Co-Adaptive Myoelectric Interface for Continuous Control [⋆]

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Abstract: Neural interfaces provide novel opportunities for augmenting human capabilities in domains like human-machine interaction, brain-computer interface, and rehabilitation. However, the performance of these interfaces varies significantly between users. Decoders that adapt to individual users have the potential to reduce variability and improve performance but introduce a "two-learners" problem as the user simultaneously adapts to the changing decoder. We propose and experimentally test a game theory framework to optimize closed-loop performance of a myoelectric interface for continuous control (based on surface electromyography, sEMG) through co-adaptation of user and decoder. Human subjects learned to use our interface to perform a two-dimensional trajectory-tracking task. Closed-loop performance was affected by decoder learning rate, but not initialization or decoder cost weights. Our study indicates the potential for co-adaptation in humans and machines to optimize the performance of neural interfaces.

Keywords: human-in-the-loop systems, neural interfaces, sensorimotor control

1. INTRODUCTION

Direct control of devices using neural activity has many applications, including brain-computer interfaces to restore function (BCIs) (Carmena, 2013; Shanechi et al., 2017), human-machine interfaces (HMIs) (De Santis, 2021), rehabilitation (Reinkensmeyer et al., 2016; Li et al., 2016), neuroprosthetics (Hochberg et al., 2012), and augmenting human capabilities (Willett et al., 2021). However, variability in the efficacy of neural interfaces across users (Zhang et al., 2020) and variability in neural signals within a single user over time (Yamagami et al., 2018) presents challenges with ensuring safety and high performance of neural interfaces across users. Should probably read these lol

In such scenarios, interfaces that seamlessly adapt to users while also shaping how the user learns to control the interface are desirable. Such co-adaptive interfaces are more robust to variability between and within users by jointly optimizing the closed-loop interaction between user and device. Previous studies explored how co-adaptation can reduce task error (Müller et al., 2017; Orsborn et al., 2014, 2012) and maximize interaction efficiency (De Santis, 2021). For example, (Orsborn et al., 2014) proposes and validates *SmoothBatch*, a closed-loop adaptation algorithm that iteratively adjusts the decoder to reduce task error. However, algorithms that only consider error and ignore user effort lack theoretical guarantees of convergence.

Co-adaptive human-machine interfaces present a "two-learner" problem. Both the human and machine are learning in a closed-loop alongside each other. Game theory has been proposed in recent years as a framework to study two-learner dynamics in sensorimotor control (Braun et al., 2009; Li et al., 2019, 2016; Müller et al., 2017; Madduri et al., 2021). In particular, game theory provides techniques for predicting convergence to and stability of stationary points in two-learner systems (Ratliff et al., 2013; Başar and Olsder, 1999). Although *general-sum* games can arise in sensorimotor interactions (Braun et al., 2009), we contend that the special case of *potential games* (Monderer and Shapley, 1996), where the incentives of both learners are aligned, are particularly relevant in neural control applications. Prior studies leveraged potential games to explore how human-decoder interactions co-adapt with practice, both in simulation (Madduri et al., 2021) and in human-subject experiments (Li et al., 2016, 2019). For example, (Li et al., 2019) modeled a robot and human physically interacting using game theory, and demonstrated that each learner estimating the other's controller will lead to convergence to the Nash equilibrium. Such two-learner models could be useful for predicting and shaping how the human and decoder learning evolves. However, predictions from the game-theoretic framework have not yet been experimentally tested for neural interfaces.

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In this paper, we propose and experimentally test a game theory framework to optimize closed-loop performance of a myoelectric interface (based on surface electromyography, sEMG) through co-adaptation of user and decoder. In particular, we model the user and decoder as two players in a potential game and implement a natural (co-)adaptation strategy for the decoder: iteratively update to minimize the decoder's cost. In a human subjects experiment with seven participants, we found that the user and decoder co-adapt to significantly improve tracking performance during a five-minute two-dimensional trajectory-tracking task. We explored three different decoder adaptation parameters: (1) decoder learning rate (i.e. rate of decoder adaptation), (2) decoder initialization, (3) decoder cost weight (i.e. scaling of the decoder cost function). We found that performance was affected by decoder learning rate: a slower learning rate leads to improved tracking performance compared to a faster learning rate. We additionally found that decoder initialization location affects final decoder location but not performance and that neither decoder initialization nor decoder cost weight affect performance. Our findings indicate the potential for game-theoretic algorithms to optimize the performance of neural interfaces.

