(Un)supervised (Co)adaptation via Incremental Learning for Myoelectric Control: Motivation, Review, and Future Directions

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***Abstract*— This paper presents a narrative review of incremental learning methods for myoelectric control, outlining both the historical trajectory and potential of adaptive prosthetic systems. Traditional myoelectric control has evolved from direct control techniques to advanced pattern recognition, yet persistent challenges such as signal non-stationarities and, consequently, the need for frequent recalibration remain. Incremental learning may enable a paradigm shift by continuously updating control models based on real-time, user-in-the-loop data, thereby addressing user-specific variations, environmental changes, and challenges from screen-guided-training based calibration. A central contribution of the paper is its taxonomy of incremental learning strategies, which divides the field into four categories: dedicated on-demand recalibration, unsupervised incremental learning, predictor-dependent incremental learning, and environment-dependent incremental learning. The methodology, strengths, and limitations of each category are discussed, providing a clear framework for evaluating current research and guiding future innovations. Further, this work establishes three settings for incremental learning: domain-incremental, task-incremental, and class-incremental continual learning. In addition, the paper highlights emerging trends such as transfer learning, domain adaptation, and self-supervised regression. It also emphasizes the potential of physiologically-inspired algorithms, novel end-effector designs to enhance prosthetic performance, and human-device co-adaptation. Finally, this paper discusses open challenges for incremental learning like attribution of signal changes to noise vs. behaviours, model complexity vs. data requirements, and user vs. model adaptation. Collectively, these insights pave the way for next-generation myoelectric systems that are more robust, intuitive, and adaptable to the dynamic needs and behaviours of users.**

***Index Terms*— Myoelectric control, incremental learning, electromyography, human-computer-interaction.**

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I. Introduction

UPPER-LIMB myoelectric control has a rich and enduring history extending back to the 1940s [1]. Initially, these systems used a conventional amplitude control paradigm (often referred to as direct control), wherein the rectified and low-pass filtered signal from one or two channels of bipolar surface electromyography (EMG) was used to modulate the aperture of a prosthetic hand [2]. As the field evolved, manual mode switching was integrated—achieved either by a button press or the simultaneous co-contraction of two EMG channels—to facilitate the control of multiple degrees of freedom, a strategy that continues to be widely prescribed in clinical settings. Despite the pervasive use of these direct control schemes, the advent of pattern recognition-

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based approaches, which are now available commercially and are covered under several national insurance programs, has marked a milestone in prosthetic technology, pursuing a more physiologically appropriate control strategy by leveraging the general muscle synergies of a larger number of residual muscles [3], [4], [5], [6], [7].

Pattern recognition systems offer more versatility than simple direct control methods by facilitating the direct selection of any available movement–often referred to as a motion class– at each time step. However, the performance of these systems is highly dependent on their initial calibration procedures, during which users provide a choreographed sequence of motions—guided by on-screen instructions or prosthesis-guided-training [8]—to establish a robust training dataset mapping EMG patterns to intended motions or gestures. These calibration sessions are critical, as they form baseline models that drive the subsequent control and daily operation of the prosthetic device. When operating conditions closely match those observed during calibration, the models routinely achieve high accuracy—often in the high 90% range—thanks to advancements in feature engineering [9] and instrumentation [10]. Since the early 2000s, significant efforts have been directed toward mitigating the influence of confounding factors such as limb position [11], contraction intensity [12], electrode shift [13], and fatigue [14], all of which can contaminate the EMG signal and degrade the laboratory assessed performance of both pattern recognition and conventional direct control systems. Through dedicated feature engineering [15] and specialized calibration procedures [16], many of these sources of degradation have been substantially improved, a feat that conventional direct control strategies lack the sophistication to accommodate.

Despite these advancements, the utility of pattern recognition-based approaches has been questioned in terms of functional outcomes [17], [18], [19], [20], [21]. Furthermore, the abandonment rates of myoelectric prostheses, regardless of how they are controlled, remain undesirably high [22]. Periodic retraining is required to accommodate non-stationarities introduced by physiological factors such as blood flow [23], as well as environmental variations including changes in socket fit [24] and skin-electrode contact characteristics [25], which introduce challenges for models to remain usable over time [26]. Further, inadequate spatial and temporal compliance with the prompts, common during regressor training, can manifest in models that drift at low intensities and elicit inadvertent off degree of freedom activity [27], [28]. Moreover, users often generate much more varied patterns of EMG signals that diverge from structured, choreographed patterns captured during calibration, especially when focused on completing real-world goal-oriented tasks rather than simply replicating prompted training gestures [29]. Importantly, optimizing classification accuracy in offline settings serves only as a reasonable proxy for functional performance during the early stages of model improvement; after high accuracy is achieved, further improvements in classification accuracy do not necessarily translate to better functional outcomes. This disconnect has fueled ongoing debates, with studies revealing both weak [30], strong [31], and coarse [32] correlations between offline and online performance metrics. Consequently, the field is left searching for strategies that more directly optimize functional performance, leveraging data that naturally arises from user-in-the-loop scenarios to update and refine myoelectric control systems.

