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Joint Action is a Framework for Understanding Partnerships Between Humans and Upper Limb Prostheses

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***Abstract*— This work contributes a conceptual analysis of upper-limb prosthesis control methods; the goal of this work is to deliver new insight into the design of future biomechatronic systems intended for human interaction. Recent advances in upper limb prostheses have led to significant improvements in the number of movements provided by a user's robotic limb. However, controlling multiple degrees of freedom via muscle-generated (myoelectric) signals remains challenging for individuals with limb difference. To address this issue, various machine learning controllers have been developed to better predict a user's movement intent. As these controllers become more intelligent and take on more autonomy in the system, the traditional approach of representing the human-machine interface as a human controlling a tool becomes limiting. We here suggest that one possible approach to improve the understanding of these interfaces is to model them as collaborative, multi-agent systems through the lens of *human-prosthesis joint action*. The field of joint action has been commonly applied to two human partners who work jointly together to effect coordinated change in their shared environment. Using a joint action framework also provides opportunities to understand the interactions between human and machine partners: how each represents the other's goal, their monitoring and prediction of each other's actions, the communication between them, and their ability to adapt to each other. In this work, we survey three different prosthesis controllers—proportional electromyography with sequential switching, pattern recognition, and adaptive switching—in terms of how they present the hallmarks of joint action. The results of this comparison contribute a new perspective for understanding how existing myoelectric systems relate to each other, along with two concrete recommendations for how to improve these systems via additional capacity for prediction learning and coordination smoothing.**

I. INTRODUCTION

The development of robotic upper limb prostheses first began in the mid-twentieth century starting with single-degree-of-freedom powered hands that were driven using voluntary surface electromyography (EMG) signals generated by residual muscles of the amputated limb [1], [2]. In these early systems, the prosthesis controller was calibrated in the clinic, fixed for day-to-day use, and considered as a standard example of human tool use. Since then, the capability and complexity of prostheses has increased dramatically with additional powered joints and multi-articulated hands becoming available. With this scaling in both sensing and actuation technology, users continue to report challenges and frustration when controlling such a high number of joints with a small number of control inputs [3], [4]. To address user concerns, machine learning methods, such as pattern recognition [5], [6], [7], deep neural networks [8], and continual learning methods like adaptive switching [9], [10], [11], [12], have been developed to learn and specialize a device to the control signal patterns and daily life needs of individual prosthesis users [2]. These machine learning methods can be retrained or adapted during day-to-day use and generally delegate more autonomy to the prosthesis control system than earlier control approaches [2]. With the addition of more advanced computing technology, the traditional approach of modeling human-prosthesis interaction as a single human controlling a fixed tool has been suggested to no longer adequately capture the complex behavior of the co-adaptation between the human and the prosthesis controller [15]. We propose herein that our understanding of these more complex systems will improve by considering the human and the prosthetic device on comparable footing as partners working together to accomplish complex tasks, such as coordinated movement and object manipulation, through the lens of what has been termed *joint action* (Fig. 1).

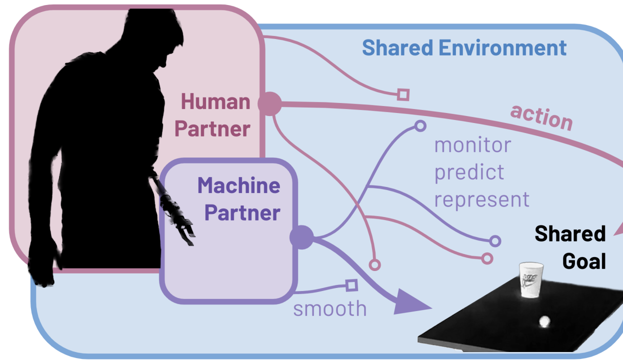

Fig. 1. **Human-prosthesis joint action**. A human and a machine partner act on the world (solid arrows) to create change in their shared environment with respect to a shared goal. In service of this pursuit, they may exhibit hallmarks of human-human joint action (c.f., [13], [14]): *representation, monitoring, prediction* (all shown via lines with circled ends), and acts of *coordination smoothing* (squared lines).

