following a clearly visible simulated hand motion displayed on a screen in front of them. This setup not only standardized the movement patterns but also provided a consistent ground truth for evaluating and comparing the regression models (NMF, AE, and soft-DTW, as detailed in Sec. 2).

The sEMG dataset for each grasp type was systematically divided into training and testing subsets. Specifically, the training subset comprised the first three motion cycles, while the remaining two cycles were allocated to the testing subset. This structured division ensured a rigorous evaluation of the regression models' performance. Further details, including comprehensive graphs and results of the regression analysis, are presented in Sec. 3.4. To maintain ethical standards, the study followed guidelines outlined in the Declaration of Helsinki. All participants received detailed explanations about the experimental procedures and signed informed consent forms before participation, ensuring full transparency and adherence to ethical practices. Moreover, during the experimental session, the participants were seated in a controlled environment, minimizing external distractions that could affect muscle activity or introduce variability in the recorded sEMG signals. Instructions were provided verbally and in written form, ensuring clarity and uniformity in the execution of the tasks. Before starting the experiment, a brief training session was conducted for each participant, familiarizing them with the simulated hand movements displayed on the screen and the expected pace of the grasping motions. This preparatory phase contributed to the consistency and reliability of the data collected across all subjects.

3.2 sEMG Acquisition Hardware and Signal Processing

For the acquisition of the sEMG signals from the forearm of the subjects engaged in our experimental session, we used a sensorized armband composed by 8-channels for the acquisition of surface muscular signals, provided by OYMotion¹ and called gForcePro Armband. For the placement of the bracelet along the forearm of the subjects, we followed the standard best practices and guidelines reported in (Perotto, 2011), according to which the armband was positioned in proximity of the predominant hand's extrinsic muscles for the finger's flexion and extension, i.e. in proximity of the *Flexor Digitorum Superficialis* and *Extensor Digitorum Communis* muscle bellies. The stream of raw sEMG signals were provided by the bracelet at a frequency of 1kHz, communicating by means of a Bluetooth channel transferring the data to a nearby computer. Then, the processing of the raw sEMG was performed

¹ <http://www.oymotion.com/>

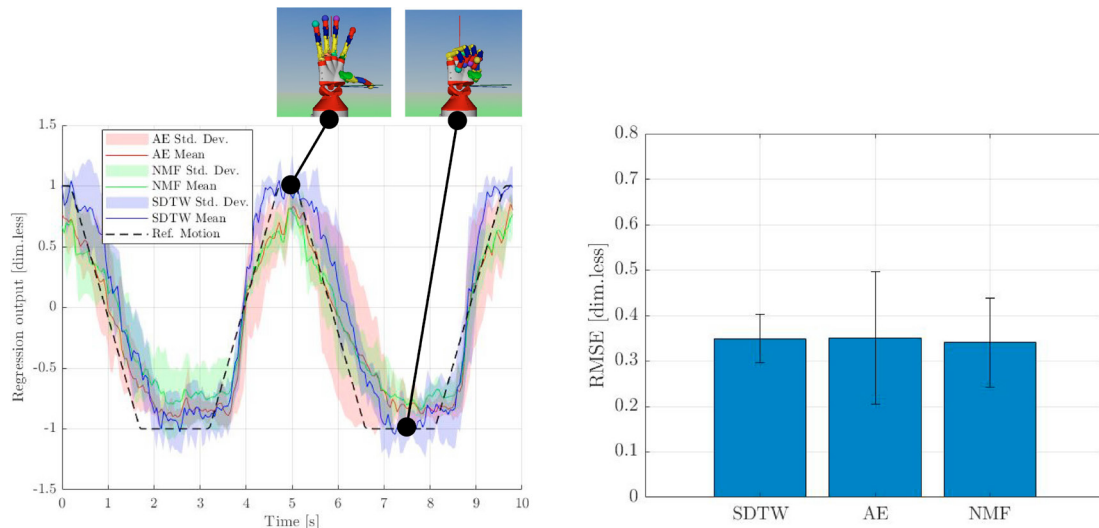


Fig. 1. Results of the sEMG regression output for the NMF, AE and soft-DTW approaches, related to the power grasp motion. Left side: mean regression output signal (solid line) computed over the subjects and reported for each regression method; std. deviation (shaded zones); reference grasp motion signal; frames of the simulated robot hand controlled by the regression output (open hand, power grasp). Right side: average RMSE over the subjects for the NMF, AE and soft-DTW regressions (black lines denote the std. deviation).

