

Online Unsupervised Adaptation of Latent Representation for Myoelectric Control During User-Decoder Co-Adaptation

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Abstract—Myoelectric control interfaces, which map electromyographic (EMG) signals into control commands for external devices, have applications in active prosthesis control. However, the statistical characteristics of EMG signals change over time (e.g., because of changes in the electrode location), which makes interfaces based on static mapping unstable. Thus the user-decoder co-adaptation is needed during online operations. Nevertheless, current online decoder adaptation approaches present several practical challenges, such as expensive data labeling and slow convergence. Thus we introduce an unsupervised decoder adaptation method that converges rapidly. We use an autoencoder to extract motor intent representation in the latent manifold space rather than the sensor space, and further introduce an online unsupervised adaptation scheme based on Moore–Penrose Inverse, a noniterative approach suited for fast network re-training, to track the evolving manifold. A validation experiment first showed that the convergence time of the proposed adaptation scheme was reduced to about 50% of that for state-of-the-art methods. Online experiments further evaluated cursor and prosthetic hand control by the proposed myoelectric interface, where perturbations were representatively introduced by shifting the electrodes. Results showed that our scheme reached comparable improvements in robustness as supervised

counterparts. Moreover, in a cup relocation test with a prosthetic hand, the completion time in the post-adaptation phase with electrode shift was comparable to that in the baseline phase without shift. These results suggest that our method effectively improves the accessibility and reliability of decoder adaptation, which has the potential to reduce the translational gap of myoelectric control interfaces by effective co-adaptation during operation.

Index Terms—Myoelectric control, decoder adaptation, unsupervised autoencoder, online manifold learning, electrode shift.

I. INTRODUCTION

SIMULTANEOUS and proportional (SP) myoelectric control interfaces allow individuals to control external devices over multiple degrees of freedom (DoFs) in a natural and intuitive way [1]. They have demonstrated potentials for functional restoration of movement in clinical applications, such as in the control of active prostheses [2], and for robotic and virtual reality rehabilitation systems [3], [4]. However, surface electromyographic (EMG) signals are non-stationary, due to variations in limb position, electrodes placement, and user muscle activation [5]. Conventional fixed decoders, which do not adapt to these non-stationarities, may result in uncontrollable interfaces [5]. Despite the possibility for the user to adapt to these non-stationarities with a fixed decoder [6], [7], which is naturally enabled by the instantaneous sensory feedback provided by closed-loop myoelectric interfaces [8], the considerably long adaptation time and great user efforts needed may not be acceptable for online operations [8], [9]. Thus, there is the need for interfaces that reactively adapt to the user while also facilitating the user adaptation to control the interface [8]. In this way, the user and the decoder would co-adapt during the online closed-loop interaction, so as to recover proficient control under unstable conditions.

While user adaptation cannot be directly controlled, recent studies highlighted that decoder adaptation could progressively shape user adaptation and in turn, influence the co-adaptive interface performance [10], [11]. The decoder adaptation consists in updating its parameters by learning from new activation patterns after an initial calibration, once the system's

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performance deteriorates [12]. To maximize the accessibility and reliability of myocontrol interfaces, two key requirements are generally imposed on designing an adaptive decoder.

First, the constraints for applying the decoder adaptation algorithm in real world cases should be as few as possible [2]. Several studies [13], [14] have presented adaptive calibration of electrode shift, where the electrode shift is first estimated and then compensated for. Though these studies show robustness to perturbations of electrode position, their success heavily relies on the original electrode location. Incremental learning has been proposed as an effective way to adapt the decoder during use, falling into offline and online categories. Offline decoder adaptation methods exhibit higher system robustness when compared to their non-adaptive counterparts [15], [16], [17], [18], [19], but they involve disruptive and lengthy offline data acquisition processes for capturing signal variabilities, which increase the burden on the users and limit the consolidation of myocontrol strategies [20]. Very recently, online decoder adaptation methods have been developed by utilizing novel input data collected during online control to refine function spaces [20], [21], [22], [23], [24], [25]. Nevertheless, most approaches [22], [23], [24], [25] operate with supervised machine learning which is costly and impractical because of the need for accurately labeling new EMG patterns. Since the user movement intent is often unknown during online operations, these methods are challenging to implement in commercial devices.

Second, the adapting of a decoder should be accomplished on a timescale comparable to the drift in EMG signals to prevent performance degradation [8]. While day-to-day variability in the signals can be overcome with methods that adapt parameters across days [26], online decoder updates are supposed to be on the timescale of minutes to counteract rapid drifts [8]. However, current online decoder adaptation methods are updated with iterative optimization methods that require relatively long time (≥ 120 s) to converge, e.g., block-coordinate descent [20], mini-batch gradient descent [21], exponential recursive least squares [22], [24], recursive Gauss-Newton [23]. When a non-stationarity has a sudden onset, the slow convergence may impede fast adaptability to perturbations, and thus frustrate the user [27].

To address the gap of current approaches from these two requirements, we developed an online unsupervised decoder adaptation method that rapidly tracks the evolving latent manifold of non-stationary EMG during online, closed-loop use. This was achieved through the use of a non-linear autoencoder (AE) trained online by non-iterative blockwise Moore–Penrose (MP) inverse [28]. The non-linear AE is well suited for learning low-dimensional curved manifold that is more consistent with the variance structure of EMG signals compared to a linear approximation [29]. As a non-iterative neural network training approach, the low-memory blockwise MP inverse learning updates parameters of the network only once, enabling a fast re-training without penalizing performance.

To validate the effectiveness of our online unsupervised decoder adaptation in restoring control following instabilities, experiments were carried out with perturbations induced by

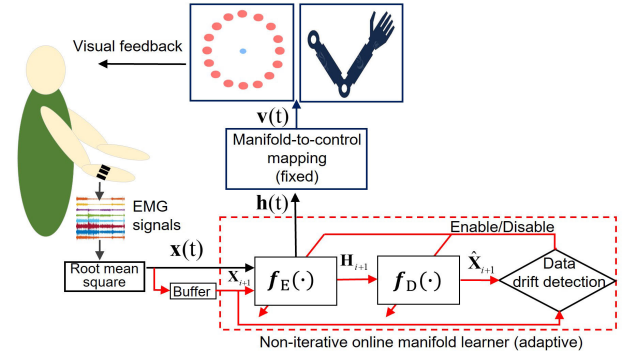


Fig. 1. Block diagram of our co-adaptive myocontrol system. EMG signals are translated via the decoder to control the velocity of a cursor or a prosthetic hand. The visual feedback from the closed-loop interaction leads the user to adapt. Once data drift is detected during real-time operations, the history batch stored in the buffer is fed to update AE for tracking the evolved manifold.

electrodes shift, as a representative example of rapid variation in signal characteristics. The proposed online updating method of a myoelectric decoder reaches the state-of-the-art convergence time (on 1-min timescale) while avoiding the constraints of current methods.

II. METHOD

Fig. 1 shows the block diagram of our myocontrol system, where the user and decoder co-adapt during closed-loop interaction. The decoder consists of a manifold learner based on an AE and a manifold-to-control mapping. Following initial AE training and decoder calibration with offline batch data, it extracts the latent manifold from EMG signals and maps it to continuous velocity control commands for the cursor or prosthesis. The real-time visual feedback enables user learning and adaptation. If data drift is detected due to EMG instabilities, the AE is updated with online sequential batch data to enhance performance and robustness. While the non-iterative online manifold learner dynamically adjusts for instabilities, the parameters of manifold-to-control mapping are held fixed over time.

