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Biosignal-based co-adaptive user-machine interfaces for motor control

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Abstract

User-machine interfaces map biological signals measured from the user to control commands for external devices. The mapping from biosignals to device inputs is performed by a decoding algorithm. Adaptation of both the user and decoder—co-adaptation—provides opportunities to improve the inclusivity and usability of interfaces for diverse users and applications. User learning leads to robust interface control that can generalize across environments and contexts. Decoder adaptation can personalize interfaces, account for day-to-day signal variability, and improve overall performance. Co-adaptation therefore creates opportunities to shape the user and decoder system to achieve robust and generalizable personalized interfaces. However, co-adaptation creates a two-learner system with dynamic interactions between the user and decoder. Engineering co-adaptive interfaces requires new tools and frameworks to analyze and design user-decoder interactions. In this article, we review adaptive decoding, user learning, and co-adaptation in user-machine interfaces, primarily brain-computer, myoelectric, and kinematic interfaces, for motor control. We then discuss performance criteria for co-adaptive interfaces and propose a game-theoretic approach to designing user-decoder co-adaptation.

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User-machine interfaces, Co-adaptation, Adaptive algorithms, Motor learning.

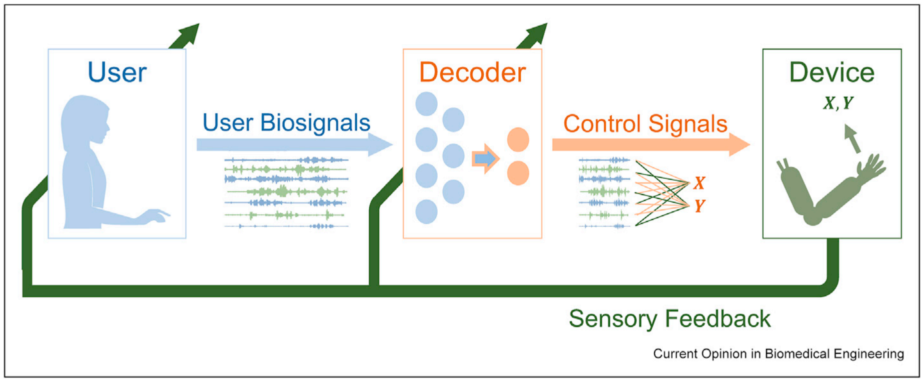
Introduction

Interfacing machines with humans provides new opportunities to restore or enhance our interactions with the world. Speech prostheses can restore verbal communication [1], handwriting-to-text interfaces can translate imagined letters to computer text [2], and neuroprosthetics can restore movements [3]. These *biosignal-based user-machine interfaces* translate biological signals like neural activity, muscle activity, or movements to control inputs for devices like computers or prosthetics. By using rich, high-dimensional inputs, these interfaces have the potential to address neurological conditions, increase access to technologies, and provide high bandwidth control of our increasingly complex devices.

However, the full promise of user-machine interfaces has not yet been realized. Adoption of any technology entails trade-offs between costs and benefits that are multi-faceted and vary across individuals (e.g., Ref. [4]). Biosignal interfaces have the potential to improve the quality-of-life or abilities of users, but these possible benefits will be weighed against costs like invasiveness, price, time investment, and more. For instance, some interfaces can use signals from wearable devices whereas others require surgical implants. Across many biosignal modalities, interfaces can be time consuming to learn (Ref. [5]). and offer variable performance across users (e.g. Refs. [6,7], or contexts [8]). Easily learnable and generalizable interfaces that can be customized to user needs will drastically improve the landscape for widespread adoption.

We propose that interface usability challenges contributing to limited adoption of biosignal interfaces stem from complex user-machine dynamics. User-machine interfaces are inherently *closed-loop*. Biosignals are transformed to control an external device via a *decoder*, and sensory feedback from the device is presented to the user (Figure 1). This closed-loop interaction naturally causes users to adapt to the interface. The

Figure 1



Example of co-adaptation in closed-loop user-machine interface. User biological signals (blue, here illustrated as electromyography signals) are translated via a decoding algorithm (orange) to control a robotic limb (green). The movement of the robotic limb provides sensory feedback (green) that creates a closed-loop system. The sensory feedback and task-related error lead the user and the decoder to update their behavior. The green arrow through the user and the decoder symbolize closed-loop adaptation based on the green feedback signal. That update leads to feedback-related (also green) changes in the user biosignals and the decoder transformation. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

inevitability of user learning motivates the use of decoders that can adapt in response. We refer to systems like these — with two agents adapting simultaneously in closed loop — as *co-adaptive*.