Joint action can be defined as "any form of social interaction whereby two or more individuals coordinate their actions in space and time to bring about a change in the environment" [14]. In the social sciences, joint action has

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been historically applied to two or more humans interacting together [16], but more recently, studies have begun to investigate interaction between human and robots [17], [18], [19]. Mathewson et al. [20] further introduced a framework for representing a prosthesis as a distinct agent—*communicative capital*. They used case studies and examples to outline the relationship between the agency of each partner in a human-prosthesis system and the capacity of the partnership. In the current article, we take these trends one step further by applying the viewpoint of joint action to what we hereafter denote *human-prosthesis interaction* (HPI). To accomplish this goal we explore how proportional EMG with sequential switching, pattern recognition, and adaptive switching controllers (a representative example of continual machine learning) fit into the framework, along with how these controllers might be further improved by incorporating additional hallmarks of joint action. We note for the reader that the comparisons in this work contribute conceptual advances as opposed to numerical advances; empirical evaluation is outside the scope of the present work. *This manuscript aims to provide a novel multiagent lens for the development and analysis of future upper limb prostheses and other medical and non-medical biomechatronic systems intended for human interaction.*

II. Joint Action

Several architectures of collaborative social interaction and joint action have been developed in the literature [13], [14], [21], [22], [23], [24]. For the purposes of this paper, we build upon the architecture of Vesper et al. [13] as it includes a clearly defined basic framework for evaluating whether a given system may develop into joint action. As per Vesper et al. [13], there are four main hallmarks that should be present for a system to be considered as jointly acting: representations, monitoring, prediction, and coordination smoothers. Joint action also requires partners, tasks, and goals. In what follows, we define these terms and relate them specifically to the domain of HPI (as summarized in Fig. 1).

A. Partners

There needs to be at least two partners collaborating on a task for joint action to occur [13]. In the case of HPI, one partner is the human partner and the other is the machine partner (in this case, we define the machine as the prosthesis and its control system).

B. Tasks & Goals

Each partner has an individual task that they are responsible for, which in combination, allows them to work towards accomplishing a shared goal [13]. The shared goal between the human and machine partner is to move the prosthesis to a particular position or use it to interact with the environment to bring about a specific, user-defined configuration of the environment. Typical tasks of the human include providing control signals to the machine partner and gross positioning of the prosthesis using body and residual limb movements [25], [26]. Typical tasks of the machine partner include interpreting the control signals from the human and selecting which motor(s) should be driven on the prosthesis.

C. Representation

As per Vesper et al. [13], every partner working together should, at a minimum, internally depict for themselves their individual task and the shared goal (e.g., portrayals in the human brain or in digital storage). It may be helpful for each partner to have a representation of the other's individual task, but Vesper et al. [13] do not list this as a requirement.

D. Monitoring

In joint action, numerous perceptions or states are continually sampled or estimated by each partner, including their own actions and their partner's actions, along with how well they are achieving their individual tasks and shared goals [13], [24]. The joint action architecture of Vesper et al. [13] does not explicitly define which of these monitoring processes should be required, but instead indicates that necessary processes may be task-specific. In the context of HPI, we note that each partner will need to at least monitor their own actions, their partner's actions, and how well they are completing their own task. The human typically monitors the movement of the prosthesis via visual feedback. Conversely, the machine partner has an array of sensors, which may capture EMG signals from the human, as well as movements and forces from the prosthesis.

E. Prediction

Across multiple joint action architectures, each partner is considered to make predictions about their own actions or the actions of their partner [13], [24]. These predictions could take many forms, including predicting the actions themselves, the timing of the actions, or the outcomes of the actions [13].

F. Coordination Smoothers

Coordination smoothers are defined broadly as anything (besides the previous hallmarks) that improves coordination between partners [13]. Examples of coordination smoothers that are particularly relevant to HPI include behaviors such as emphasizing actions and sending coordination signals. A complementary model of joint action [24] specifically mentions the continuous improvement of predictions as a type of coordination smoother, which we have also included in our evaluation, due to its pertinence to the HPI setting.

III. Myoelectric Controllers Included in This Comparison

The prosthesis controllers selected for comparison under the joint action architecture are representative cases from three main categories of control: proportional EMG control with sequential switching (no machine learning), pattern recognition (batch/offline machine learning), and adaptive switching (continual/online machine learning) (Fig. 2). We now introduce each controller and review their specifics.