A. Initial Offline Calibration of AE

Our approach leverages the scientific finding that a low-dimensional latent manifold structure is present in EMG signals [30]. Following [29] and [31], we used a single-hidden-layer AE (Fig. 2) for extracting this manifold representation in this study. The rationale of this method is based on several considerations. First, this configuration is motivated by the physiological generative model based on muscle synergies that suggests direction-wise estimation of DoF control [30], [31]. Second, thanks to its higher variance capture and unbiased variance allocation across latent dimensions as opposed to principal component analysis (PCA), AE has been demonstrated as a powerful tool for extracting such a non-linear manifold representation [32], [33], with which accurate myocontrol could be further obtained. Lastly, employing such a parsimonious architecture instead of a deeper network may facilitate short calibration of an initial decoder and fast updates afterwards.

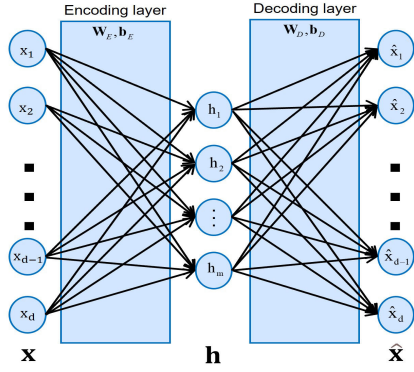


Fig. 2. The structure of the single-hidden-layer autoencoder.

Given the d -dimensional current activation pattern $\mathbf{x}(t)$ as an input, the m -dimensional ($m < d$) hidden latent representation is obtained with an encoder layer

$$\mathbf{h}(t) = f_E(\mathbf{x}(t)) = g(\mathbf{x}(t)\mathbf{W}_E + \mathbf{b}_E), \quad (1)$$

which encodes commands for the control of the external device. $\mathbf{h}(t)$ is further fed into a decoder layer that outputs the d -dimensional reconstructed vector,

$$\hat{\mathbf{x}}(t) = f_D(\mathbf{h}(t)) = g(\mathbf{h}(t)\mathbf{W}_D + \mathbf{b}_D), \quad (2)$$

where $g(\cdot)$ is an invertible nonlinear activation function (this study used leaky ReLU: $g(x) = 0.01x$ for $x < 0$, and $g(x) = x$ for $x \geq 0$), $\mathbf{W}_E \in \mathcal{R}^{d \times m}$ and $\mathbf{b}_E \in \mathcal{R}^{1 \times m}$ denote the weights and bias of the encoding layer, respectively; $\mathbf{W}_D \in \mathcal{R}^{m \times d}$ and $\mathbf{b}_D \in \mathcal{R}^{m \times 1}$ are those for the decoding layer, respectively. Parameters for AE are determined by solving the problem that minimizes the mean squared error between $\mathbf{x}(t)$ and $\hat{\mathbf{x}}(t)$.

In this study, m was set to 4, i.e., twice the control DoFs. Given a set of activation patterns $\mathbf{X}$ of size $n \times d$ (n is the number of samples) pertaining to a set of constrained motions (see section III-C), we trained an initial AE with a non-iterative MP inverse learning method [28]. This reduces the training time without penalizing performance, compared to the more commonly used gradient descent methods.

- 1) *Step 1*: Randomly initialize the orthogonal matrix and vector $\mathbf{W}_E, \mathbf{b}_E$, where they satisfy

$$\mathbf{W}_E^\top \mathbf{W}_E = \mathbf{I}_{m \times m}, \mathbf{b}_E^\top \mathbf{b}_E = 1, \quad (3)$$

and $\mathbf{I}_{m \times m}$ denotes an $m \times m$ identity matrix. Then the encoding layer outputs $\mathbf{H}$ by

$$\mathbf{H} = g(\mathbf{X}\mathbf{W}_E + \mathbf{b}_E). \quad (4)$$

- 2) *Step 2*: Calculate the parameters for the decoding layer as in [34] and [35]:

$$\begin{aligned} \mathbf{W}_D &= \mathbf{H}^\dagger g^{-1}(\mathbf{X}) \\ &= (\mathbf{H}^\top \mathbf{H} + (\mathbf{I}_{m \times m})/c)^{-1} \mathbf{H}^\top g^{-1}(\mathbf{X}), \end{aligned} \quad (5)$$

$$\mathbf{b}_D = rmse(\mathbf{H}\mathbf{W}_D - g^{-1}(\mathbf{X})), \quad (6)$$

where $\mathbf{H}^\dagger$ represents the pseudo-inverse of $\mathbf{H}$, c is a positive constant (typical values are ≥ 100 [28], we set to 125 in this study) and $g^{-1}(\cdot)$ is the inverse function of $g(\cdot)$, $rmse(\cdot)$ is the root mean square error.

The chosen single-hidden-layer AE architecture was justified by comparing it with multi-hidden-layer AEs in section III-D.

B. Online Unsupervised Adaptation of AE

To implement unsupervised online adaptation of AE, a buffer of length l is used to store the sequentially arrived data (see Fig. 1). When the buffer is filled, the drift detection is conducted on such a mini-batch in the buffer (see section II-B1), and AE gets updated with this mini-batch once drift is detected. Such a process repeats during the online myocontrol operation.

We use $\mathbf{X}_i$ to denote the i th ($i = 0, 1, 2, \dots$) mini-batch training data. Accordingly, $\mathbf{H}_i$ represents the output of the encoding layer for the input $\mathbf{X}_i$, $\{\mathbf{W}_E^{(i)}, \mathbf{b}_E^{(i)}\}$ and $\{\mathbf{W}_D^{(i)}, \mathbf{b}_D^{(i)}\}$ are the parameters for the encoding and decoding layers updated with the i th mini-batch training data, respectively. After the initial training with offline batch data $\mathbf{X}_0$, we have $\mathbf{W}_D^{(0)}$ according to Eq. (5):

$$\begin{aligned} \mathbf{W}_D^{(0)} &= (\mathbf{H}_0^\top \mathbf{H}_0 + (\mathbf{I}_{m \times m})/c)^{-1} \mathbf{H}_0^\top g^{-1}(\mathbf{X}_0) \\ &= \mathbf{K}_0^{-1} \mathbf{H}_0^\top g^{-1}(\mathbf{X}_0). \end{aligned} \quad (7)$$

Upon the arrival of the second training mini-batch training data $\mathbf{X}_1$, via the concatenation, we get

$$\mathbf{W}_D^{(1)} = \mathbf{K}_1^{-1} \begin{bmatrix} \mathbf{H}_0 \\ \mathbf{H}_1 \end{bmatrix}^\top \begin{bmatrix} g^{-1}(\mathbf{X}_0) \\ g^{-1}(\mathbf{X}_1) \end{bmatrix}, \quad (8)$$

where

$$\begin{aligned} \mathbf{K}_1 &= (\mathbf{I}_{m \times m})/c + \begin{bmatrix} \mathbf{H}_0 \\ \mathbf{H}_1 \end{bmatrix}^\top \begin{bmatrix} \mathbf{H}_0 \\ \mathbf{H}_1 \end{bmatrix} \\ &= (\mathbf{I}_{m \times m})/c + \mathbf{H}_0^\top \mathbf{H}_0 + \mathbf{H}_1^\top \mathbf{H}_1 \\ &= \mathbf{K}_0 + \mathbf{H}_1^\top \mathbf{H}_1, \end{aligned} \quad (9)$$

and

$$\begin{aligned} \begin{bmatrix} \mathbf{H}_0 \\ \mathbf{H}_1 \end{bmatrix}^\top \begin{bmatrix} g^{-1}(\mathbf{X}_0) \\ g^{-1}(\mathbf{X}_1) \end{bmatrix} &= \mathbf{H}_0^\top g^{-1}(\mathbf{X}_0) + \mathbf{H}_1^\top g^{-1}(\mathbf{X}_1) \\ &= \mathbf{K}_0 \mathbf{K}_0^{-1} \mathbf{H}_0^\top g^{-1}(\mathbf{X}_0) + \mathbf{H}_1^\top g^{-1}(\mathbf{X}_1) \\ &= \mathbf{K}_0 \mathbf{W}_D^{(0)} + \mathbf{H}_1^\top g^{-1}(\mathbf{X}_1) \\ &= (\mathbf{K}_1 - \mathbf{H}_1^\top \mathbf{H}_1) \mathbf{W}_D^{(0)} + \mathbf{H}_1^\top g^{-1}(\mathbf{X}_1) \\ &= \mathbf{K}_1 \mathbf{W}_D^{(0)} - \mathbf{H}_1^\top \mathbf{H}_1 \mathbf{W}_D^{(0)} + \mathbf{H}_1^\top g^{-1}(\mathbf{X}_1). \end{aligned} \quad (10)$$