Recognizing the limitations of static pattern recognition (wherein a model is trained, frozen, and then applied), incremental learning strategies [33] have attracted growing attention as a means to continuously adapt myoelectric models to the evolving nature of user behaviours and signal variability. Incremental learning represents a paradigm shift: rather than relying on a fixed dataset collected during a dedicated training session, these methods allow models to be updated, refined, and improved as the user interacts with the system. Over time, such adaptive approaches may maintain more robust intent recognition accuracy despite shifts in sensor signals [34], user behaviours [29], and external environments [35]. As a result, incremental learning has become a core focus in the effort to develop long-lasting, user-centric, and adaptable myoelectric control systems [36].

This manuscript aims to provide a unifying taxonomy and perspective of incremental learning methods for myoelectric control. We categorize existing incremental learning strategies into four key categories: (1) dedicated on-demand recalibration (DODR), (2) unsupervised incremental learning (UIL), (3) predictor-dependent incremental learning (PDIL), and (4) environment-dependent incremental learning (EDIL). We also present a taxonomy of incremental learning studies based on the intended outcome, consisting of: (1) domain-incremental continual learning, (2) task-incremental continual learning, and (3) class-incremental continual learning. We then highlight notable contributions in associated topics, such as: transfer learning and domain adaptation, self-supervised regression in simultaneous proportional myoelectric control, neural-level intent detection via HDsEMG, novel end-effect design, human-device co-adaptation via dual learning, and user acceptability and user-centred design. Finally, we share our perspective on several open challenges associated with incremental learning, namely, sensitivity to signal changes from noise vs. user behaviours, model complexity vs. data requirements, and user learning vs. model adaptation. Ultimately, this work identifies emerging directions that promise to shape the future of incremental learning in myoelectric prosthesis control.

II. Methodology

This narrative review was conceptualized following a workshop titled "(Un)supervised (Co)adaptation via Incremental Learning for Myoelectric Control", which occurred during the 2024 International Conference on NeuroRehabilitation. The paper combines insights gained from the presentations and discussions during the workshop, drawing on the collective expertise of the organizers, presenters, and active audience members. Additional colleagues were invited—who themselves conduct research in the incremental learning