2. PROBLEM FORMULATION

We model the user and decoder as two players that interact in a closed-loop *dynamic game* (Başar and Olsder, 1999) wherein the user produces myoelectric signal $s(t) \in \mathbb{R}^N$ that the decoder transforms into cursor position $y(t) \in \mathbb{R}^2$ to track the target trajectory $\tau(t) \in \mathbb{R}^2$.

We use a velocity-based decoder,

$$v(t) = D \cdot s(t), \; y(t) = y(0) + \int_0^t v(\sigma)\, d\sigma, \qquad (1)$$

where the matrix $D \in \mathbb{R}^{2\times N}$ is synthesized by minimizing a linear combination of two costs – task *error* and decoder *effort* – defined by

$$\text{error} = \|D \cdot s - (\dot{\tau} - \dot{y})\|_2^2\,, \;\text{effort} = \|D\|_F^2\,; \qquad (2)$$

here $\dot{x}$ denotes the time derivative and $\|x\|_2$ denotes the 2-norm of signal $x : [0, t] \to \mathbb{R}^d$, and $\|M\|_F$ denotes the Frobenius norm of matrix $M \in \mathbb{R}^{m\times n}$. Minimizing *velocity error* (2) is a common objective for invasive BCI (Orsborn et al., 2014; Wodlinger et al., 2015); we additionally consider the decoder effort in (2) because our theoretical analysis that suggests it is necessary to ensure the co-adaptation game has well-defined stationary points (Madduri et al., 2021).

The linear combination of error and effort that defines decoder cost $c(D)$ is determined by weighting $\lambda > 0$ as

$$c(D) = \|D \cdot s - (\dot{\tau} - \dot{y})\|_2^2 + \lambda \|D\|_F^2\,. \qquad (3)$$

Under the hypothesis that users also seek to optimize a linear combination of task error and user effort analogous to (2), the user and decoder play a *potential game* (Hespanha, 2017, Ch. 12) whose theoretical properties have been the subject of a previous study (Madduri et al., 2021).

3. EXPERIMENTAL METHODS

Human subjects participants gave their informed consent prior to experimentation, according to study procedures approved by the University of Washington's Institutional Review Board (IRB #STUDY00014060).

3.1 Task

Participants were tasked with producing myographic signals to control a cursor to follow a target trajectory on a 2-dimensional computer display (Fig. 1). Participants were instructed to keep their cursor as close to the target as possible at all times.

The target trajectory was generated as a sum of two sinusoids with frequencies 0.10 and 0.25 Hz in the horizontal direction and 0.15 and 0.35 Hz in the vertical direction; to reduce predictability of the target trajectory, the phases of the sinusoids were selecting uniformly at random at the beginning of each trial. The target and cursor positions were updated and displayed at 60 Hz.

3.2 Conditions

The role of (1) decoder adaptation learning rate, (2) decoder initialization and (3) decoder cost weight on co-adaptive system performance was tested.

(1) two different decoder learning rates were tested: *slow* ($\alpha = 0.75$) and *fast* ($\alpha = 0.25$).
(2) two randomized initializations of the D decoder matrix were used: *positive* (matrix elements chosen uniformly at random in the range $[0, 10^{-2}]$) and *negative* (elements chosen uniformly at random in $[-10^{-2}, 0]$).
(3) two decoder cost weights were tested: *low* ($\lambda = 10^{-4}$) and *high* ($\lambda = 10^{-3}$).

All combinations of the 2 learning rates, 2 initializations and 2 decoder cost weights were tested for a total of 8 different conditions (2 learning rates × 2 initializations × 2 decoder cost weights). Each trial was 5 minutes long. This block of 8 trials was repeated twice for each participant and the order of conditions was randomized within blocks.

3.3 Data Acquisition, Filtering, and Processing

EMG signals were obtained using a Quattrocento system (Bioelettronica, Italy). A 64-channel electrode array (4mm inter-electrode spacing, 5x13 electrode rectangular layout) was placed around the forearm to target recordings from the Extensor Carpi Radialis. Electrodes were placed on the dominant arm for each subject. Once placed, the electrode array was wrapped with Coban self-adherent wrap (3M, Saint Paul, Minnesota).

Raw EMG signals were obtained using Biolite Software (Bioelecttronica, Italy) at 2048 Hz on Differential Mode with the built-in low-pass filter of 130 Hz and a high-pass filter of 10 Hz. The EMG signals were then filtered by delinearizing two consecutive 50 ms time windows with no overlap, and then taking the average of the delinearized signal to be used as the user input s (Yamagami et al., 2020). EMG data were mapped to cursor position as in (1).