Then Eq. (8) can be rewritten as follows:

$$\mathbf{W}_D^{(1)} = \mathbf{W}_D^{(0)} + \mathbf{K}_1^{-1} \mathbf{H}_1^\top \begin{bmatrix} g^{-1}(\mathbf{X}_1) - \mathbf{H}_1 \mathbf{W}_D^{(0)} \end{bmatrix}. \quad (11)$$

By generalizing from Eq. (11), the update rule for $\mathbf{W}_D^{(i+1)}$ can be derived as:

$$\mathbf{W}_D^{(i+1)} = \mathbf{W}_D^{(i)} + \mathbf{K}_{i+1}^{-1} \mathbf{H}_{i+1}^\top \begin{bmatrix} g^{-1}(\mathbf{X}_{i+1}) - \mathbf{H}_{i+1} \mathbf{W}_D^{(i)} \end{bmatrix}, \quad (12)$$

and $\mathbf{b}_D^{(i+1)}$ can be obtained according to Eq. (6):

$$\mathbf{b}_D^{(i+1)} = rmse(\mathbf{H}_{i+1} \mathbf{W}_D^{(i+1)} - g^{-1}(\mathbf{X}_{i+1})), \quad (13)$$

where

$$\mathbf{H}_{i+1} = g(\mathbf{X}_{i+1} \mathbf{W}_E^{(i+1)} + \mathbf{b}_E^{(i+1)}), \quad (14)$$

$$\mathbf{K}_{i+1} = \mathbf{K}_i + \mathbf{H}_{i+1}^\top \mathbf{H}_{i+1}. \quad (15)$$

Subsequently, to facilitate the AE tracking the evolving latent manifold, the parameters of the encoding layer are copied from the decoding layer for processing the next incoming block:

$$\mathbf{W}_E^{(i+2)} \leftarrow \mathbf{W}_D^{(i+1)\top}, \mathbf{b}_E^{(i+2)} \leftarrow \mathbf{b}_D^{(i+1)}. \quad (16)$$

It can be seen in Eq. (12) and Eq. (15) that previously learned knowledge is retained in $\mathbf{K}_{i+1}$. From Eq. (15), one can observe that the space complexity for storing $\mathbf{K}_{i+1}$ is $\mathcal{O}(m^2)$, being independent of the block length l .

1) Adaptation Trigger: We have adopted a self-diagnosed strategy, where AE is adapted when new emerging features are substantially discriminant from the current ones, i.e., data drift is detected. In specific, each time a buffer is filled, i.e., when a new block (i.e., $\mathbf{X}_{i+1}$) is ready (see Fig. 1), we calculated the value of variance accounted for (VAF), defined as [21]:

$$VAF_{i+1} = 1 - \frac{\text{var}(\mathbf{X}_{i+1} - \hat{\mathbf{X}}_{i+1})}{\text{var}(\mathbf{X}_{i+1})}. \quad (17)$$

It reflects the goodness-of-fit (ranging from 0 to 1) of current AE for the new block of data, where $\hat{\mathbf{X}}_{i+1}$ is the reconstructed block with AE and $\text{var}(\cdot)$ denotes the variance function. The higher VAF is, the better tracking ability of AE towards user's latest muscle activation patterns is. During the online operations, VAF is continuously monitored, once it is below the threshold, the adaptation of AE is triggered. The pseudo-code of the AE adaptation is shown in Algorithm 1.

Algorithm 1 Pseudo-Code of the AE Adaptation

Input: $\mathbf{W}_D^{(0)}, \mathbf{b}_D^{(0)}, \mathbf{K}_0$, buffer length l , trigger threshold

ϵ_{VAF}

Output: $\{\mathbf{W}_E^{(i+1)}, \mathbf{b}_E^{(i+1)}\}$ and $\{\mathbf{W}_D^{(i+1)}, \mathbf{b}_D^{(i+1)}\}$

for $i = 0, 1, \dots$ **do**

 # 1. Updating buffer:

$\mathbf{X}_{i+1} = \text{append}(\mathbf{X}_{i+1}, \mathbf{x}(t))$

if $\text{length}(\mathbf{X}_{i+1}) > l$, $\text{pop}(\mathbf{X}_{i+1}[0])$

 # 2. Updating AE:

 Calculate VAF_{i+1} with Eq. (17)

if $VAF_{i+1} < \epsilon_{VAF}$ **then**

$\mathbf{W}_E^{(i+1)} \leftarrow \mathbf{W}_D^{(i)\top}, \mathbf{b}_E^{(i+1)} \leftarrow \mathbf{b}_D^{(i)}$

 Calculate $\mathbf{H}_{i+1}$ with Eq. (14)

 Calculate $\mathbf{K}_{i+1}$ with Eq. (15)

 Update $\mathbf{W}_D^{(i+1)}$ with Eq. (12)

 Update $\mathbf{b}_D^{(i+1)}$ with Eq. (13)

end

end

2) Setting of Hyper-Parameters: The proposed AE adaptation procedure involves two hyper-parameters: the adaptation trigger threshold ϵ_{VAF} and the buffer (new block) size l . On one hand, according to [21] and [36], VAF higher than 0.8 indicates a satisfactory goodness-of-fit of

manifold-extractor on testing data. On the other hand, a threshold too close to 1 may trigger excessively frequent decoder adaptation. Therefore, default ϵ_{VAF} was set to 0.8. For the buffer size l , a larger l could better capture instabilities in signals, promoting more accurate updates of AE. In addition, a larger buffer size helps to reduce the differences in distribution among blocks of data, mitigating the discontinuity of the interface at the moment of AE update (known as the catastrophic forgetting problem for online learning [37]). Ultimately, to reach a speed-memory trade-off, $l = 1500$ was chosen which corresponds to a block of data from the last 30s, which is also comparable to the buffer lengths utilized by several online decoder adaptation methods (40s [20], 20s [21]).

C. Manifold-to-Control Mapping

After the m -dimensional latent manifold vector $\mathbf{h}(t)$ is extracted from current activation pattern $\mathbf{x}(t)$ via the encoding layer of AE, it is further mapped into a 2-dimensional SP velocity commands $\mathbf{v}(t) = f_V(\mathbf{h}(t))$ for devices. This manifold-to-control mapping function is implemented with a regression neural network (RNN) following [38], resulting in control signals with appropriate range of movement in the respective DoF, determined during the calibration phase (see Section III-C). After the calibration of such a mapping function, its parameters are held fixed over time.

III. EXPERIMENTS

Experiments were conducted for validating our method following instabilities, with electrodes shift as a typical source of signal non-stationarity. Experiment I was carried out for justifying the chosen single-hidden-layer AE architecture in our study. Experiment II was performed for verifying whether the proposed approach could quickly converge. Experiment III, a virtual target reaching task was conducted in multiple sessions to investigate progressive co-adaptation. In this study, our unsupervised decoder adaptation (UDA) scheme was also compared with the supervised counterpart (SDA). Experiment IV involved the application of the proposed UDA applied to the control of an emulated robotic prosthesis worn by non-disabled users, with redonning of the prosthesis.