TABLE I
COLLECTION OF INCREMENTAL LEARNING STUDIES AND GENERAL OUTCOMES

Ref	Algorithm	Frequency	Subjects	Test	Outcome	Compared Against
Dedicated On-Demand Recalibration (DODR)						
[43]	SH, SL, SHL, SA	BT	7-AB, 4-LD	OA	Reduced error by at least 26% compared to non-adapting classifier	NAC
[39]	iRR-RFF	BT	10-AB	OA, (RTC)	iRR-RFF outperformed iRR, incremental updates support a stable level of performance	iRR, KRR
[40]	iRR-RFF	BS	1-LD	RTC	Mastering increasingly complex ADLs over 13 months	-
[41], [44]	iRR	BT	6-AB, 5-LD	TAC	Improving or stable objective and subjective myocontrol scores over four sessions	-
[36]	RF-RLSC	BS	6-AB, 1-LD	OA	Maintained stable accuracy over months	LDA, kNN, RF-SVM, RF, MLP
[42]	SA	BT	3-LD	OA	Users needed to recalibrate less often and reported improved quality	NAC
Unsupervised Incremental Learning (UIL)						
[45]	NNMF	N/A	7-AB, 7-LD	TAC	NNMF outperformed mode-switching pattern recognition (MSRPR)	MSPR
[46]	sNNMF	N/A	8-AB, 2-LD	TAC	Higher throughput and shorter completion time than NNMF or LR	NMF, LR
[47]	iNNMF	C	10-AB, 2-LD	TAC, RCT	Mitigated degradation due to electrode shift, comparable robustness to DODR	NAC, DODR
[48]	iNNMF	C	8-AB	TAC	Comparable performance with DODR, but higher workload	iRR-RFF
[49]	piNNMF	C	10-AB, 2-LD	TAC	Possibility to progressively activate new actions	iNNMF
[50]	iNNMF	C	8-AB	TAC	Up to six controllable muscle synergies utilizing higher-density sEMG	-
[51]	SotF	C	3-AB	OA	SotF reduced learning time by 89% while maintaining accuracy	NAC
Predictor-Dependent Incremental Learning (PDIL)						
[52]	UB	C	2-AB, 1LD	RTC	UB improved stability	NAC
[43]	UH, UL, UB	BT	7-AB, 4-LD	OA	Provided small reductions in error, UH showed promise	NAC
[53]	MV	BT	DS	OA	Improved performance over no recalibration	NAC
[54]	SCADANN	BT	DS	OA, TAC	Outperformed other methods across weeks, but performance below supervised recalibration	NAC, MV, AdaBN, UDA-M, SR
[55]	scRF	P	66-AB	OA	scRF gradually improved accuracy over 5 weeks, visual feedback reduced muscle effort	NAC, RF, LDA
[56]	dfRLS	C	5-AB	TAC	Improved adaptation stability over exponential forgetting	efRLS, User Learning
[34]	SS-BSL	C	6-AB	OA	Maintained classification accuracy over time	aLDA, ST-S3VM, GCM
[57]	LCU, SMU, ER	BT	12-AB, 2-LD	OA	Improved decoder adaptation with only 3.2 minutes of selected data	Random Sampling
Environment-Dependent Incremental Learning (EDIL)						
[58]	CCLR	C	10-AB, 2-LD	RTC	Improved simultaneity	NAR
[59]	Closed-Loop Feedback	C	20-AB, 4-LD	TAC	Improved path efficiency and success rate for amputee	NAR
[60]	Environment Feedback	C (5m)	16-AB, 4-LD	TAC	Improved classifier performance	NAC
[35]	CIIL	C (2m/5m)	32-AB	TAC	Robust adaptation to catastrophic changes (electrode shift)	UHC, NAC
[29]	CIIL	C (10m)	16-AB	TAC	Zero-shot models outperformed SGT models within 200s; better proportional control.	NAC
[61]	CIIL	C	9-AB	RTC	Reduce transport time by $\sim$50%	NAC
[62]	tCIIL, oCIIL	C	16-AB	TAC	tCIIL reduced drift and action interference over oCIIL, NAR	NAR
[63]	ACRL	C	1-AB	RTC	Improved control accuracy, also cf. [64]	NAR
[65]	ACRL	C (300s)	3-AB	RTC	Non-amputated arm provided guidance for training, also cf. [66]	-
[67]	General Value Functions	C (3x3m)	4-AB, 1-LD	RTC	Reduced switching effort and improved control efficiency, also cf. [68]–[70]	Fixed switching order
[71]	AWAC	C	15-AB	OA	AWAC provided $\sim$2x increase in decoding accuracy compared to user learning	NAC
[72]	Adaptive Wiener Filter	C	14-AB	TAC	Slower adaptation improved user adaptation	Wiener Filter
[73]	Gaze-Guided Labels	C	5-AB	TAC	Eliminated the need for instrumented environment though an instrumented user	NAR

Algorithm acronyms: supervised high confidence (SH), supervised low confidence (SL) supervised high and low confidence (SHL), supervised all (SA), non-adapting classifier (NAC), incremental Ridge Regression with Random Fourier Features (iRR-RFF), random features regularized least squares for classification (RF-RLSC), linear discriminant analysis (LDA), k-nearest neighbors (kNN), random feature support vector machine (RF-SVM), random forest (RF), multi-layer perceptron (MLP), sparse non-negative matrix factorization (sNNMF), *progressive* incremental non-negative matrix factorization (*pi*NNMF), survival of the fittest (SotF), unsupervised high confidence (UHC), unsupervised low confidence (ULC), unsupervised blip (UB), self-correcting random forest (scRF), directional-forgetting recursive least squares (dfRLS), exponential-forgetting recursive least squares (ef-RLS), semi-supervised Bayesian sequential learning (SS-BSL), adaptive linear discriminant analysis (aLDA), Self-Calibrating Asynchronous Domain Adversarial Neural Network (SCADANN), Unsupervised Domain Adversarial-Methods (UDA-M), Multi-votes (MV), Supervised Recalibration (SR), self-training semi-supervised support vector machine (ST-S3VM), Gaussian classification model (GCM), least confidence uncertainty (LCU), smallest margin uncertainty (SMU), entropy reduction (ER), co-adaptive closed loop regression (CCLR), context informed incremental learning (CIIL), tolerant context informed incremental learning (tCIIL), oracle context informed incremental learning (oCIIL), actor-critic reinforcement learning (ACRL), advantage weighted actor-critic (AWAC), non-adapting regressor (NAR). **Frequency acronyms**: between trials (BT), between sessions (BS), continuous (C), periodic (P), minutes (m), seconds (s). **Subjects acronyms**: able-bodied (AB), limb difference (LD), dataset (DS) **Test acronyms**: offline accuracy (OA), target achievement control (TAC), real-time control (RTC).

field—and contributed valuable perspectives that have shaped the manuscript.

III. TAXONOMY OF INCREMENTAL LEARNING STRATEGIES

A taxonomy of existing incremental learning literature resulted, yielding the following categories: (1) dedicated on-demand recalibration, (2) unsupervised incremental learning, (3) predictor-dependent incremental learning, and (4) environment-dependent incremental learning. A summary of general details from exemplar incremental learning studies is given in Table I.