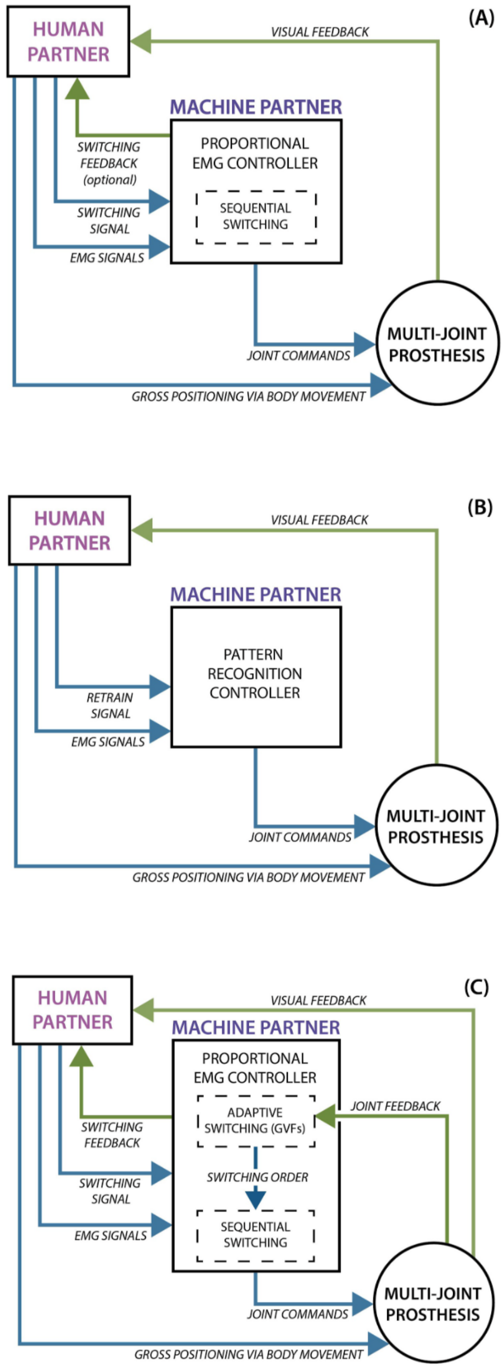

Fig. 2. Block Diagrams of three different prosthesis controllers and how they interact with the prosthesis user. (A) Conventional myoelectric control with proportional EMG and sequential switching. (B) Pattern recognition controller with single class output and episodic (batched offline) training. (C) Adaptive switching, a continual learning method that dynamically adjusts the order of the sequential switching list. One common feature that is present in all three controllers is a physical connection between the prosthesis user and the multi-joint prosthesis via a prosthetic socket. EMG electrodes are integrated inside the socket, over residual muscles, and provide EMG signals to each prosthesis controller. The prosthesis user is also able to grossly position the prosthesis in space by moving their feet, trunk, or joints of their residual limb. Actuation of the motorized joints on the prosthesis is handled by the prosthesis controller. Another feature common to all three controllers is that the current state (e.g. position and velocity) of the multi-joint prosthesis is monitored by the human by visually attending to it.

A. *Proportional EMG*

The specific type of proportional EMG controller we focus on in this analysis is a two-state proportional controller with sequential switching (hereafter shortened to *proportional EMG*) [27], [28], as illustrated in Fig. 2A. EMG signals are acquired from residual antagonistic muscles (e.g. biceps/triceps), rectified and averaged, and then directly mapped to the velocity of a joint (e.g. hand open/close) on the prosthesis. This can be thought of in terms of a simple algorithmic mapping

$$a_t \leftarrow f(\vec{x_t}|j_t),$$

where $\vec{x}$ is a representation of the system's input state (in this case EMG signals), $f(\vec{x_t}|j_t)$ is a fixed continuous or piece-wise function mapping state to action, j_t is the joint or function selected at time t, and a_t is the velocity action used to drive the prosthesis's motors. After exceeding a threshold, the proportionality allows for slower or faster motor speeds, depending on the strength of the EMG signal, and the sequential switching allows the prosthesis user to sequentially switch between different joints on the arm (e.g. j_t in hand open/close, wrist rotation, elbow flexion). The switching signal is typically communicated from the human to the machine partner by co-contracting antagonistic muscles, pressing a button, or pulling on a cable.