Here we consider whether co-adaptation can be deliberately designed to improve the interaction between users and machines. Creating interfaces that facilitate user learning may be critical to restore complex behaviors and to enable interfaces with entirely novel technologies. Furthermore, as user-machine interfaces become ubiquitous, the spectrum of users will expand. Decoders that adapt to users have the potential to accommodate user diversity and offer customization to individuals. These observations underscore the value of studying approaches that consider both user and decoder learning.

Co-adaptation introduces a two-learner problem: both the user and decoder are adapting and interacting in real-time, similar to two agents playing a game [9]. Methods to analyze and synthesize these two-learner interactions are still active areas of research, both within the context of user-machine interfaces [10,11] and dynamic game theory [12]. We need principled and experimentally validated frameworks to understand existing co-adaptive interfaces and create future interfaces.

This article surveys evidence for the benefits of combining user and decoder adaptation, as well as existing co-adaptive frameworks. We then outline outstanding questions and the need for improved frameworks. While the term "user-machine interfaces" can encompass everything from therapeutic intracortical BCIs to consumer technologies like computer mice, this review focuses on closed-loop motor interfaces that translate high-dimensional user biosignals into a lower-dimensional control signal for a device. Examples include brain-computer interfaces (BCIs), myoelectric interfaces, and kinematic (body-machine) interfaces. We choose this broad range of biosignals to discuss co-adaptation principles that may be beneficial across many technologies.

Benefits of Co-adaptation

Decoder or user adaptation each provide unique challenges and opportunities. We first discuss the abilities of each learner considered individually. As an example, adaptive decoding is commonly used to train decoders for initial interface use and to retrain decoders to address day-to-day measurement variability, without explicitly considering user learning that may occur simultaneously. We then discuss the importance of fully considering the co-adaptation of both learners for creating accessible and generalizable interfaces.

Adaptive decoders

Closed-loop dynamics in user interfaces influences decoder design and training. Motivated by machine learning approaches, many decoders are trained in *open-loop*: data is recorded as users make or imagine moving, and statistical relationships between biosignals and intended behaviors are identified with no feedback to the user [13]; Y [14]. Performance of a decoder on open-loop datasets does not necessarily predict performance when the decoder is used in closed-loop, where feedback allows the user to alter their behavior [13,15].

An alternative to open-loop decoder training is to train the decoder in the same closed-loop context in which it will be used. *Closed-loop decoder adaptation* (CLDA) updates decoding parameters using real-time user activity [16]. Updating the decoder's parameters in real-time can better capture how each user actually interfaces with the device during closed-loop operation. In this way, CLDA can provide rapid calibration and customization of an interface on initial use [10,17,18]. Indeed, in BCIs, closed-loop decoder updates improve performance compared to open-loop calibration [19–21].

Beyond calibrating interfaces to accommodate differences between users, CLDA can also be used to account for within-user variability over time. For example, once customized to a user, changes in the signals being measured can degrade performance (e.g., Refs. [22,23]). Adapting a decoder on a timescale comparable to the drift in biosignals can help prevent performance degradation. Day-to-day variability in the neurons recorded by an implant can be overcome with methods to adapt parameters across days [22]. Continual decoder updates can maintain performance despite rapid drifts in neural measurements on the timescale of minutes [24]. In BCIs, CLDA has been shown to provide consistent performance across months [25].

Decoder adaptation has undeniable advantages for accessibility, stability, and performance, but any decoder model is only as good as its inputs. Even with an adaptive decoder, an electroencephalography (EEG) BCI study of 168 naive users found that *22%* could not achieve efficient control, possibly because users were unable to modulate the biosignal features used as decoder inputs [6]. Decoding algorithms inherently depend on the user's encoding. Encouraging user adaptation, which changes their encoding, then, may be equally critical for providing robust and generalizable interfaces.