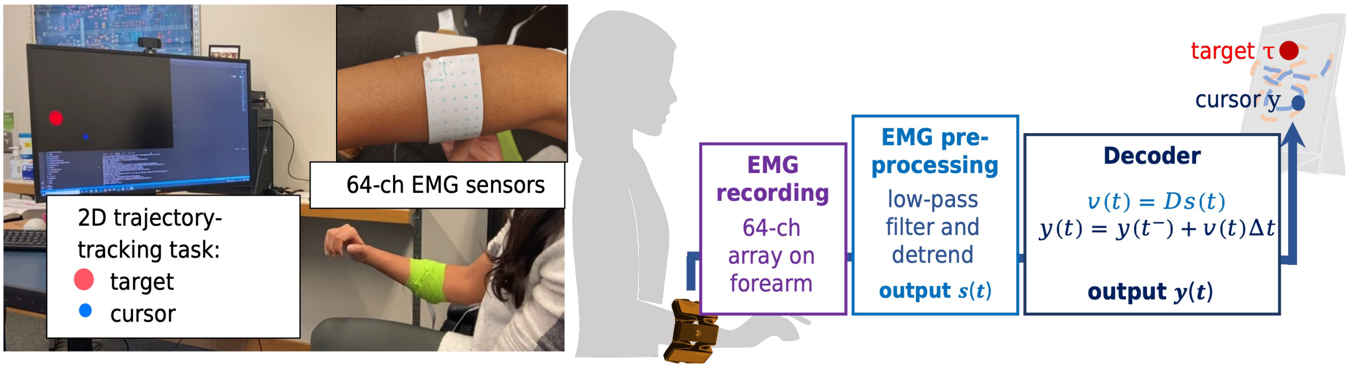

Fig. 1. (Left) The participant is tasked with following the red target by controlling a blue cursor. Participants controlled the blue cursor with the 64-channel Quattrocento EMG sensor on their forearm. (Right) Block diagram illustrating transformation of myographic signals to computer display.

3.4 Decoder Adaptation

The closed-loop decoder adaptation was performed to update the EMG-cursor movement transformation as the participant controlled the interface. Decoder adaptation used a supervised learning algorithm. The training signal is provided by inferring the user's intended velocity based on task goals, by assuming they intend to move towards the provided target (Orsborn et al., 2012; Gilja et al., 2012). Decoder parameters were updated using a framework building off the SmoothBatch algorithm (Orsborn et al., 2012), but minimizing the cost function in (3) that combines *error* and *effort* to determine optimal decoder parameters rather than minimizing only task error.

The decoder was updated iteratively using 20 second batches of data. Given a batch of data, the minimum D^* of the cost (3) was computed,

$$D^* = \min_D c(D), \tag{4}$$

and the updated decoder D^+ was determined using the SmoothBatch scheme (Orsborn et al., 2012), that is, by a convex combination of D and D^*,

$$D^+ = \alpha D + (1 - \alpha) D^*. \tag{5}$$

3.5 Data Analysis

Our primary metric for task performance was time-domain tracking error computed as the square of the 2-norm between the target and cursor signals, $\|\tau - y\|_2^2$. We also compared the distance between decoders of different initializations by computing the Euclidean distance between them. To do so, we computed the average final decoder for each initialization (averaging across learning rates, blocks, and subjects), and then compared the distance between each initialization and the initialization mean.

The average performance of the *first* and *last* decoders were used to compute statistical significance of changes within trials. All analyses treat subjects as individual data points and average across other conditions (learning rate, initialization, decoder effort weight, and trial block). Statistical signifance was assessed using the non-parametric paired Wilcoxon signed-rank tests.

4. EXPERIMENTAL RESULTS

A total of 7 people (3 women, 3 men, 1 declined to answer) participated in the study. Participants were primarily right-handed (6 right-hand, 1 left-hand; 57% all dominant, 29% mostly dominant and 14% ambidextrous in handedness), with an average weight and standard deviation of 141 ± 19.3 lbs, a height of 66 ± 3.5 in, a forearm circumference of 9.6 ± 1.0 in and an age of 23 ± 3.0 years. All participants were daily computer users.