Auditory or vibrotactile feedback to indicate the occurrence of a switching event is available in some commercial devices, but is mostly used for training and then turned off. In practice, given that it is challenging for prosthesis users to remember where they are in the switching order and it can be tiring to switch multiple times to activate the joint they want, the number of joints that are controlled using this method is usually three or less. To alleviate this issue, such controllers sometimes include options for implementing a time out period, after which the controller will switch back to a default joint (e.g. hand open/close).

B. *Pattern Recognition*

The pattern recognition controller [6], as illustrated in Fig. 2B, is an offline or batch machine learning classifier that predicts the movement intent of the prosthesis user based on the pattern of their EMG signals. In contrast to proportional EMG controllers, pattern recognition controllers typically use additional EMG electrodes placed over muscles on the residual limb [2], [5], [6], [7]. Instead of relying solely on signal strength, pattern recognition controllers extract multiple features from the time and frequency domains. These features include more information that can help the classifier make accurate predictions. Similar to proportional EMG control, pattern recognition controllers in contemporary clinical use are typically limited to controlling a single joint on the prosthesis at a time. If the predictions are accurate enough, then the classifier can sometimes classify as many as five or six different joints on the prosthesis. However, predicting two to three joints is more common.

The prosthesis user can initially train or retrain the classifier by momentarily activating the retrain signal (Fig. 2B), which can be a button on the prosthesis or accessed via a phone application. A physical or virtual representation of the prosthesis will then move each joint one at a time in a prescribed manner while the human demonstrates their EMG signal pattern for each movement. After the demonstration period, the classifier will use the labeled samples to compute the parameters of the classifier that allow it to make predictions. Using the notation above, the algorithmic mapping for pattern recognition

$$\vec{a}_t \leftarrow f_{\vec{w}}(\vec{x}_t),$$

now sees $f_{\vec{w}}(\vec{x}_t)$ parameterized by a vector $\vec{w} \in \mathbb{R}$; the output of $f_{\vec{w}}(\vec{x}_t)$ is also now no longer conditioned on j_t, as the mapping from inputs to a vector of possible outputs $\vec{a}_t$ is made possible by the flexibility of $f_{\vec{w}}(\vec{x}_t)$. The training process that leads to a new set of fixed parameters $\vec{w}$ can take roughly one to two minutes depending on the classifier. After training, the pattern recognition controller is ready for use by the prosthesis user to control in real-time the powered joints on their prosthesis. Retraining of the classifier can be done as often as required, which can range between a few times a day to a few times a month. A common reason for retraining is a noticable change in user EMG signals, such as fatigue or shifting of electrodes in the prosthetic socket.

C. Adaptive Switching

As an example of continual or online machine learning selected for this analysis, adaptive switching, as illustrated in Fig. 2C, has a similar structure to a proportional EMG controller. However, instead of using a fixed switching list, adaptive switching uses the magnitude of a collection of learned general value functions (GVFs [29]) to dynamically adapt the order of the switching list [9], [11]. GVF learning is a prediction approach, based on reinforcement learning (RL) methods, that can learn expected temporally extended accumulations of signals of interest based on a continuing stream of observations [10], [29], which in the adaptive switching case includes learned forecasts of prosthesis mode or function use (c.f., [9]). One key difference, compared to the other controllers, is that adaptive switching monitors the joint feedback from the prosthesis to make its predictions about which joint the human may want to use next. The improvement to the adaptive switching predictions happens continuously in real-time, during regular use, without the need for an explicit training period. For clarity, the algorithmic mapping for adaptive switching can be thought of as

$$\vec{j}_t \leftarrow f_{\vec{w}_t}(\vec{x}_t),$$

where $f_{\vec{w}_t}(\vec{x}_t)$ is now parameterized by a vector $\vec{w}_t \in \mathbb{R}$ that is conditioned on t as it is updated continually in real time; the output of $f_{\vec{w}_t}(\vec{x}_t)$ is also now a ranked vector of modes or functions available to the user, $\vec{j}_t$, sorted via $f_{\vec{w}_t}(\vec{x}_t)$ according to temporally extended predictions stored in the learned parameters $\vec{w}_t$. An example of a common behavior that adaptive switching will learn is that after the prosthesis user moves the elbow joint of the prosthesis near a desk or table surface they will likely want to use the hand next to grasp an object.