Adaptive users

Controlling a user-machine interface should be similar to riding a bike – once you learn, you can quickly ride with ease any time you grab a bike. The impressive capability underlying this colloquialism is natural motor skill learning, where training and practice yield robust "motor memories". Research suggests that similar skill learning mechanisms may help achieve robust, generalizable, and rich control in user-machine interfaces.

Feedback provided by a closed-loop device allows users to learn and adapt [26,27]. While user-machine interfaces involve artificial or altered sensorimotor pathways, this learning shows notable parallels to natural sensorimotor learning [26–28]. For instance, extended practice with a stable BCI (neural measurements and decoder parameters fixed) results in performance improvements that are rapidly recalled each day [29]. This long-term learning in BCI also yields a stable neural encoding [29]. These learned neural encoders are heavily influenced by the decoder. In a kinematic interface study with fixed decoders, subjects formed an internal model that converged towards the decoder inverse [30]. Similarly, in BCI experiments with fixed decoders, neural activity patterns reorganize to align with the decoder [31]. These findings suggest users can form a motor memory specific to an interface that enables robust control.

A key property of motor memories is that, once consolidated, they remain stable as we learn additional tasks. Iteratively adding control dimensions has been used to achieve high-dimensional BCI control [3,25]. Interestingly, Silversmith and colleagues (2020) showed that, once a stable neural encoding of a two-dimensional BCI task had formed, the participant could learn to control an additional discrete behavior (a 'mouse click') without altering performance of the continuous behavior. This highlights the potential benefits of user learning for achieving robust performance across different contexts.

Beyond potential benefits of user learning, game theory formulations of the two-learner problem suggest that ignoring user learning could actually hinder performance. Indeed, adaptive decoding learning rates must be tuned appropriately relative to the rate of user learning to ensure the system will converge at all [32,33], and the solution a co-adaptive system converges to could be one of any number of game-theoretic stationary points (e.g. *Nash* or *Stackelberg* equilibria, Box 1) [34].

While user learning offers potential benefits and should be considered in interface design, relying on user learning alone may be limiting. Learning to control a novel interface can be slow, taking anywhere from hours to days of practice depending on the biosignal modality [27]. A static interface that requires significant practice for users to master is likely to produce frustrating devices that are quickly abandoned. For instance, even with the recent advancements in myoelectric prostheses, abandonment rates of upper-limb prosthetics remain at over 40% due in part to poor ease of use [35]. More broadly, fixed interfaces that make assumptions about users may reduce the subset of people who can use these devices. An example from airplane design illustrates the pitfalls of fixed interfaces [36]: the 1940s, airplane cockpit designs based on averages of pilot measurements fit no individual pilot well, leading to the development of adjustable cockpits.

Combining adaptive decoders and adaptive users

Co-adaptation can combine the strengths of decoder *and* user adaptation by leveraging interplay between the two learners. For example, because users learn encoders that are influenced by the decoder, gradual changes to a

Box 1. Game theory: utility functions, equilibria, and order of play.