A. Subjects

The experimental procedures conducted under ethical approval from the Ethics Committee of Southeast University (2022ZDSYLL038-P01). Twenty-five right-handed able-bodied subjects with no history of neurological impairment (20 males and 5 females, aged 27.5 ± 4 years), who had no prior experience with myoelectric control, were recruited for the study. Subjects were randomly split into four groups, each group participated in one of four experiments, and informed consent was obtained.

B. Data Acquisition and Processing

EMG signals were recorded from the dominant forearm using a Myo Armband (Thalmic Labs, Canada). The device,

equipped with eight bipolar EMG electrodes, sampled EMG signals at a rate of 200 Hz, and it contained an integrated 50-Hz notch filter for the removal of noise from the power grid [39]. A 2nd-order Butterworth high-pass filter with cut-off frequency at 15 Hz was applied for baseline and motion artefacts removal [40]. Following [20], we used the root-mean-square (RMS) values of the 8-channel EMG as the input vector of AE, which were obtained using moving windows of 100-ms duration with a step of 20 ms. A custom program in Matlab (2013a 64-bit) was developed for the real-time processing of EMG signals, online AE adaptation and control of the cursor or prosthetic hand.

C. Initial Calibration for Our Decoder

For the online control, we used wrist flexion/extension and ulnar/radial deviation as control motions, according to [2] and [41]. During the calibration phase, participants were instructed to execute single-DoF full-range wrist motions (wrist flexion/extension and ulnar/radial deviation) in a predetermined order cued on a monitor. EMG signals were recorded during four repetitions of these motions. As discussed above, our decoder comprises an encoding layer from AE, followed by a manifold-to-control mapping, which were calibrated as discussed below. With the method described in Section II-A, the offline batch training of the AE was repeated 20 times with different initial parameters for encoding layer, resulting in 20 AE networks. The optimal initial AE was selected as that corresponding to the minimum reconstruction error. To calibrate the manifold-to-control mapping, the 4-dimensional manifold vector $\mathbf{h}(t)$ were first extracted from the activation pattern $\mathbf{x}(t)$ by AE, and then the DoF-wise continuous labels were generated from $\mathbf{h}(t)$ following [38], which consisted of a first phase to segment the motion and a second phase of automated labeling. Subsequently, a RNN was trained with $\mathbf{h}(t)$ and its continuous label. The calibration of an initial decoder for the compared supervised adaptation scheme in Experiment III followed the method described in [12].

D. Experiment I: Single-Hidden-Layer v.s. Multi-Hidden-Layer AE

Experiment I was conducted to justify the chosen single-hidden-layer AE architecture over deeper ones in our study.

1) *Experimental Procedure*: Six subjects from Group 1 participated Experiment I, where they underwent an offline data collection and an online control evaluation. During the offline data collection, each subject was first instructed to execute 4 types of single-DoF wrist motions (i.e., wrist flexion/extension, ulnar/radial deviation), 6 trials per motion, and EMG signals were collected. Two trials from each motion were randomly selected and combined to form the test set, while the remaining trials were used as the training set. The decoders based on the single-hidden-layer AE and multi-hidden-layer AE were then calibrated on the training set, respectively. Next, using the virtual target reaching task (section III-D3), the subject conducted a short-period online control evaluations with each decoder, where the order of the three decoders was randomized across the subjects.

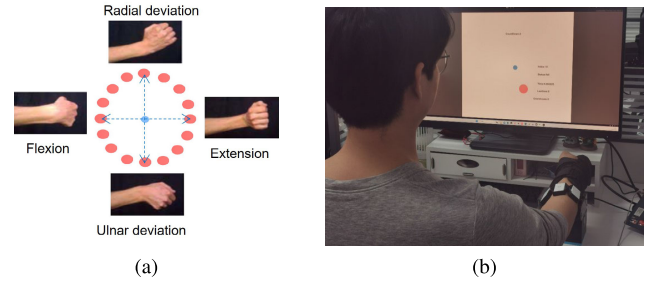


Fig. 3. (a) The space layout for the virtual target reaching paradigm. The target is shown as a circle in red while a blue circle is displayed as the cursor. EMG signals recorded during wrist motions (flexion/extension and ulnar/radial deviation) are mapped to SP velocity commands. (b) Experimental setup for the virtual target reaching paradigm.

2) Calibration for Multi-Hidden-Layer AE Based Decoders:

Real-world applications often requires a short-calibration setting, with the full training set in Experiment I consisted of $4 \times 4 = 16$ trials, only the following AEs are compared with our single-hidden-layer (SingleHL) AE:

- *two-hidden-layer (TwoHL) AE*: with a 4D code-units layer and two hidden layers (one in the encoder sub-network and the other in the decoder subnetwork), with 8 neurons per layer.
- *four-hidden-layer (FourHL) AE*: with a 4D code-units layer and four hidden layers (two in the encoder sub-network and two in the decoder subnetwork), with 8 neurons per layer.

Both AE architectures above were based on the same non-linear leaky ReLU activation function as our SingleHL AE. Twenty TwoHL/FourHL AEs were trained with different initializations, and the one with the minimum reconstruction error was selected. Implementation details were given as follows: Adam optimizer was used, the learning rate: 0.001, the maximum iterations: 1000. The calibration of the manifold-to-control mapping for multi-hidden-layer AE based decoders was the same as our singleHL AE based decoder.

3) *Task Description*: The virtual target reaching paradigm, well-established in evaluating myoelectric control methods [20], [42], was employed for guiding user's wrist motions. As shown in Fig. 3, sixteen target circles, evenly distributed in a ring, were displayed one by one in a random order. For each trial, the subject maneuvered the cursor from the ring's origin to the target within 5 seconds, dwelling within the target for at least 250 ms. Each round consisted of 16 trials, and the round ended after all the 16 targets had been tested. The chosen task parameters followed previous studies [20], [42], allowing to distinguish between accurately directed movements and those merely brushing the target. Target locations ensured a mix of single and multiple DoF control. Participants were seated comfortably with the forearm supported by an armrest.

4) *Evaluation Metrics and Statistical Analysis*: To evaluate the information-preserving capability by each AE calibrated with different amounts of training set (1 trial, 2 trials, 3 trials and 4 trials per wrist motion type, respectively), the VAF on the test set of the offline data was reported.

We employed several task-related metrics commonly used in past studies (e.g., [29], [42]) to evaluate the online control

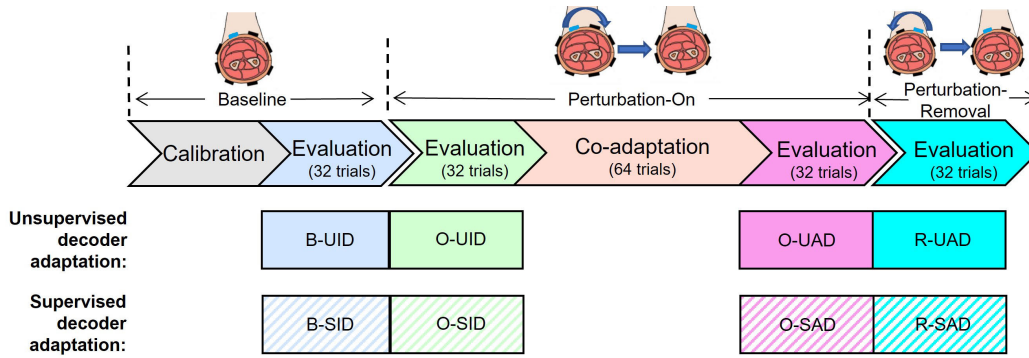


Fig. 4. The trial sequence of Experiment III. The tag for each evaluation block is specified underneath, where UID/SID/UAD/SAD denotes the fixed decoder used in each evaluation block. UID and SID are unsupervisedly and supervisedly initialized decoders, respectively. UAD and SAD are unsupervisedly and supervisedly adapted decoders, respectively.

performance of decoders based on SingleHL, TwoHL and FourHL AE, all calibrated with the full training set (4 trials per motion). The Completion Rate (CR, [%]) quantifies the ratio between the number of targets reached and the total number of targets. Completion Time (CT, [s]) represents the time needed to reach an intended target (5s is assigned to a failure trial where user fails to reach the target during its 5s-appearance). The Path Efficiency (PE, [%]) measures the ratio between the straight-line distance from origin to target and the length of actual cursor trajectory. Throughput (TP, [bit/s]) gauges the information transfer capabilities of the human-machine interface, considering task difficulty and execution time [43]. With 32 trials of virtual reaching paradigm per subject, the one-way repeated measures analysis of variance (RM-ANOVA) was utilized for statistical analysis of the difference among these task-related metrics by three decoders.