Once a switching event is initiated by the human via a switching signal, the adaptive switching controller momentarily freezes the switching list while the human selects the joint and then resumes re-ordering once they start moving the joint (indicating that the correct joint was selected) [11]. For simple tasks, the adaptive switching controller can predict the correct switching order after a single iteration. However, for more complex tasks that have more variation, the controller may need to see several iterations of the task before it can make functional predictions [11]. Another difference between adaptive switching and the proportional EMG controller is that to achieve good performance, the controller needs to minimally communicate back to the human when a switching event has occurred and which joint was selected. This feedback can be communicated visually or auditorily on a computer or on a display screen integrated to the prosthesis. Since adaptive switching substantially reduces the amount of switching required it can feasibly increase the number of joints in the switching list to five or more.

IV. ANALYSIS & DISCUSSION

To determine whether the partnerships in each control setting were presenting, possibly presenting, or not presenting a hallmark of joint action (summarized in Fig. 3, first row), we examined in detail the variations in the sensorimotor streams and internal computing mechanisms that comprise the different controller models under comparison. We considered control information, feedback information, system state representations and transitions, system memory and learned parameters, and other related factors in the environment of use surrounding the human-machine partnership (e.g., factors like $\vec{a}_t$, $\vec{j}_t$, $\vec{w}_t$, $f_{\vec{w}}(.)$, and $\vec{x}_t$, as schematically depicted in Fig. 2). We then solicited interdisciplinary perspectives on these factors from our authors who come from diverse backgrounds including neuroscience, medicine, computing science, and engineering. We compared the controllers using the joint action lens and after reaching consensus recorded the assessment in the analysis grid of Fig. 3.

For all control schemes, the human partner was considered to reasonably demonstrate all of the hallmarks of joint action related to representations, monitoring, and predictions—that humans demonstrate these hallmarks of joint action is well supported in the literature by studies showing that prosthesis users adapt their internal models to take into account features of their prosthesis and its controller [30], [31], [32], [33]. With respect to the machine partner, our analysis suggests that all three prosthesis controllers do exhibit many of the hallmarks of joint action, but that *in all cases key hallmarks were missing or inadequate to fulfill the complete definition of joint action* from Vesper et al. [13].

It is clear that joint action between a proportional EMG controller and the human is *not* occurring due to the fact that the proportional controller (Fig. 2A) lacks the necessary representation and prediction processes: such systems do not contain modifiable memory elements (e.g., no $\vec{w}$) and input percepts ($\vec{x}_t$) that would be necessary to internally contain features relating to user task and goal, to forecast the future outcomes of sensorimotor signals and states, and to modulate action in response to the need for coordination smoothing (no contemplated smoothing update like $a'_t \leftarrow f_{\vec{w}}(a_t|\vec{x}_t)$). In this case, proportional EMG control is in line with the common conception of prosthesis use as standard human tool use.

Unlike proportional EMG control, both batch and continual machine learning methodologies contain modifiable parameter vectors ($\vec{w}$ and $\vec{w}_t$) deliberately designed to predict the future of the user's motor outcomes or other elements of system operation (Fig. 2B,C); importantly, both also have an explicitly constructed loss or error function that is the source of persistent changes to the way the system predicts partner actions and relates sensorimotor activity to a computational analog of the shared goal. If the controllers' representations and specific loss or error function can be well thought of as capturing all or part of shared and partner goals, then it is likely that joint action may in fact be occurring in some way with the human partner during their use (e.g., via classification or regression loss in pattern recognition [6], or the temporal-difference errors in predicting the signals of interest in adaptive switching [11]). However, if the shared goal is not within the scope of learning controllers' representations or loss functions, or their perceptual stream lacks a key modality to inform these factors then joint action is arguably not occurring; we could consider it to be not expressly facilitated by their component machine learning processes or the capacity of their representations.