The field of game theory considers interactions between multiple decision-makers that act independently in their own self-interest [9,34,49]. One common paradigm models these actors (also referred to as *agents* or *players*) as making decisions *rationally* by optimizing individual *utility functions* (also referred to as *costs* or *rewards*) whose values are determined by all player decision variables. In such *games*, individual player decisions influence those of their opponents and are, in turn, influenced by their opponents' decisions. Depending on the relationship between player utility functions, these games can be *zero-sum* (utilities exactly opposed), *potential* (utilities exactly aligned), or *general-sum* (utilities neither exactly opposed nor aligned). If players are not willing or able to collude, the game is termed *non-cooperative*. In the context of co-adaptive user-machine interfaces, it is generally appropriate to regard the user and machine as independent decision-making agents playing a non-cooperative game since neither of the "intelligent" agents can know exactly what is on the other's "mind". Human decision-making may be influenced by a variety of factors including task performance, physical exertion, or personal preferences. Games that arise in user-machine interfaces are unlikely to be zero-sum by design, assuming the machine's goal is to assist the user. However, it may not be possible to perfectly align player utilities if the factors the human attends to and their relative weights in the human's utility are unknown or uncertain, hence the general-sum setting may be appropriate in many cases. Game theory is commonly used to predict the outcome of agent interactions using different notions of *stationary* or *equilibrium* play. Multiple equilibria can arise in the same game depending on the details of how agents adapt. For instance, Figure 2 illustrates a co-adaptive system that converges to either *Nash* or one of two *Stackelberg* equilibria depending on the ratio of human and machine adaptation rates, which determines an *order of play* for the game. Game-theoretic equilibria generally represent tradeoffs between players' conflicting goals. In the design of human–machine interfaces, we may seek machine adaptation schemes yielding equilibrium.

decoder could progressively shape user learning. By encouraging users to form a stable encoder, such co-adaption could provide high-performance and generalizable interfaces.

Experimental studies hint at the promise of co-adaptive strategies. BCI studies in animals and humans demonstrate that stable neural encodings still form when decoders adapt over time [25,37]. Stable encoder formation in co-adaptive BCIs also correlates with high performance that is rapidly recalled each day [37]. Towards generalizable interfaces, user learning in a co-adaptive BCI resulted in control that resisted interference from context changes [37]. Similarly, co-adaptation enabled a human user to add additional control dimensions to a BCI [25]. Gradual decoder changes have also been shown to help users control BCIs that are initially challenging to learn [38], which may be critical for increasing interface accessibility.

Experimental observations highlight the interdependency between decoders and encoders in co-adaptive systems. The degree of decoder adaptation performed in a BCI influences the amount of changes in a user's encoder [37]. The number of neurons needed to successfully control a BCI has been shown to decrease in systems where decoders adapt alongside users [39]. In kinematic interfaces, altering the alignment between a decoder and the user's movement encoding space impacts the redundancy and efficiency of user movements [40]. Thus, adaptive decoding may influence the form of learned encoders. This outcome may be beneficial for yielding robust interface performance and opens opportunities to use co-adaptation for rehabilitation (e.g., Ref. [40]).

Designing co-adaptive systems

The performance of a co-adaptive system is determined by the dynamic interaction between the two learners. Here, we discuss key observations about co-adaptive dynamics and describe emerging frameworks for principled system design. Because co-adaptation involves adaptation of both the user and decoder, we focus on approaches that actively consider both learners. Interfaces should ultimately facilitate stable, high-performance control throughout repeated use. This outcome can be thought of as corresponding to an equilibrium where the user-decoder system remains stable (Box 1).

Key design parameters for co-adaptation

As engineers, we only have direct control and full knowledge of one learner in a co-adaptive interface. While we can influence how the user learns by manipulating the decoder or sensory feedback pathways, we cannot directly control user adaptation in the same way we can readily modify decoders and their algorithms. Recent studies highlight key ways in which manipulating decoders can influence co-adaptation.

Decoder adaptation rates affect user learning and, in turn, the entire interface performance. For example, intuition might suggest that mismatch in adaptation rates between the user and decoder could lead to scenarios where the decoder changes too frequently, disrupting users' ability to learn. Indeed, kinematic interface experiments found that users struggled to control the interfaces when they rapidly adapted [41]. Models of co-adaptive BCIs and experiments corroborate that the relative learning rates of users and decoders is important for system convergence [33], and the potential for unstable system dynamics when algorithm learning rates are not well calibrated to users [32]. Such models often assume users are idealized learners that are always motivated to try the task, but this assumption may not always hold. Experimentally, the frequency of decoder updates has been shown to influence user engagement during initial interface calibration [10], further highlighting the impact of algorithm design on overall interface performance.