4.1 Co-Adaptation Improved Trajectory-Tracking

Tracking performance improved within individual trials (Fig. 2): comparing tracking error for the *first* versus *last* decoder across all conditions (learning rate, initialization, and decoder effort weight, trial block), we found that performance significantly improved within trials (Fig. 3).

4.2 Decoder Learning Rate Affected Performance

Slower learning rate yielded better tracking performance (Fig. 4): comparing the percent error difference between the *first* and *last* decoders, we found that the slower adaptation rate yielded better performance (Fig. 5a).

4.3 Decoder Initialization Affected Final Decoder

Comparing the percent error difference of the *first* and *last* decoders between *positive* and *negative* decoder initializations, we found no significant impact on performance (Fig. 5b). Task performance also did not differ significantly between initializations. However, the learned decoder solutions were influenced by initialization: the distance between final decoders were smaller within the same initialization than between initializations (Fig. 6).

4.4 Decoder Cost Weight Affected Decoder Effort

Comparing the percent error difference of the *first* and *last* decoders between the *high* and *low* decoder cost weights, we found no significant effect on task performance (Fig. 5c). However, we did observe a effect on the Frobenius norm of the decoder based on the decoder cost weight (Fig. 7). The Frobenius norm of the decoder is overall higher for the *low* decoder weight than the *high* decoder weight.

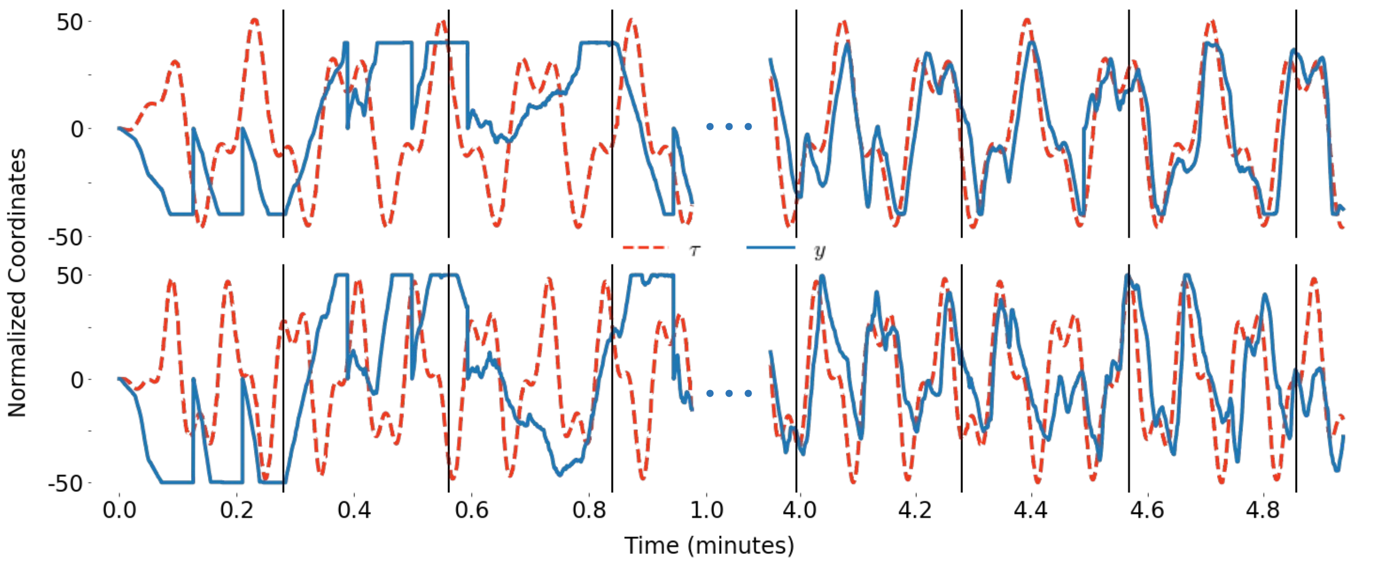

Fig. 2. Comparison of target (red dashed trace, τ) and cursor (blue straight trace, y) positions over time for one example trial for one subject. The y-axis is the display extent (%) and the x-axis is the time in minutes within the trial. The black vertical lines represent decoder adaptations. Horizontal (x) and vertical (y) positions shown in the top and bottom plots, respectively.