A. Representations, Monitoring, Tasks, and Goals

Monitoring, a consistent element of control engineering and human motor control, is prominent in regard to signals and states well within the observable space for a given partner (e.g., the machine partner monitoring the operation of its own inputs, outputs and state), but naturally less prominent for things that require more complete or nuanced representations of the full environment (e.g., partner and goals). Proportional EMG controllers employ fixed, direct mappings between inputs and outputs; such controllers do not have an explicit representation of any of the tasks or goals. However, it is less clear whether or not pattern recognition and adaptive switching have representations of their own tasks, the shared goal, or their partner's task. For pattern recognition, if the shared goal is to move to a particular position based on a pattern of EMG signals, then this controller may maintain some of these representations. However, if the shared goal is more complex and involves interacting with the environment (e.g., picking up an object), then from Fig. 2B, we can see that the classifier does not have access to this type of information and likely would not have the required representations. The GVFs in adaptive switching do have access to position sensors and a load sensor in the gripper, which may help them infer the location of objects in the environment, so for these kinds of shared goals, the controller may have some of the required representations. However, if we abstract the shared goal to be a higher level task (e.g., folding a towel), then the controller likely does not have the required representations (e.g., cases where shared

Hallmarks of Joint Action	Proportional EMG		Pattern Recognition		Adaptive Switching	
Representation of:	Human Partner	Machine Partner	Human Partner	Machine Partner	Human Partner	Machine Partner
Own Task*	✓	X	✓	?	✓	?
Shared Goal*	✓	X	✓	?	✓	?
Partner Task	✓	X	✓	?	✓	?
Monitor:						
Own Actions*	✓	✓	✓	✓	✓	✓
Own Task*	✓	✓	✓	✓	✓	✓
Partner Actions*	✓	✓	✓	✓	✓	✓
Partner Task	✓	X	✓	?	✓	?
Shared Goal	✓	X	✓	?	✓	?
Predict:						
Own Actions	✓	X	✓	X	✓	X
Partner Actions*	✓	X	✓	✓	✓	✓
Coordination Smoothers:						
Make Actions More Predictable	✓	X	✓	✓	✓	✓
Coordination Signals	X	✓	✓	✓	X	✓
Continuously Adapt predictions	✓	X	✓	X	✓	✓

Fig. 3. Evaluation of myoelectric controllers through a joint action lens. A green checkmark, yellow question mark, or red X symbol indicates that the controller presents, possibly presents, or does not present the listed hallmark. * indicates minimal requirements for joint action as per Vesper et al. [13].

goals might unfold over great temporally extended spans, or integrate higher-level planning processes). We note that while not a candidate for our analysis in the present work, RL algorithms with an externally provided reward signal would be well thought of as machine partners that represent and make decisions with respect to a goal (c.f., [20], [34]).

B. Predictions and Coordination Smoothers

As outlined above, none of the controllers in this comparison were configured to predict their own actions. There is potential capacity for this in both pattern recognition and adaptive switching. However, both pattern recognition and adaptive switching do predict the movement intent of the human partner, which helps them better achieve the shared goal. With regard to coordination smoothers, there is evidence that humans make their actions more predictable by trying to generate more distinct EMG signals for all types of controllers, which can help improve their performance [35]. Additionally, pattern recognition controllers often try to make their actions more predictable by mitigating the effects of incorrect predictions via techniques such as majority voting and velocity ramps [36], [37]. Although adaptive switching is inherently less predictable than a stable ordered list, at critical moments it does make its actions more predictable by freezing the list when the human partner has triggered a switching event. Continuously adapting predictions are likely performed in all cases by the human as part of their learning process. Since the parameters for proportional EMG are typically only modified in the clinic, and given that the retraining of the classifier in pattern recognition only occurs intermittently, they do not learn continuously. Adapting and improving predictions in real-time are built into the regular operation of the GVFs in adaptive switching and so they demonstrated this hallmark. For coordination signals, we observe that proportional EMG and adaptive switching both meet the condition by sending switching feedback to the human. However, the human does not send any explicit coordinating signals back to the machine partner. The coordination signals for pattern recognition mostly occur during the training phase, where the human sends the retrain signal and the pattern recognition visually displays the movements to guide the collection of EMG data.