E. Experiment II: Convergence of Decoder Adaptation Scheme

A simulation was conducted to verify whether the AE models adapted via the proposed unsupervised adaptation scheme could converge after instabilities onset, using the EMG signals recorded during virtual target reaching tasks.

1) *Experimental Procedure*: Group 2 that consisted of three subjects participated Experiment II. After subjects familiarized with the myocontrol for the virtual reaching task, a perturbation condition was introduced by transversely shifting electrodes approximately 2.5 cm (a distance of single sensor pod) from their initial positions in line with past works [19], [44], and then subjects continued the task following visual cues. EMG signals during the task after the perturbation were recorded for further analysis.

2) *Evaluation Metrics*: After the perturbation onset in the task, the evolution of AE models via our adaptation method throughout the following 200s was quantified, in terms of VAF and relative model disparity at each time instance. The relative model disparity was calculated as the difference between parameters of the encoding layer before and after each update.

F. Experiment III: Co-Adaptation in Virtual Target Reaching Task

Using the same virtual target reaching task, a set of online experiments was performed to assess the ability of the

co-adaptive myocontrol system to overcome the perturbation caused by electrodes shift.

1) *Experimental Procedure*: 10 subjects from Group 3 took part in Experiment III. Each subject finished an experimental session with the unsupervised decoder and another session with the supervised decoder on the same day, the order of these two experimental sessions was randomized across the participants. Each experimental session included three consecutive phases: “Baseline”, “Perturbation-On”, and “Perturbation-Removal” as depicted in Fig. 4, where each phase involved several blocks of trials. Participants were allowed to rest between blocks as long as needed to reduce fatigue.

a) *Baseline phase*: An experimental session commenced with the calibration of the initial baseline decoder (see section III-C). Following this, a block of 32 trials (denoted as B-UID/B-SID in Fig. 4) was then run to evaluate the baseline myocontrol performance using the initial decoder in the absence of perturbations.

b) *Perturbation-on phase*: We then introduced a perturbation by transversally shifting electrodes 2.5cm from their original positions. After this, a block of 32 trials (denoted as O-UID/O-SID in Fig. 4) were performed to evaluate the performance following introduction of perturbation with the initial decoder. During the next block of 64 adaptation trials (denoted as Co-adaptation in Fig. 4), the adaptation scheme (UDA or SDA) updated the decoder parameters when triggered while the subject continued the target reaching task with the myocontrol interface. For UDA, the adaptation was enabled once failures for AE to track the manifold of latest muscle activation patterns were detected (see Section II-B1). For SDA, the decoder was updated in a supervised fashion every 16 trials (a round of reaching tasks), using the data labeled by oracle knowledge of user intent [45] during the adaptation trials, as proposed in [12]. At the end of this block, the decoder updates were stopped, and an adaptation evaluation block of 32 trials (denoted as O-UAD/O-SAD in Fig. 4) was performed to assess performance in the presence of perturbation, with the final set of adapted decoder parameters.

c) *Perturbation-removal phase*: With the same decoder in O-UAD/O-SAD, a final evaluation block of 32 trials (denoted as R-UAD/R-SAD in Fig. 4) was conducted with removed perturbation (transversally shifted electrodes back to original

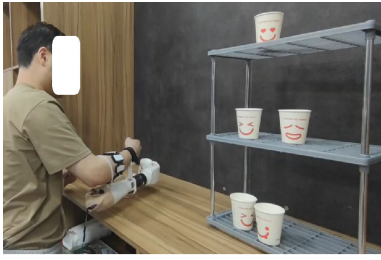


Fig. 5. Experimental setup for Experiment IV.

positions) at the end of each experimental session. This was to assess whether there were transient differences in performance with the same decoder under two electrode conditions (unshifted and shifted), which may be attributed to user learning. It is noteworthy that the decoders were administered to all participants under identical perturbation settings, and subjects were not informed of the type of current decoder.

2) *Evaluation Metrics and Statistical Analysis:* Task-related metrics (CR, CT, PE, TP) obtained from 10 subjects were subjected to a two-way RM-ANOVA, where one factor is the electrode condition (levels include unshifted and shifted) and the other is the myocontrol decoder (levels include UID, UAD, SID, SAD). Prior to this, the Shapiro-Wilk's test of normality and the Mauchly's test of sphericity were conducted. Results from adaptation trials were not included in the analysis, as the myocontrol decoder was updating and the target reaching were machine-assisted during those trials. If a significant interaction between factors was detected from the two-way RM-ANOVA, a focused one-way RM-ANOVA was conducted for each level of both factors, otherwise only the main effects were analyzed. If the non-fixed factor was found to have significant effects, multiple pairwise comparisons with Bonferroni correction were carried out to identify statistically significant differences. All analyses were performed in IBM SPSS Statistics.

G. Experiment IV: Cup Relocation With Prosthetic Hand

The proposed method was applied to myocontrol of a custom-designed robotic prosthetic hand. This cable-actuated prosthetic hand, weighing approximately 700 g, featured a freely rotating wrist. Able-bodied participants were mounted the robotic hand using a customized socket interface on their forearms (Fig. 5). EMG signals from wrist flexion/extension controlled the velocity for hand opening/closing, while radial/ulnar deviation signals controlled the velocity for wrist rotation.

1) *Task Description:* Six cups were originally placed on a desk (3 face up and 3 face down), the subject was instructed to place a upward-facing cup, turn a downward-facing cup upward and place it, on each tier of a three-tiered shelf, where the tier located at waist, chest, and head level, respectively. This task was chosen for several reasons: its simplicity allows the user to quickly learn and operate the task; its short duration allows several trials to be completed rapidly, which minimizes muscle fatigue.

2) *Experimental Procedure:* The experimental procedure consisted of four phases, see Fig. 6. In the **Baseline phase**, the subject first conducted the task with an initial decoder.

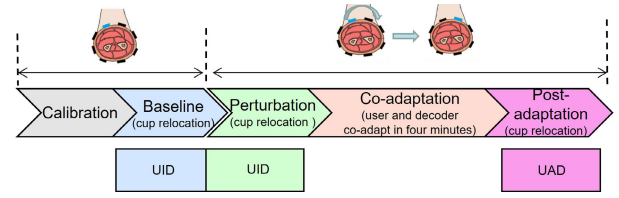


Fig. 6. The trial sequence of Experiment IV. The fixed decoders used in the Baseline, Perturbation and Post-adaptation phase are given underneath.

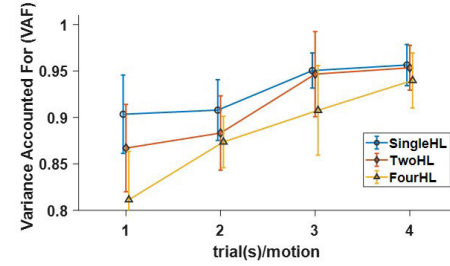


Fig. 7. VAF on test set by the three AE architectures with different amounts of training data.