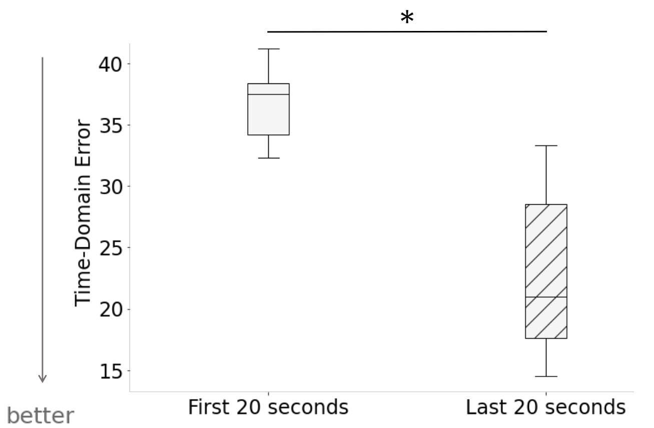

Fig. 3. Average time domain tracking error ($||\tau - y||_2$) for the first 20 seconds and the last 20 seconds (each decoder batch time = 20 seconds). Median performance across all conditions (learning rates, decoder initializations, decoder cost weights, blocks) for each subject; statistical comparisons across subjects ($N = 7$) with a paired Wilcoxon signed-rank test ($p = 0.016$).

5. DISCUSSION

This is the first study to test co-adaptive myoelectric interfaces for 2D-continuous control. We observed that updating a randomly-initialized decoder to minimize *task error* and *decoder effort* enabled users to learn to perform a 2-dimensional trajectory-tracking task with no calibration. Performance was affected by decoder learning rate, but not initialization nor cost weights. However, decoder initialization and cost weights influenced the learned decoder, suggesting a potential avenue to influence user learning.

In contrast to prior work that optimized exclusively for task error (Orsborn et al., 2012, 2014; Müller et al., 2017) or interaction efficiency (De Santis, 2021), our experiments

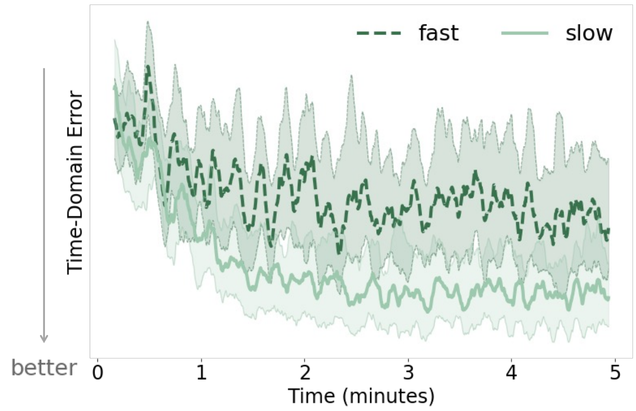

Fig. 4. Average time-domain task error over the five-minute trial, separated by decoder learning rate (slow vs fast, N = 7). Error was at each time and smoothed with a low-pass filter over 5 seconds to make the plot more interpretable, but the trend of the data remains. Solid lines show the median, shading shows 25% interquartiles.

employed a new decoder adaptation scheme that optimized a cost function that captures the trade-offs of a two-learner human-decoder interface. Similar to previous studies (Orsborn et al., 2012), our co-adaptive framework yielded rapid calibration independent of initialization. But our framework can potentially shape both the decoder *and* the human by changing parameters such as decoder learning rate, initialization, and cost weights.

Similarly to previous studies of learning rate on human-decoder co-adaptation that optimized for task error (Müller et al., 2017), we found that a slow learning rate results in a lower task error than a fast learning rate. This may be because slow decoder learning is less affected by random fluctuations in myoelectric activity or changes in human effort Performance outcomes could possibly differ with

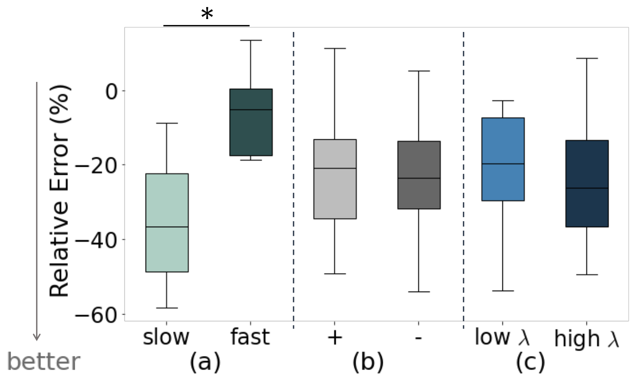

Fig. 5. Relative Error is $\frac{error_{fi}}{error_i} \times 100\%$, where error$_{fi}$ = error$_{final}$ - error$_{initial}$ Performance averaged across all blocks and (a) for each learning rates for each subject, (b) for each decoder initialization for each subject, (c) for each decoder cost weight λ for each subject; statistical comparisons across learning rates (N = 7) with a paired Wilcoxon signed-rank test ((a) $p = 0.016$, (b) $p = 0.938$, (c) $p = 0.469$).
. Only (a) is statistically significant ($p < 0.05$).