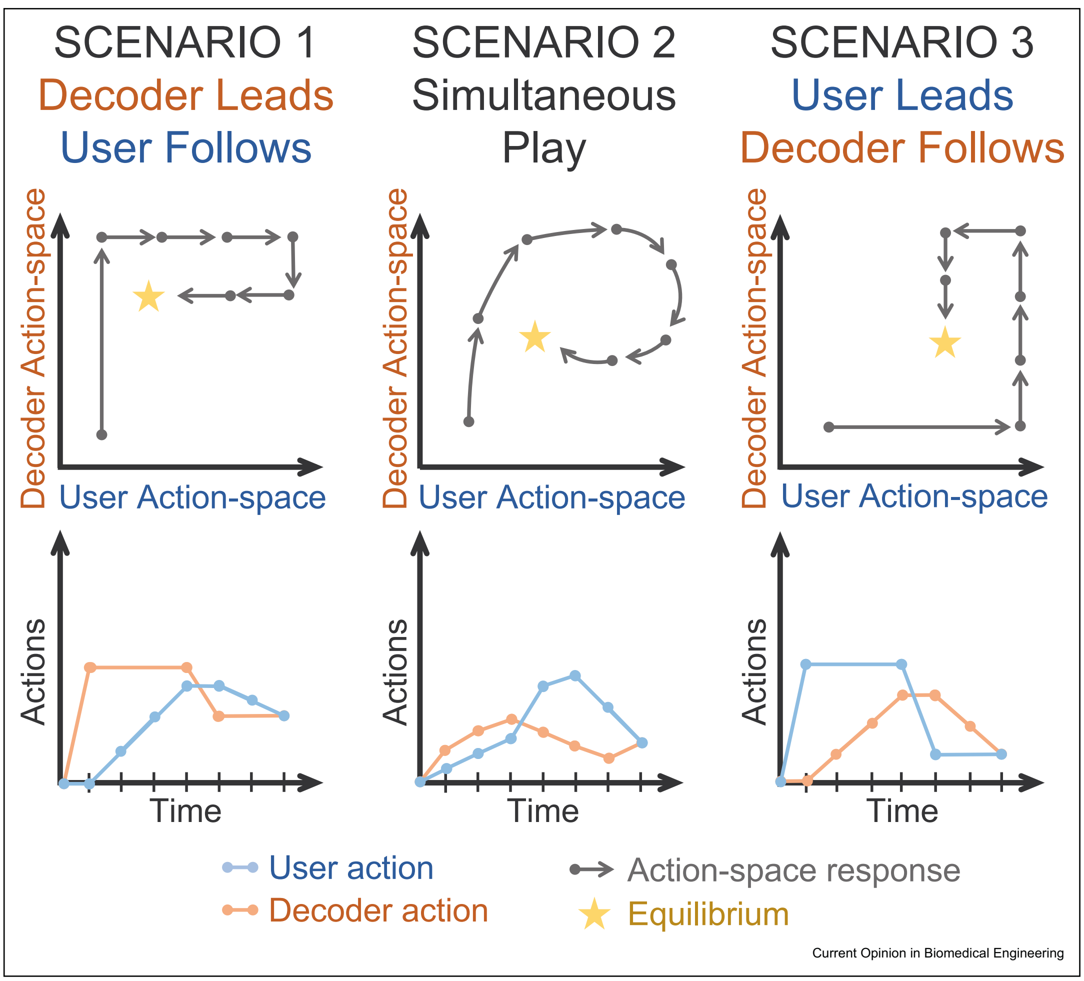
Because users learn via sensory feedback of decoding errors, how a decoder provides feedback will influence co-adaptive system performance. In closed-loop myoelectric interfaces, users could correct for simulated input noise with a regression-based decoder better than with a classification-based decoder [42]. In fact, this study suggests that users were better able to compensate in the regression decoder because it provided richer feedback of errors compared to the classifier. Indeed, BCI studies in animals highlight that binary task feedback (correct/incorrect) without continuous sensory feedback may be insufficient to drive learning [43]. Systematically manipulating feedback rates in BCI also shows that users incorporate real-time feedback to guide control [44]. Feedback modalities and rates must therefore be considered when designing a co-adaptive system.