In the **Perturbation phase**, the EMG sensor band was rotated by 2.5cm from its original position to emulate the real-world case when amputees re-don the prosthesis. Then the user performed the task again with the initial decoder. In the **Co-adaptation phase**, our automatic online unsupervised decoder adaptation scheme was applied for 4 minutes to facilitate the co-adaptation of user and decoder. In the **Post-adaptation phase**, the task was conducted again with the fixed decoder that was obtained in the last phase. There was no time limit for finishing the task, unless the user gave up because of inability to control the interface. The completion time of successful six-cup relocations was employed as the evaluation metric, whose values in the Baseline, Perturbation and Post-adaptation phases were reported. The task was tested with six subjects from group 4. After shifting electrodes in the Perturbation phase, three subjects found that the myocontrol interface with the initial decoder was too uncontrollable to conduct the task, no matter how hard they tried, and thus got frustrated and quit the experiment. Thereby, results on remaining three subjects were reported.

IV. RESULTS

A. Results of Experiment I

Fig. 7 summarized the VAF on test set by the three AE architectures. As can be seen, all the three AEs with different amounts training data demonstrated satisfactory goodness-of-fit ($VAF > 0.8$). Besides, the average VAF by SingleHL AE is higher than those by TwoHL and FourHL with 1 trial/motion and 2 trials/motion from the training set, implying that its information-preservation capability is better than the more complex architectures calibrated with insufficient training data.

The online-control task metrics for Experiment I are summarized in Fig. 8. When calibrated with full training set, the decoders based on the SingleHL, TwoHL and FourHL AEs all achieved satisfying online control performance. No significant difference in CR, CT, PE and TP was found among the three

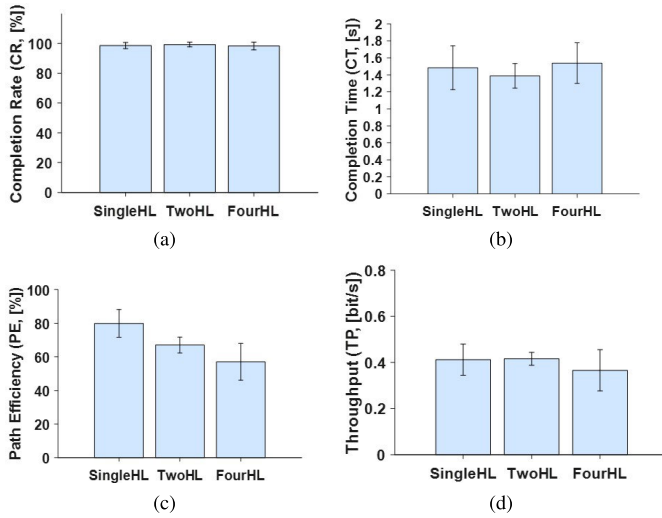


Fig. 8. Summary of online-control task metrics for Experiment I.

decoders ($P > 0.05$). This indicates that the all of them can generalize well on unseen samples spanned from the latent space learned on the offline calibration data.

To sum up, with sufficient calibration data, the SingleHL-AE-based decoder performed similarly to TwoHL/FourHL-AE-based decoder during short-period online myoelectric control, while it could capture more motion information than the other two with little calibration data. In real-world myoelectric control applications, the user calibration should be as short as possible, thus the single-hidden-layer AE is preferable and was also used in our study.

B. Results of Experiment II

The evolution process of AE models throughout a 200-second adaptation after the onset of perturbation is shown in Fig. 9. The normalized model disparity between AE models from sequential updates rapidly decreases near zero within 50s (about a half duration of a single round), and remains close to zero afterwards. On one hand, such results have verified the fast convergence of our unsupervised adaptation scheme after sudden perturbations in EMG signals. On the other hand, the stability of AE models obtained via our adaptation scheme is also validated by these results. Accordingly, the average VAF continued to increase in the first 50s until stabilizing around 0.8 afterwards, suggesting that the AE model online updated quickly and stably tracked the manifold of novel EMG signals after the perturbation.

C. Results of Experiment III

1) *Evolution of Performance Over Phases*: For block B-UID in the absence of perturbation, performance was acceptable (Fig. 10, B-UID, CR: $99\% \pm 2\%$; CT: 1.67 ± 0.32 s; PE: $76\% \pm 4\%$; TP: 0.37 ± 0.08 bit/s), with cursor trajectories being nearly straight to each target (Fig. 11(a)).

Following introduction of the recording perturbation, performance in block O-UID degraded (Fig. 10, O-UID, CR: $43\% \pm 15\%$; CT: 4.20 ± 0.37 s; PE: $39\% \pm 4\%$; TP: 0.19 ± 0.01 bit/s), and some targets could not be reached

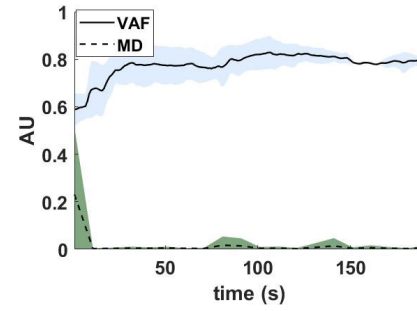


Fig. 9. The evolutions of VAF and relative model disparity (MD) over time after the online unsupervised decoder adaptation scheme was applied in Experiment II. MD was calculated as the difference between the parameters of the encoding layer before and after each update, normalized by the maximum one throughout the process. Shaded areas indicate the standard deviations.

anymore (Fig. 11(b)). During the Co-adaptation block, updates of the decoder progressively improved the performance (Fig. 10, Co-adaptation), and the cursor trajectories were uniformly distributed toward 16 targets with continual updates (Fig. 11(c) and Fig. 11(d)). With the final decoder obtained in block end of Co-adaptation, acceptable-performance myoelectric control was restored in block O-UAD (Fig. 10, O-UAD, CR: $98\% \pm 5\%$; CT: 1.93 ± 0.65 s; PE: $62\% \pm 11\%$; average TP: 0.34 ± 0.07 bit/s), and cursor control (Fig. 11(e)) was comparable to that of block B-UID.

After shifting the electrodes back to their initial positions, performance in block R-UAD (Fig. 10, R-UAD, CR: $99\% \pm 3\%$; CT: 1.82 ± 0.33 s; PE: $72\% \pm 7\%$; TP: 0.33 ± 0.05 bit/s) was close to that of block O-UAD, so were cursor trajectories (Fig. 11(f)).

2) *Differences in Performance Across Conditions*: Fig. 12 summarizes the results for different conditions. Significant interaction was observed between the decoders and the electrode conditions in all metrics (CR: $F_{3,27} = 69.47$, $P < 0.001$; CT: $F_{3,27} = 104.35$, $P < 0.001$; PE: $F_{3,27} = 42.85$, $P < 0.001$; TP: $F_{1.4,27} = 60.65$, $P < 0.001$). Focused one-factor RM-ANOVA revealed significant differences in CR ($P < 0.001$, effect size = 0.55), CT ($P < 0.001$, effect size = 2.53), PE ($P < 0.001$, effect size = 0.37), and TP ($P < 0.001$, effect size = 0.22) at electrodes unshifted (B-UID block) and shifted (O-UID block) conditions for UID. These findings suggest that the user adaptation alone, without the aid of decoder adaptation, was unable to overcome deleterious consequences due to electrode shifts.