V. RECOMMENDATIONS FOR IMPROVING HUMAN-PROSTHESIS INTERACTION

In the previous section, we compared how hallmarks of joint action presented in different candidate human-prosthesis partnerships; whether joint action is occurring in these controllers is perhaps less important than what our analysis reveals in terms of recommendations for improving HPI by incorporating ideas from the field of joint action.

We suggest one powerful way to improve the HPI is to improve the representations or internal models of the human and prosthesis controller, for example by providing additional coordination smoothers. This could be done by increasing or improving the signals that each partner monitors about themselves or the task. This suggestion is supported by related literature—Shehata et al. [38] found that feedback about a control system to a human partner showed promise in increasing the strength of the internal model formed in the human brain about a prosthetic device and its control system, as well as the tasks performed. Specifically, feedback from the partner relayed through auditory, visual, and cutaneous sensory cues enabled the development of a strong internal model and allowed the human to better adapt to changes in the task and the prosthetic device [39]. While task-specific feedback to the human is known to improve performance for a given task [40], feedback from a machine partner about the control states and signals to the human partner has been shown to improve the human understanding of how a prosthetic device operates and thus improved the overall system integration [41]. Achieving the optimal balance between providing information-rich feedback about how the machine partner is controlling the prosthetic device and task-specific feedback is key to improving the overall system performance without increasing the human's mental effort and information processing costs. Further opportunities also remain for exploring how subtle and ostensive cues and signaling from the human to the machine partner can further smooth their ongoing interactions (either emergent conventions or pre-established conventions) [42], [43]. For example, low hanging fruit for the human partner could be to provide explicit (or, preferably, implicit) feedback to a pattern recognition controller on the correctness of its predictions in order to decrease misclassifications over time and adapt to changing conditions.

We suggest a second pathway to improving HPI is enhancing the ability of the partners to make predictions about themselves and each other. This could be accomplished by blending control solutions, and by strengthening predictive capabilities of algorithms via additional sensors and communication channels that facilitate more comprehensive representations, and thus can be used in contextually nuanced prediction learning. One such predictive enhancement has been made to adaptive switching through a technique called *autonomous switching*, which not only predicts what movement the prosthesis user wants to switch to next, but also predicts when they will want to switch movements [12]. With this method, when the autonomous switching controller reaches a minimum level of confidence, it will automatically switch (but will also allow the prosthesis user to manually switch if the controller guesses incorrectly); vibrotactile feedback to the user about prediction magnitude and future switching activity serves as a learned coordination smoother [12]. During the prediction process, autonomous switching can be seen to resemble a continually learning variation of pattern recognition controllers, although via a very different computational approach. Furthermore, we suggest predictions from pattern recognition could be improved in a straightforward way by increasing the contextual awareness of the classifier, through the use of additional sensors that describe the task or the human partner [2], [7]. As a recent example, data from multiple sensors have been used to facilitate precise classification of user-intended prosthesis movements for upper limb device control across multiple limb positions [8]. Devices' abilities to predict and represent elements of both partners and goals have also been enhanced by way of myoelectric controllers that use camera data alongside RL or deep learning methods to help their human partners more easily select from multiple grasp patterns and wrist functions [44], [45], [46].

VI. CONCLUSIONS

To our knowledge, this work is the first to propose human-prosthesis joint action and suggest the impact of translating ideas from human-human joint action to the realm of neuroprosthetics; we believe this is a valuable contribution to the rehabilitation robotics and assistive technology literature. As supported through the comparative assessment herein, we consider joint action to be a useful framework for thinking about and improving myoelectric control, and more broadly, for considering the human and their prosthesis as a dyad of interacting agents. This article presented a focused, literature-based treatment of the hallmarks of joint action as arising in three representative examples: conventional myoelectric control, batch machine learning, and continual machine learning. It further presented two paths to improving myoelectric control using insights from the joint action perspective: 1) enhancing the capacity for coordination smoothing and 2) strengthening the foundations for both human and machine partners to form and leverage predictive knowledge during their ongoing interactions. We recommend further study into the impact of joint action ideas on the wider field of neuroprosthetic control; we suggest that doing so will have a significant impact on the design and use of next generation individual-focused assistive rehabilitation technologies and other human-facing biomechatronic systems.

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