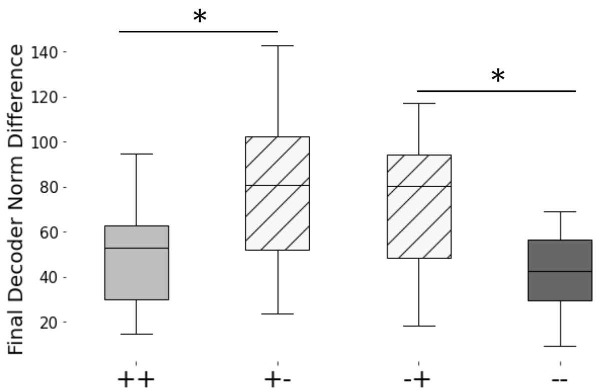

Fig. 6. Average sum of squares difference (Euclidian distance) from the group mean for final decoders with both initializations ($||D_{final,avg} - D_{final,subj}||_F^2$). Statistical comparisons across subjects (N=7) with a paired Wilcoxon signed-rank test ($+-$: $p = 0.016$, $-+$: $p = 0.016$).

longer trials. Studying the variability and performance outcomes over longer time-scales is an important point for future work.

Our preliminary analysis suggests that decoder initialization location does not affect task performance, but initialization location does affect final decoder. The robustness of task performance despite varying decoder initialization location is congruent with prior co-adaptative algorithms that solely optimized for task performance (Orsborn et al., 2012; Shanechi et al., 2016). Our finding that the decoder initialization location affects learned decoders is consistent with prior work that theoretically highlighted the existence of multiple equilibria in co-adaptive human-decoder systems (Madduri et al., 2021). In particular, the theoretical analysis in (Madduri et al., 2021) suggested that decoder initialization may bias the system towards different equilibria, which we may be observing in this

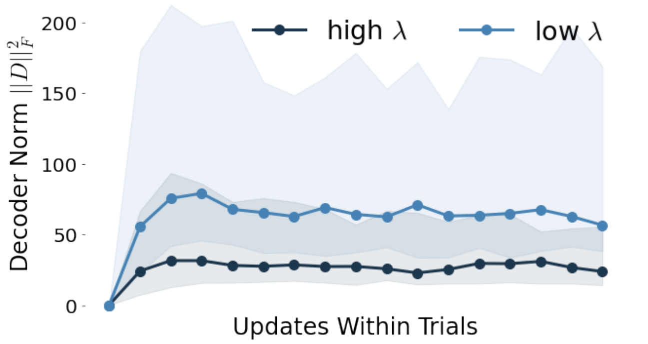

Fig. 7. Decoder norm ($||D||_F^2$) distributions (median, interquartile) for each decoder cost weight across blocks, subjects and other conditions (learning rate, decoder initialization).

study. Additional analyses and potentially longer-term experiments may help quantify the system equilibria and understand how decoder initialization location affects final decoder location.

Lastly, our experiments suggest that decoder cost weights influence the learned decoder without impacting task performance. This finding that a higher decoder cost weight leads to a lower decoder Frobenius norm is consistent with theoretical expectations of minimizing the decoder cost. Different decoder cost weights leading to different final decoders without affecting task performance suggest that users might be able to learn multiple decoders. Users might be potentially compensating for different decoders in their learned strategies. A particularly compelling question for future work is whether the user's encoding or control strategy is biased by the decoder parameters of learning rate, initialization and cost weights as well.

6. CONCLUSION

Designing neural interfaces that can adapt to a wide range of users is key to improving neural interface adoption and usability. Neural interfaces that adapt to individual users and shape user learning through co-adaptation could lead to individualized and robust neural interfaces. We approach the analysis and synthesis of co-adaptive neural interfaces from a game-theoretic perspective that treats the human and decoder as two independent agents in a game. This paper forms an initial exploration of the effect of a game-theoretic adaptive decoder framework and differing parameters on user learning. Our future work plans to further explore the effect of decoder initialization and decoder cost parameters on user encoding and learning.

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