A. Dedicated On-Demand Recalibration (DODR)

On-demand recalibration is possibly the simplest form of incremental learning. It consists of performing a full or partial data collection each time the system performance is deemed to have become suboptimal due to, e.g., the natural change in the user's signals or user feedback. Alternatively, this approach can be useful to extend the capability of a user when they attempt to control the prosthesis in situations or environments that may not have been contemplated in the lab or clinic. This strategy is enforced by prompting the user to perform one or more rounds of the actions of interest, e.g., power grasp, wrist pronation, etc. The stimulus can be provided either graphically on a laptop or smartphone, including the visualization of the

signal patterns, or by having the prosthesis itself perform the actions in an automated round. Both commercially available myoelectric control systems, the Coapt Gen2 by Coapt LLC [37] and the Myo Plus by Ottobock [38], provide such a (re)calibration procedure, which the user or attending clinician can request at any time. It should be noted that the Coapt Gen2 system also incorporates a continuous learning capability (Adaptive Advance® [37]), enabling ongoing refinement of the control model during use. By contrast, the Myo Plus system discards previous models and fully retrains during each recalibration.

Dedicated on-demand incremental learning approaches build off the previous models [39], [40], [41] and allow the model to be updated sample by sample without the need to buffer or store previous data. The very low computational and storage requirements of these models allow for a very lightweight implementation with real-time updates while the prosthesis is in operation. Although simple, such a procedure provides a way to keep the model up-to-date with the user's latest signals. Although preliminary data is promising [42], more is required to better evaluate the approach. To the best of our knowledge, no large-scale comparative studies trying to assess, e.g., the data quality after each recalibration with respect to data collected in the beginning have been completed. Also, the timing of the data collection is essential, since the required actions are visualized in a scripted way: the user must enforce the corresponding muscle activation patterns at very specific times.

B. Unsupervised Incremental Learning (UIL)

Despite promising results, systems supporting on-demand recalibration face drawbacks. Offline data gathering disrupts user interactions and provides no immediate feedback, leaving users unsure of the efficacy of their inputs [43], [46]. Furthermore, supervised learning-based adaptation requires tight synchronization between the choreography and user, which can be especially challenging to acquire from users with inconsistent neural activation patterns [58] and frequently manifests in problematic spatial or temporal misalignment of labels [74]. Importantly, these adaptive methods also tend to rely on specialized prompting equipment, complicating commercial integration.

To address these challenges, Unsupervised Incremental Learning (UIL) methods have been proposed, which allow the model to adapt without explicit prompting from the user. A notable example is the approach presented in [75], which introduced a novel strategy for decoder design and adaptation. Bio-inspired regression-based techniques create a continuous mapping between EMG signals and estimated user intentions [45]. These decoders build on top of neuromotor control principles, thus transforming muscle activation patterns into controller output. Similar to conventional motor tasks, modular recruitment of muscle synergies is observed during myoelectric control [76]. Muscle synergies, representing locally time-invariant weights associated with groups of muscles [77], are thus effectively utilized in this control framework as an underlying model [45], [46]. These methods offer multifunctional control and promote motor learning by aligning with natural motor modules [46]. However, these studies have primarily evaluated unsupervised learning in an emulated, non-adaptive setting with dedicated calibrations. Rigorous demonstrations of their efficacy during real-time, user-in-the-loop operation remain lacking.

Nevertheless, some verification of UIL has been performed under co-adaptive settings [47], [48], [49], [50], where data are gathered from the user-in-the-loop setting to adapt the model. Furthermore, in [49] myocontrol actions were added over time, allowing the user to adjust to the increasing complexity of the control. As mentioned above, under conditions where correct labelling of data is impossible, automated detection of prominent muscle synergies and arbitrary mapping to DOFs can help to overcome this limitation. At the same time, the arbitrary motor mapping can pose a challenge to the user because it struggles to create natural and anthropomorphic control.

C. Predictor-Dependent Incremental Learning (PDIL)

Although unsupervised incremental learning can reinitialize basis vectors—thereby addressing distributional shifts over time—this approach cannot attribute incoming samples to specific classes or regression targets. In contrast, predictor-dependent incremental learning strategies leverage the model's own prediction outputs to guide further adaptation, directly supplying a categorical output or regression target as a pseudo-label. While initially relying on the model calibrated during the training phase to generate these pseudo-labels, predictor-dependent methods gradually become more self-consistent, aligning the adaptation process with the user's evolving internal model of the control scheme and alleviating conflict caused by fresh recalibration each session [78].