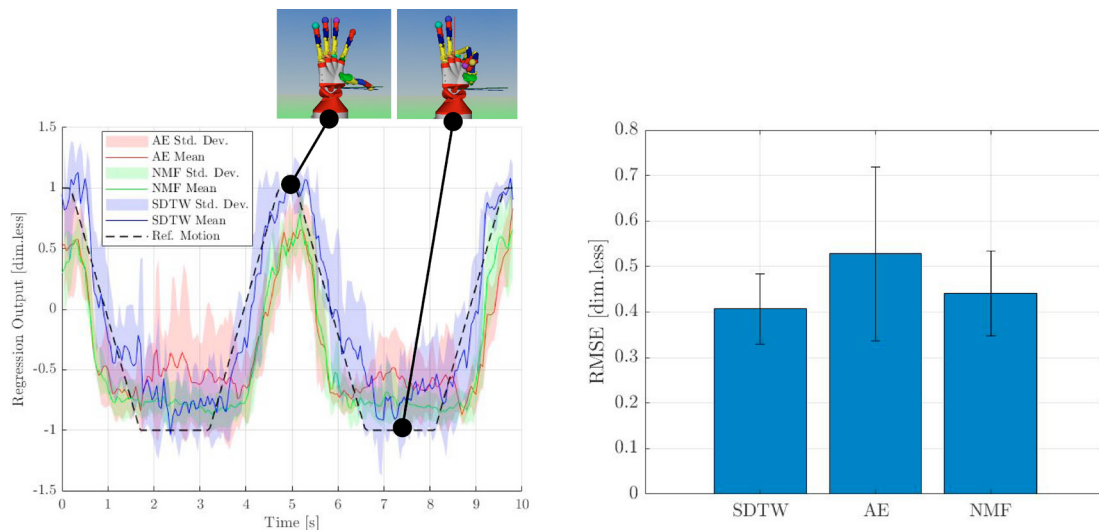


Fig. 2. Results of the sEMG regression output for the NMF, AE and soft-DTW approaches, related to the tripodal grasp motion. Left side: mean regression output signal (solid line) computed over the subjects and reported for each regression method; std. deviation (shaded zones); reference grasp motion signal; frames of the simulated robot hand controlled by the regression output (open hand, tripodal grasp). Right side: average RMSE over the subjects for the NMF, AE and soft-DTW regressions (black lines denote the std. deviation).

according to the following filtering operations: (Meattini et al., 2018): (i) 50 Hz notch filter for powerline interference cancellation, (ii) 20 Hz highpass filter for baseline noise reduction, and (iii) computation of the root mean square (RMS) value of the signal over a 200 ms running window.

3.3 Usage of the sEMG Regression Output for the Simulated Robot Hand Control

The output of the regression models tested on the sEMG data acquired during the experimental session described in the previous subsection, are used to control a simulator of the UB Hand grasping device (see Figs 1, 2, 3), that

is a dexterous anthropomorphic robotic hand (Melchiorri et al., 2013). The hand is fully actuated with $n_j = 15$ degrees of freedom. The definition of the joint reference configuration θ_J^{ref} is given at a higher synergy control level, computed as

$$\theta_J^{ref} = S_G \rho^{ref}(t), \quad (10)$$

where ρ^{ref} is the synergistic hand closure reference given by the output of the different considered sEMG-based regression approaches, and $S_G \in \mathbb{R}^{n_j \times 1}$ is here referred to as the synergy matrix that contains, for each considered grasp, proper weights for the realization of the power,