When fixed on the shifted electrodes level, significant differences in all four metrics were detected between decoders (CR: $F_{1.70,27} = 55.942$, $P < 0.001$; CT: $F_{1.61,27} = 95.125$, $P < 0.001$; PE: $F_{3,27} = 60.212$, $P < 0.001$; TP: $F_{3,27} = 91.404$, $P < 0.001$). O-UAD block had better performance than O-UID block, and the post-hoc analysis showed that differences in their performance were statistically significant: CR ($P < 0.001$, effect size = 0.54), CT ($P < 0.001$, effect size = 2.27), PE ($P < 0.001$, effect size = 0.226) and TP ($P < 0.001$, effect size = 0.19). Moreover, significant differences in all four metrics were also observed between O-SAD and O-SID: CR ($P < 0.001$, effect size = 0.46),

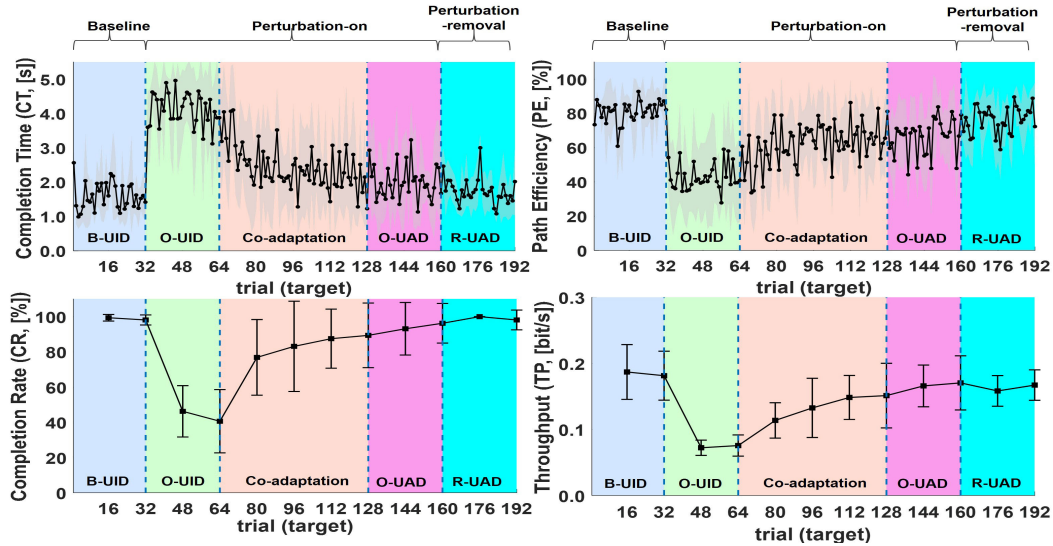


Fig. 10. The evolution of cursor control performance in Experiment III for all participants with unsupervisedly initialized and adaptive decoders. For CT and PE, the black dot represents the averaged value across participants for each trial, the gray shadow refers to the standard deviation. For CR and TP, the average and standard deviation across participants are depicted as black square and error bar at each round, respectively.

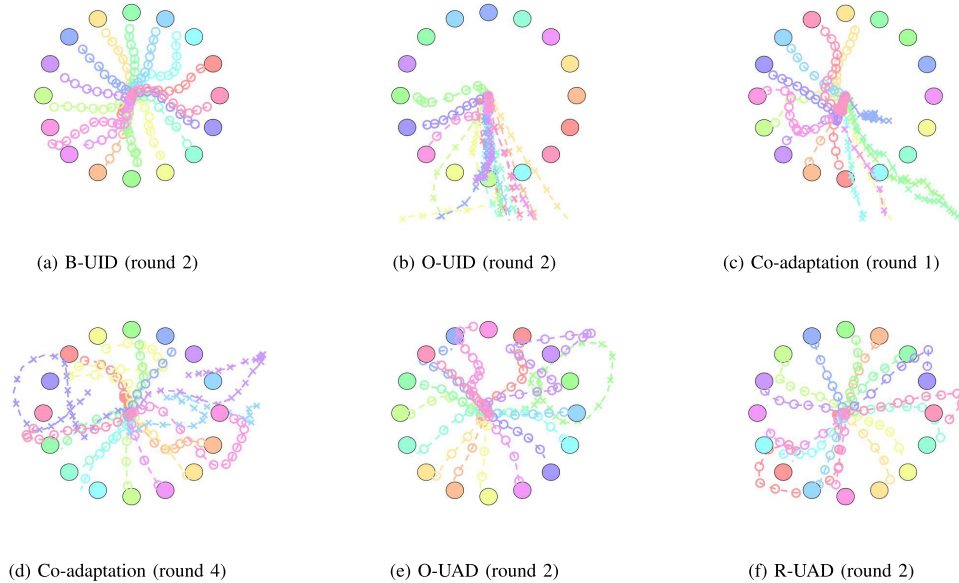


Fig. 11. Cursor trajectories during selected rounds from a representative session of Experiment III. Trajectories for successful trials are marked by “o”, and failed trials by “x”.

CT ($P < 0.001$, effect size = 2.33), PE ($P < 0.001$, effect size = 0.42), and TP ($P < 0.001$, effect size = 0.24). Such results indicate that the signal variability caused by electrodes offset can be mitigated by both unsupervised and supervised continual decoder adaptation.

For UAD, no significant difference was found in CR/CT/PE/TP between electrodes unshifted (R-UAD block) and shifted (O-UAD block) conditions. This indicates that the online co-adaptation process may have encouraged the user to form a stable internal model generalizable to different electrodes conditions.

D. Results of Experiment IV

Fig. 13 reports the completion time in each phase. As can be seen, after shifting the electrodes, the completion time increased greatly in Perturbation phase (274.61 ± 31.56 s)

compared to that in Baseline phase (137.67 ± 12.22 s). After 4-minute application of our online unsupervised adaptation scheme, which promotes co-adaptation of user and decoder for fully SP myocontrol of the combined two DoFs, the completion time in the Post-adaptation phase (161.16 ± 7.94 s) returned to values comparable with the Baseline phase. A video of Experiment III and IV is provided in the supplementary materials.

V. DISCUSSIONS

A. Online Unsupervised Adaptation Increases Interface Accessibility

Signal instabilities remain one of primary causes for myocontrol performance degradation [5]. We demonstrated that the proposed method quickly restored control after

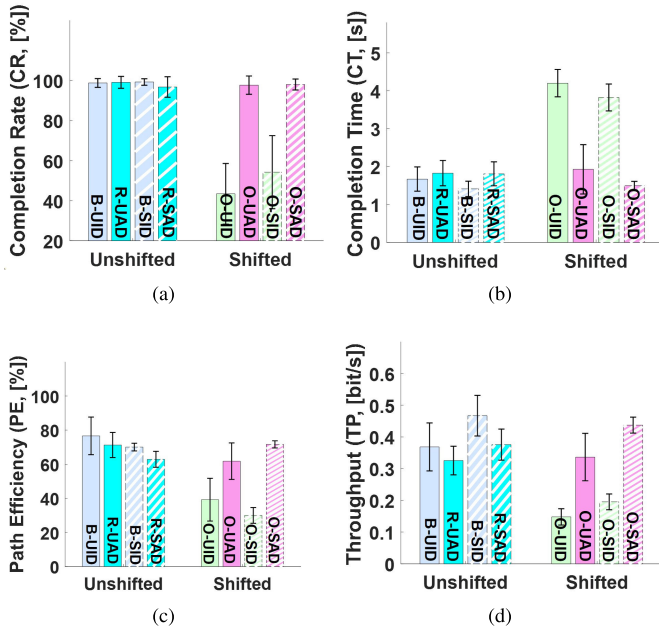


Fig. 12. Summary of results for Experiment III.