As pseudo-labels produced by a classifier can be erroneous, successful predictor-dependent incremental learning strategies have employed a variety of filtering mechanisms to enhance reliability. An illustration of the pseudo-labels assigned for various filters is given in Figure 1. The most common filter is the unsupervised high-confidence filter, which incorporates pseudo-labels into subsequent adaptation only when the model exhibits sufficient certainty in its decision (e.g., $P(y_i|\bar{x}_t) > 0.99$) [43]. This approach ensures that samples located in well-described regions of feature space—where errors are less likely—are leveraged to gradually expand and refine the known space conservatively, ultimately resulting in improvements in both accuracy [43] and throughput [35] compared to initial calibration. However, classifiers can sometimes provide deceptively high confidences, particularly when a sample lies far from all known classes yet is marginally closer to one, prompting the exploration of augmentations such as the smallest margin uncertainty filter [57]. This method identifies samples near decision boundaries by searching for low differences between the highest and second-highest probability classes. In addition, the unsupervised low confidence filter [43] and the entropy reduction filter [57] have been proposed, correcting samples with the greatest ambiguity by suggesting a pseudo-label reflecting the prediction of adjacent time windows if that class ranked the second most likely. And finally, a blip filter supplies pseudo-labels reflecting nearby

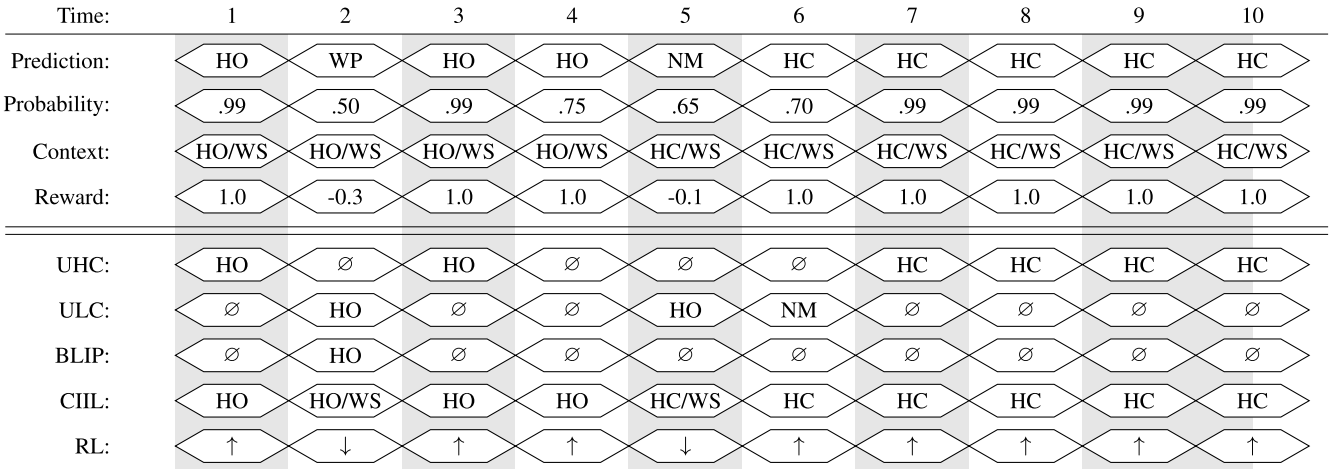

Fig. 1. Consider a hypothetical ten classification window horizon controlling an environment-aware myoelectric prosthesis capable of performing hand open (HO), hand closed (HC), wrist pronation (WP), wrist supination (WS) and no motion (NM). In this scenario, to complete the task the user must first increase the aperture of the hand via hand open, then maintain contact with an object via hand closed. The classification predictions, probabilities, environmental context, and environmental reward signal are given in the top block of the diagram. A selection of predictor-dependent incremental learning (UHC, ULC, BLIP) and environment-dependent incremental learning (CIIL, RL) algorithms are given in the bottom block of the diagram to illustrate the assigned pseudo-label or discarding of the sample (∅) in subsequent updates for UHC, ULC, BLIP, and CIIL; and whether the prediction was reinforced (↑) or dissuaded (↓) for similar EMG inputs for RL.

classes when an isolated prediction is surrounded by other predictions of a single class—operating under the assumption that such momentary blips are physiologically implausible [52]. In general, unless performing active learning where it is possible to retrieve ground truth labels upon a query [57], low confidence-based approaches struggle to improve the performance of the underlying model [43]; however, high confidence-based approaches are generally successful as long as no catastrophic shift has occurred [11], [43].

D. Environmental-Dependent Incremental Learning (EDIL)

Predictor-dependent incremental learning relies on the current model's decision stream, which can lead to performance degradation when an unaddressed covariate shift occurs—such as an unseen limb rotation—even if the shift is momentary. In contrast, environment-dependent incremental learning leverages an external oracle or environmental feedback to assess and validate actions with no dependence on how well the model performs. As such, environment-dependent approaches have been shown to result in well-performing online models without any initial calibration data provided [29], [67]. Currently, there are two primary strategies for environment-dependent incremental learning: reinforcement learning (RL) and context informed incremental learning (CIIL).