Principled design of co-adaptive interfaces

Current empirical observations suggest decoder adaptation can be used to shape user adaptation, opening new ways to improve user interface performance. However, tuning current co-adaptive interfaces is challenging and largely done based on heuristics. Computational frameworks that predict decoder performance by modeling online user behavior (e.g. Refs. [13,45]), suggest models may be useful for optimizing decoder performance. However, while these frameworks account for the closed-loop nature of interfaces, they are not designed to capture user adaptation. Developing a toolkit for co-adaptation will enable rigorous design of user interfaces that fully leverages the benefits of co-adaptive systems.

A key consideration for co-adaptive systems is the relative timing of adaptation for the two learners. The user

Figure 2



Conceptual illustration of leader–follower relationships in co-adaptive user interfaces. The top graphs show the combined user-decoder action space, which represents the action taken by either the decoder, the user, or both simultaneously. The bottom graphs represent the user and the decoder actions across time. Scenario 1 (left) shows the leader–follower relationship when the decoder is leading. The decoder starts with an action and the user follows in response with multiple actions. This repeats until convergence is met. Scenario 2 (middle) shows simultaneous play, both the user and decoder update at the same time. Scenario 3 (right) is also a leader-follower interaction, but with the user leading. Importantly, the relationship between player actions will lead the system to converge to different equilibria (see also Box 1).

and decoder do not necessarily have to adapt in lockstep with one another. The user or decoder could *lead*, guiding the other to *follow* (Figure 2). Existing co-adaptive user-machine interface frameworks can be viewed through this leader-follower lens. Merel and colleagues [51] propose a method to estimate the optimal decoder that "anticipates" user adaptation. They find that users, as followers, can adapt to match the fixed estimated optimal decoder mapping. So long as the users obey the statistical modeling assumptions of their model, this could produce desirable co-adaptation. On the other end of the spectrum [46], proposes a co-adaptive framework where users lead, and decoders adapt to them. Their method modifies decoders to optimize the interaction efficiency between the user and decoder. This approach assumes that users adapt to maximize rewards while the decoder adapts to approximate the covariance of the user's activity. Many co-adaptive schemes in BCI are structured such that users lead while decoders follow [25,37,39].

We believe the potential power of co-adaptation arises from dynamic interactions *between* the two learners. Frameworks that can flexibly capture the full spectrum of potential users and decoder interaction timescales are needed. For example, early interactions like interface calibration might benefit from decoders following users to maximize initial performance and encourage engagement. But later interactions might require decoders to lead users towards new strategies that improve overall performance or to encourage motor recovery in rehabilitation applications. A linear two-learner model, where the user and decoder both adapt concurrently according to a joint cost function, allowed Müller and colleagues (2017) to explore the influence of adaptation timescales on co-adaptive systems [33].

The studies described above represent existing theoretical approaches to co-adaptation in biosignal interfaces. To create an even more versatile framework to explore user-decoder co-adaptation, we have proposed directly modeling the system as a *game* [32]. Game theory provides a suite of tools to analyze and design learning dynamics and provides ways to encourage co-adaptive systems to converge to stable user-decoder equilibria (Box 1). Game-theoretic techniques have been used to develop a framework for defining dyadic interactions [47] and to design a human-robot controller that estimates each agent's cost and adapts to complete a shared goal [48]. We adopted the perspective that the user and decoder are playing a *dynamic game* [49], treating the user and decoder as two agents adapting according to individual cost functions [32]. This framework allows us to analyze the stability of user-decoder learning dynamics, and suggests that learning rates, decoder cost functions, and initial decoder parameters can all be used to influence overall system behavior. Initial experimental implementation of this framework using myoelectric interfaces suggests that initial decoder parameters may influence learned decoders without degrading system performance [50], though more studies are needed to explore the impacts on users.

While the game-theoretic framework provides a promising approach to model and implement rich co-adaptive dynamics, this and other existing frameworks are still limited. For example, current models are confined to 1 or 2 degrees of freedom of task control and simple low-order machine dynamics. Advancing models and computational tools for analyzing co-adaptation in high-dimensional interfaces will be critical for practical deployment in real-world contexts like assistive devices or rehabilitative interventions. Additionally, these frameworks rely on models of user learning that are relatively simplistic and require further validation. For instance, incorporating models of how different forms of sensory feedback influence user learning may be critical for methods to shape user strategies and encoders.