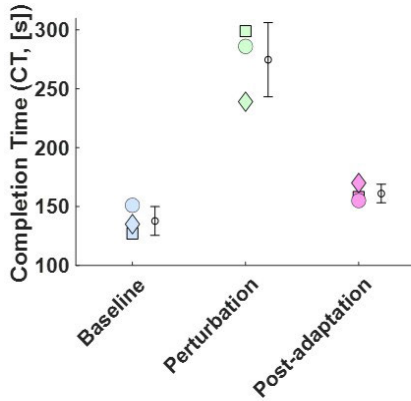


Fig. 13. Results for Experiment IV. The completion time by each subject, mean and standard deviation across participants, are plotted for each phase.

sudden perturbations by electrode displacement mimicking a real-world setting associated with amputees doffing and donning the prosthesis, which results in a near-complete loss of control. Our approach is based on two scientific findings. The first is that the representation of movement intent tends to lie on a low-dimensional latent manifold space [30], which de-emphasizes the role of sensor space in myoelectric control. The second is that the true latent representation within the manifold associated with consistent motion is likely to be stable across time [46]. Thus, after electrode displacements misaligned the activation patterns in sensor space, we updated an AE with block data online collected to track the latent manifold while the user continued the task. In our method, the AE was updated as needed to reach the desired goodness-of-fit characterized by $VAF \geq 0.8$. In this way, we obtained consistent intent representations across data blocks despite perturbations in the sensor space, leading to accurate output of the EMG decoder aligned with the intended movement. The users' burden is

then mitigated as their control strategies do not demand sharp changes after sudden perturbations. Experimental results showed that user adaptation alone with fixed initial decoder often failed to compensate sudden perturbations within the allowed time (see Fig. 10 and 13).

Moreover, the proposed approach offers distinct accessibility advantages over other state-of-the-art interfaces, as it avoids common constraints. First, compared to [5], a large set of initial calibration data, including those collected under perturbation conditions, is no longer needed. The proposed method requires only a small amount of initial calibration data that can be collected within minutes. Second, our approach avoids interrupting the operation of the device with offline data collection, which is required in [15], [16], [17], [18], and [19]. In the meanwhile, a decoder recalibrated offline does not guarantee its performance during online operation [47], which further highlights the benefits of our online decoder adaptation. Third, although the online supervised adaptive decoder produced better average metrics in O-SAD than its unsupervised counterpart in O-UAD (see Fig. 12), the supervised approach relies on information about the state of task (or intended task goals), which poses challenges in the translation to real-world control tasks. In contrast to online supervised decoder adaptation approaches [22], [23], [24], [25], the proposed method did not need measurements of kinematics or forces neither for the initial calibration, nor for the adaptation. Fourth, the scheduled triggering strategy used in online adaptation methods [21], [24] largely relies on the prior knowledge of task pacing, affecting its generalizability across tasks. By contrast, our online decoder adaptation adopted a self-diagnosed triggering strategy, i.e., the AE is updated when a drift characterized by a low VAF value is detected, indicating a defective decoder. Lastly, several recent studies on robust myoelectric decoding [13], [14] propose to estimate the electrode shift online and compensate for it accordingly. However, they highly rely on the initial electrode positions, and can only deal with the non-stationarity due to electrode shift. Conversely, our method does not rely on the initial electrode positions, and may be applied to handle other signal variations in addition to electrode shift. In summary, our adaptive decoder helped to increase the interface accessibility.

B. Fast Decoder Adaptation Facilitates Reliable Control Restoration

In a related field, i.e., brain-machine interfaces (BMI), two studies [27], [48] have shown that the close-loop decoder adaptation timescale may be of particular importance when the initial performance is relatively poor. Those studies concluded that user learning may be negatively influenced if updates of the decoder fail to converge on an intermediate (1)–2 min timescale.

In our AE adaptation scheme (Algorithm 1), we employed a non-iterative MP inverse learning method, which has been verified to be able to reduce training time compared to iterative ones [28], for obtaining the parameters of decoding layer with the current data block. Moreover, such parameters were transferred to seed the encoding layer of the AE model in the next update, which projects the new coming data on the

same latent manifold derived from the last block. To reach a trade-off between being prone to overfit (decoders abruptly change during online operations) with a short history block and being computationally expensive with a long one, we adopted a 30s-long batch for our closed-loop myocontrol system. In the simulation with buffer length comparable to [20] and [21], results showed that the proposed adaptation scheme rapidly converged within 50s (on a 1-min timescale, see Fig. 9).

By contrast, recent adaptive interface studies in myocontrol [20], [23] and IMU-based body-machine interfacing [21] report that decoders updated block-wisely with iterative optimization methods (i.e., recursive Gauss-Newton [23], block-coordinate descent [20] and batch gradient descent [21]) reach the convergence within around 120s, 120s and 159s, respectively. Compared to [20], [21], and [23], a shorter convergence time of our decoder adaptation may better alleviate user's burden and frustration on using the degraded interface, by more efficiently recovering a consistent mapping between the intended and actual motions with which to practice and learn. Experimental results (Section IV-C and Section IV-D) demonstrated that the myocontrol performance was reliably restored from signal instabilities following electrodes shift, with the application of our decoder adaptation scheme during online operations.

C. Stability of the User-Decoder Co-Adaptation

During the period when our online unsupervised decoder adaptation scheme was applied, gradual improvements on the decoder progressively shaped user learning, i.e., the decoder and the user co-adapted in a two-learner setting. The stability issue for such concurrent adaptations is a major concern for co-adaptive learning systems. A few past theoretical studies [49] have concluded that the co-adaptation may be stable if one learner adapts faster than the other.

On one hand, our experimental results showed that the adaptation of the decoder converged on the 1-min timescale (Fig. 9), which is apparently faster than the time that a user generally may need for adapting the control strategy (from minutes to hours [9]). On the other hand, the user unlikely changed substantially the control strategy in 1-min timescale. Thereby, the decoder was sufficiently fast to adapt to the strategy that the user adopted. From the view of decoder adaptation, the user is quasi-stable; from the view of user adaptation, the decoder is also quasi-stable (since the decoder adaptation finishes much faster compared to the user adaptation). As such, a stable co-adaptive myocontrol system was achieved. Note that since the impacts of user and decoder adaptation were unable to be thoroughly separated in task evaluation metrics, we did not quantify the user adaptation in this work, which is only possible for studies focusing on user adaptation only, with non-adaptive decoders (e.g., [9]).

D. Limitations and Future Work

In our study, we primarily introduced electrode displacement as a perturbation, without considering other sources of signal instability (e.g., variations in limb position, muscle fatigue and user muscle activation). Future work will validate

the ability of the proposed method to compensate for other EMG signal instabilities. Another limitation of our study is that only wrist flexion/extension and ulnar/radial deviation were used to verify the decoder adaptation; additional finger/hand/wrist motions, such as individual finger motion, hand opening and closing, wrist pronation and supination, will be studied in future work. In addition, the hyper-parameters for the decoder adaptation algorithm were not optimized for each individual in this study. Effective individualized optimization methods for the hyper-parameters will be studied in the future. Furthermore, the extensive applicability of our adaptation scheme for the targeted amputee population will be tested in future studies.

VI. CONCLUSION

In this study, we presented an unsupervised decoder that co-adapts with the user during online myocontrol. The convergence validation experiment has verified that the proposed adaptation scheme converged on a 1-min timescale, which corresponds to approximately 50% over existing online decoder adaptation methods. Results of the virtual target reaching experiment showed that our method reached comparable improvements in robustness comparable to its supervised counterparts when perturbations were present due to electrode shifts. Besides, during the cup relocation test with the prosthetic hand, the electrode shift had a negligible effect on the performance of our adaptive decoder. These results demonstrate that the proposed method, with improved accessibility and reliability, has the potential for accelerating the clinical deployment of myoelectric control interfaces.

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