RL is a paradigm where an agent learns a control policy by interacting with its environment and maximizing cumulative reward. Simply put, RL is a very appealing approach whenever it is more practical to critique the suitability of a model's behaviour than to explicitly define the desired behaviour using labels for each time step. In myoelectric control, RL methods derive mappings directly from EMG signals and a reward signal, without relying on explicit biomechanics models [79], choreographed supervised training protocols [65], or potentially flawed pseudo-labels. When compared with supervised models, RL-based decoders provide significant performance improvements [71], enhance robustness to various factors (e.g., movement speed [80]), and offer more intuitive or more flexible training approaches. Examples include demonstrating desired behaviours through contra-lateral, non-amputated limb movements (learning from demonstration [65], [66]), learning joint synergies based on reward or predicted future actuator changes [64], [70], providing learned vibrotacticle or auditory feedback signals [68], [69], [81], and even delivering real-time human-provided reward signals relating to correct or invalid decoder outputs (e.g., directly training a multi-joint myoelectric regression controller using reward given to the system via an up/down key press [63]). Further, techniques from the field of RL have been demonstrated to enable beneficial adaptive switching in prosthesis control by applying temporal-difference learning to both optimize and in some cases replace manual human switching between prosthetic modes and functions [67], [68]. Unfortunately, sample efficiency can be low when the RL policy performs poorly or is initialized poorly; if the model experiences a catastrophic shift or starts with no calibration, RL approaches have been shown to require extensive exploration to converge or re-converge to effective policies. However, with a good initial calibration, dimensionality reduction, reward shaping, or training scaffolding, RL has been found to converge to an optimal (or user-functional) policy very rapidly.

Instead of relying on exploration through continued interaction, CIIL relies on richer environmental feedback that suggests suitable classes or regression targets. By tapping into this feedback, such approaches can jump-start training when the model performs poorly, and operate similarly to reinforcement learning when the model is already producing appropriate outputs (see Figure 1). This environmental feedback can come from various sources (see Figure 2). Several studies have demonstrated that environmental feedback from game environments can drive model improvements even

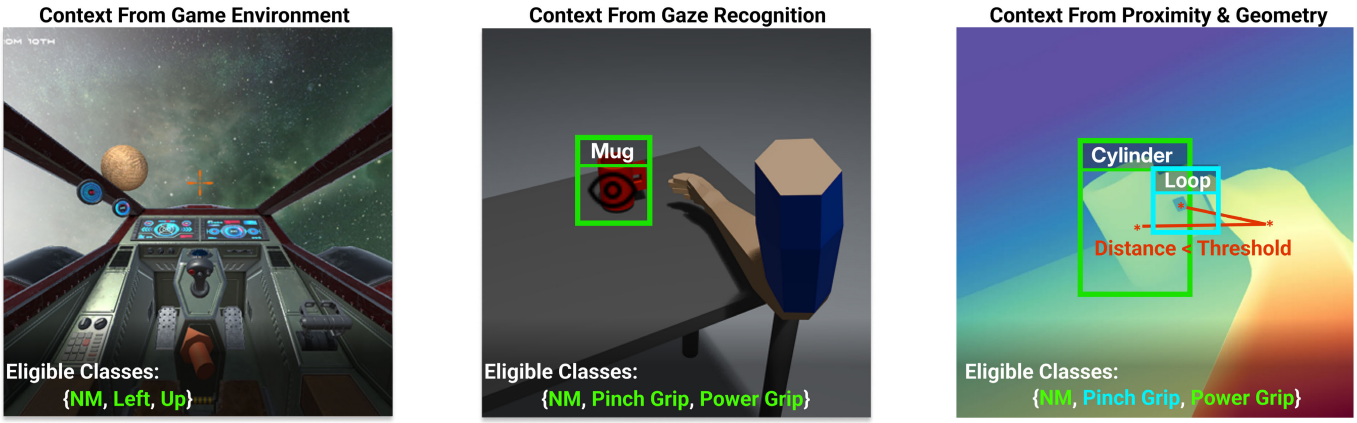

Fig. 2. Illustration of sources of environmental feedback viable for environment-dependent incremental learning. The scenes demonstrate how cues from game environments, gaze recognition, and geometry of proximal objects could provide rich contextual information to guide model adaptation. Context informed incremental learning leverages the eligible classes to form pseudo-labels; whereas reinforcement learning would establish a continuous value reward corresponding to the suitability of the performed action.