Conclusion

Using biological signals as inputs to devices provides exciting new opportunities to treat neurological disorders and expand how humans can interact with technology. Wide adoption of these technologies will require ensuring interfaces work reliably for diverse users and applications.

We propose that providing reliable high-performance user-machine interfaces requires grappling with the rich closed-loop dynamics inherent in these systems, where users and machines can both adapt. Empirically, combining user and machine adaptation holds promise to improve interface performance, and opens avenues to guide user learning to ensure all users achieve robust control. Yet co-adaptive interfaces have complex two-learner dynamics that we currently do not fully understand and cannot rigorously design. Expanding our frameworks, for instance by leveraging tools from game theory, could enable us to fully harness the power of co-adaptive interfaces.

While co-adaptation presents challenges, it also serves to expand the engineering toolkits for designing user-machine interfaces. We believe leveraging both user learning and machine learning will enable us to move beyond interfaces optimized for specific applications and select users, providing a path to accessible and useful user-interfaces.

Declaration of competing interest

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Data availability

No data was used for the research described in the article.

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* of special interest
** of outstanding interest

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This paper aimed to produce "plug-and-play" control (long-term stable performance without recalibration) of an intracortical BCI. Using a 128-channel ECoG implant in a patient with tetraplegia, the authors showed that, compared to daily decoder reinitialization, long-term closed-loop decoder adaptation (ltCLDA) – holding decoder parameters across multiple days – could promote plug-and-play control and lead to formation of stable, consolidated neural representations that enabled control of additional dimensions. The experiments lasted over 6 months and impressively illustrated a path towards long-term BCIs for a paralyzed patient populations though chronic ECoG implants and CLDA.

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The aim of this paper is to introduce a mathematical model for co-adaptation that could inform adaptation schemes for both the user and machine. The user and machine are modeled as two linear systems and are coupled by a joint loss function. Simulations of this framework show a range of parameters, specifically of learning rates, that could lead to convergence of the two learners. This range was tested with humans controlling a cursor in a 1-dimensional mouse-control task. This paper presents a useful outlook for considering the design of two-learner, co-adaptive user-machine interfaces.

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With a 128-channel chronic neural implant in the motor cortex, two non-human primates learned to control a two-dimensional cursor with an adaptive decoder. Decoder parameters were updated infrequently to improve initial performance and to address signal nonstationarities. The authors found that neural adaptation and decoder adaptation could occur concurrently and result in beneficial neuroplasticity that was robust, retained across days, and resistant to interference from changes in task context. The authors also found that neural tuning properties were partly influenced by the decoder. This paper provides a pre-clinical demonstration of the feasibility and benefits of combining decoder and neural adaptation towards producing high-performing, long-term neural interfaces. The Silversmith et al., 2020 study highlights translation of many of these observations to human subjects.

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In a body–machine interface (BoMI) experiment with an inertial sensor placed on their arms, 20 healthy participants learned to control a computer cursor through body movements to perform both reaching and tracking tasks. Ten participants used a closed-loop adaptive decoder that was updated by recalculating the principal components of the user's movements. The goal of the decoder adaptation was to maximize the user's projection of movement onto the decoder's potent subspace. Participants with the adaptive decoder were able to align their movement subspace with the decoder subspace better than participants with the fixed decoder, resulting in less movement in the decoder null space and increasing user movement efficiency. The authors suggest this scheme of aligning user and decoder potent subspaces can guide users to more desirable movement patterns in BoMIs.

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This paper compares two different closed-loop decoder adaptation approaches: classification- and regression-based learning. While artificially injecting signal non-stationarities, both adaptation schemes were tested in myoelectric interfaces with ten able-bodied and one transradial amputee. Offline, both algorithms reacted similarly to signal non-stationarities. However, online, the regression-based approach was significantly less affected by the non-stationaries than the classification-based approach, suggesting that regression-based approaches may enable users to adapt and account for signal noise better than classification-based approaches.

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