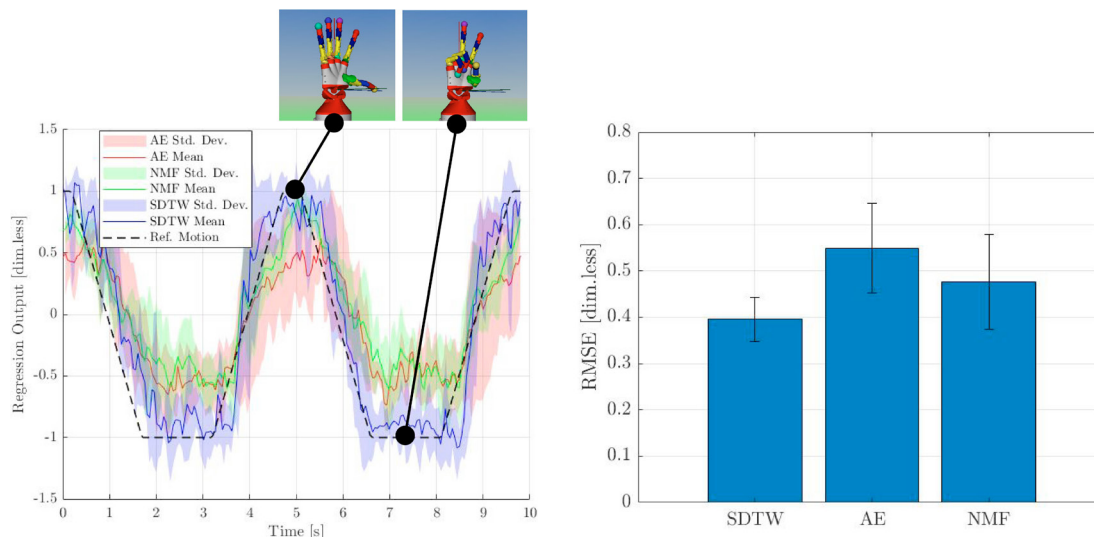


Fig. 3. Results of the sEMG regression output for the NMF, AE and soft-DTW approaches, related to the ulnar grasp motion. Left side: mean regression output signal (solid line) computed over the subjects and reported for each regression method; std. deviation (shaded zones); reference grasp motion signal; frames of the simulated robot hand controlled by the regression output (open hand, ulnar grasp). Right side: average RMSE over the subjects for the NMF, AE and soft-DTW regressions (black lines denote the std. deviation).

tripodal and ulnar grasping motions – for additional details refer to our previous work (Meattini et al., 2018).

3.4 Results

The testing results of the regression approaches studied here (NMF, AE, and soft-DTW) on sEMG signals acquired from five subjects, as detailed in Sec. 3.1, are shown in Figs. 1, 2, and 3. These figures display the mean (solid lines) and standard deviation (shaded regions) of the output signals from the regression methods, computed across subjects, as functions of time. The black dotted line represents the reference grasp motion signals replicated by the subjects during sEMG acquisition, against which regression outputs are compared. Additionally, the right side of Figs. 1, 2, and 3 presents aggregated results, with bar graphs showing the average root-mean-square error (RMSE) across subjects for each approach. Frames depicting simulated robot hands controlled by regression outputs are also included.

For the power grasp motion (Fig. 1), the NMF, AE, and soft-DTW methods yield nearly identical results, with no notable performance differences. This outcome aligns with prior studies demonstrating that power grasp motions can be effectively decoded from forearm sEMG signals using linear regression methods (Meattini et al., 2015, 2018). This effectiveness arises because all fingers flex and extend together in the power grasp, avoiding the complexity of simultaneous independent finger movements.

Conversely, for the tripodal grasp (Fig. 2), soft-DTW exhibits lower regression errors compared to the reference grasp motion, outperforming the other approaches. A similar trend is observed for the ulnar grasp motion (Fig. 3), where soft-DTW outperforms NMF and AE, which exhibit higher average RMSEs relative to the reference motion. These findings are consistent with the challenges posed by decoding grasp motions involving simultaneous flexion and extension of different fingers using unsupervised methods.

In summary, this pilot study provides preliminary insights into the comparison between weakly supervised soft-DTW regression and the state-of-the-art unsupervised approaches NMF and AE. While all methods show comparable performance for power grasp motions, soft-DTW demonstrates superior accuracy for the more complex tripodal and ulnar grasp motions. These results suggest the potential of soft-DTW for decoding challenging grasp motions from sEMG signals. Future work should involve larger subject groups, including amputees, and more complex online grasping tasks to enable statistical analyses and draw more generalizable conclusions.

4. CONCLUSIONS

In this paper we have reported the preliminary results of a pilot study about the comparison of machine learning based regression techniques for sEMG signals that does not require instant-by-instant labelling of the training dataset in order to control grasping actions of a robot hand. This is a relevant research direction in order to avoid data acquisition procedures that are complex and frustrating from the user point of view, and that, summed up to the systematic imprecisions introduced by instant-by-instant labelling techniques, really play a role in the evergreen problem of reliability of human grasping intention decoding from sEMG signals. We have therefore preliminarily compared two state-of-the-art unsupervised regression techniques, based on NMF and AE approaches, with a novel weakly supervised technique based on the soft-DTW divergence as loss function of a flexible neural network architecture. The reported results of an experimental evaluation involving five subjects show that the soft-DTW-based regression provided outcomes comparable with the NMF and AE when power grasp motions are considered, which was expected since the power grasp can be consistently decoded by linear regression methods, whereas showed better performances with respect to

NMF and AE in the case of tripod and ulnar grasping motions, which in general require nonlinear data fitting capabilities due to the fact that different fingers flex and extend during the execution of the grasps. This pilot study provides therefore positive perspectives and justification for carrying out future experiments on a larger group of subjects, in order to also perform appropriate statistical analyses to better investigate the performance of the soft-DTW-based regression of forearm's sEMG signals for the control of robot hands.

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