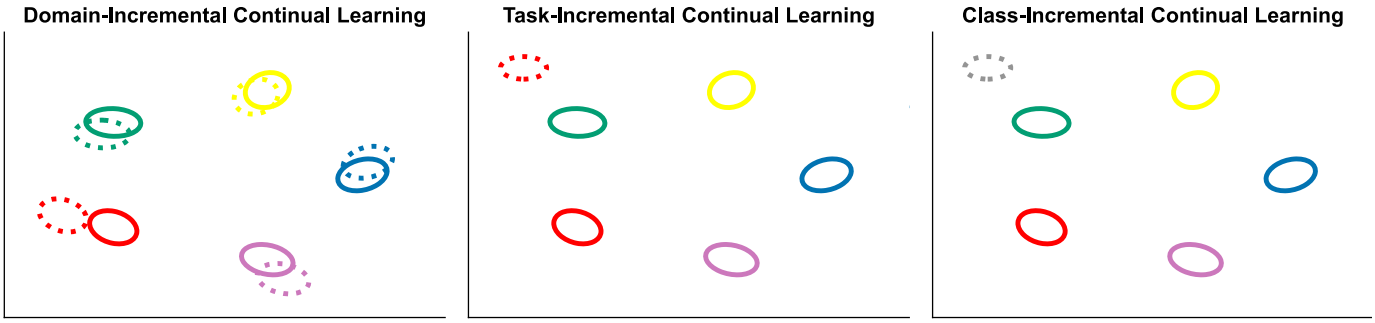

Fig. 3. Illustration of an abstract feature space representing an initial model configuration of five well-separated motion classes shown as different coloured ellipses. Domain-incremental continual learning is represented by shifts to each ellipse. Task-incremental continual learning is represented by a new red ellipse appearing in a novel location. Class-incremental continual learning is represented by a new grey class appearing in a new location.

under a sparse calibration [35], following a large catastrophic electrode shift [35], and has simultaneously learned proportional control mappings alongside classification boundaries from scratch [29]. Moreover, in addition to applications on classification models, CIIL has been successfully applied to regression models, resulting in higher throughput, reduced drift, and lower action interference than models trained with the same duration of screen-guided training [62]. Beyond feedback received directly from the game, relying on gaze recognition has also proven effective for target achievement tests [73]. Moreover, as a step towards more realistic prosthesis use cases, CIIL has been implemented in an object transport task in virtual reality, where feedback derived from proximal objects decreased transport time per item by approximately 50% compared to a well-calibrated, non-adapting classifier [61]. A central challenge for environment-dependent incremental learning in prosthesis applications, especially for CIIL which requires richer feedback, remains the deployment of reliable perception models.

IV. Taxonomy of Incremental Learning Goals

The capacity to incorporate new muscle activation patterns depends on the intended adaptation goal—-whether refining known functions, repurposing new inputs, or expanding the set of control actions. Each scenario requires different architectural and algorithmic capabilities. These needs are not strictly aligned with any single category of the myoelectric incremental learning taxonomy, but can be phrased more generally as three continual learning challenges: domain-incremental continual learning, task-incremental continual learning, and class-incremental continual learning. Figure 3 provides a depiction of these three continual learning problems.

A. Domain-Incremental Continual Learning: Variations of Existing Patterns

This scenario has the goal of maintaining intent recognition performance across natural variations in muscle signals for existing motion classes and control outputs. These variations can come from factors like muscle fatigue, limb position changes, perspiration, or minor electrode shift. All of these factors cause the input distribution to drift over time, often degrading control performance if left unaddressed. In dealing with these within-class changes, several incremental learning strategies have already proven effective to combat model degradation. For example, Nishikawa et al. [82] employed DODR to recalibrate the intent recognition model and combat performance loss over prolonged use of myoelectric control. Likewise, Campbell et al. [35] employed EDIL to recover from

a large electrode shift that had degraded the model substantially. Generally, DODR and EDIL strategies can guarantee that, if the feedback from the environment isn't corrupted and the user is indeed operating as expected (following a choreographed routine or seeking an identifiable goal), the model will eventually recover after any domain shift.

When an incoming muscle pattern is merely a mild variation of a well-described gesture (i.e., it is still within previous decision boundaries), any incremental learning strategy should incorporate the incoming pattern beneficially. However, if the variation is large or sudden (e.g., a 45° electrode shift), strategies without reliable labels struggle—often mislabeling the new signals, and through subsequent model updates, may worsen performance [35]. Using safeguards like the filtering strategies in PDIL and regularization in UIL can help to provide more robustness to these input distribution shifts, but there is no consensus on how big a distributional shift can be handled by PDIL and UIL strategies.

B. Task-Incremental Continual Learning: New Patterns Triggering Existing Actions

Here we consider the scenario where a user develops a new muscle activation pattern to achieve an already-supported function. For example, imagine the system was initially calibrated to move a cursor downward using wrist pronation, but over time, the user finds ulnar deviation more desirable to achieve the same action. The intended control output (move cursor down) hasn't changed, but they are now producing a muscle pattern that the system has never seen for that action. The challenge introduced here is not model failure but a natural evolution in user preference or motor strategy, which leads to two or more distinct inputs corresponding to the same output command.

Unimodal classifiers like LDA and linear SVM often struggle with this type of remapping. Their structure assumes a single, compact representation per class, making it difficult to accommodate multiple modes without degrading decision boundaries. In contrast, models like KNN or deep neural networks can support multi-modal mappings, making them more robust when users adapt their control strategies over time. Among incremental strategies, EDIL (CIIL) and DODR are well-suited to this case, as they can establish the novel mappings using explicit labels; whereas, UIL and PDIL would struggle to associate the new pattern with the correct output.

C. Class-Incremental Continual Learning: New Patterns Triggering New Actions

When a new muscle activation pattern associated with a previously unsupported function is introduced, the system must expand its output space—requiring not just parameter updates but structural changes to the intent recognition model. Among current approaches, DODR remains the most reliable strategy for this class-incremental scenario, as users can explicitly label new gestures to integrate them into the model. When an individual with limb difference learns to use pattern recognition in a clinic, DODR is sometimes used, first introducing 1-3 motions before expanding the model to support more motions when the user achieves reliable control [83]. UIL, likewise, has shown the ability to progressively add control outputs for novel input patterns upon request using piNNMF [49] – similarly adding a new control action when reliable control was achieved. EDIL may also support this case, provided that contextual signals or environmental cues are available to infer new class boundaries; however, no study has validated this. In contrast, PDIL is constrained by its reliance on existing model outputs and lacks the mechanisms needed to establish entirely new control actions. While new muscle activation patterns have been tangentially addressed in open set myoelectric control (i.e., explicit rejection of activities of daily living [84]), harnessing emergent distinguishable motions from the user-in-the-loop setting for class-incremental continual learning has been a relatively neglected area.

V. Emerging Themes Within Incremental Learning Studies

A. Advancements in Transfer Learning and Domain Adaptation

Myoelectric control systems inherently suffer from significant domain shift challenges: models trained on one subject or under specific conditions often perform suboptimally when deployed for new users or under altered experimental setups (e.g. different limb positions, electrode placements, or across days) [11], [85], [86]. While conventional methods yield excellent within-subject offline performance, they generalize poorly across users [87], [88], [89] and typically demand extensive per-user calibration data—capturing variability in limb posture, contraction intensity, and electrode position—to ensure robust operation [88], [90]. In light of these challenges, recent research has increasingly turned to transfer learning and domain adaptation techniques that exploit either data from other users or the abundance of unlabelled signals generated during real-world use, reducing the calibration burden.

1) Cross-User Transfer Learning: To tackle inter-subject variability, several studies have explored cross-user transfer learning [91], [92]. CôtéAllard et al. proposed the Adaptive Domain Adversarial Neural Network (ADANN), which employs multi-domain adversarial training—drawing inspiration from Ganin et al.'s DANN framework [93]—to penalize subject-specific representations and enforce domain-invariant feature learning [87]. This yielded a marked 19.4% accuracy improvement in cross-subject gesture recognition compared to standard training, underlining the promise of adversarial domain alignment for myoelectric transfer learning. Building on this, Campbell et al. extended ADANN to a cross-user modelling framework requiring minimal new data from a target user [88]. Their deep transfer approach significantly outperformed an established cross-subject adaptation method for myoelectric control, canonical correlation analysis (CCA) [94], boosting classification accuracy from 86.8% to 96.2% for users without limb differences, and 64.1% to 84.2% for users with limb differences. Notably, the adaptation procedure was also substantially faster than a full per-user retraining, demonstrating efficient transfer learning that reduces the end-user training burden. These results establish that deep

domain-adversarial transfer can leverage inter-user variance (the "vast" data across many users) to produce a model that quickly adapts to new users with only a few calibration samples, or even none at all in some cases. Indeed, a single repetition (few-shot learning) or none at all (zero-shot learning) of each gesture by a new user can suffice when using such pre-trained cross-user models [88], [95], a drastic reduction from conventional protocols requiring dozens of repetitions per user. Importantly, these types of transfer learning approaches are especially well suited in combination with the methods for Dedicated On-Demand Recalibration [95] and worth exploring in future work as a starting point for Predictor Dependent Incremental Learning or Environment Dependent Incremental Learning strategies.

2) Unsupervised Domain Adaptation and Intra-User Calibration: In parallel, the observation that real-world operation of myoelectric systems continuously produce vast amounts of unlabelled data has spurred advances in unsupervised domain adaptation and intra-user calibration within the field. A key lightweight strategy in this domain is Adaptive Batch Normalization (AdaBN) [96]. AdaBN adjusts the batch normalization statistics of a pre-trained network—assuming that while the network's weights capture gesture-discriminative features, the BN layers reflect domain-specific signal properties—to align the target distribution using only unlabelled new-session data. This simple yet effective method has been shown to restore 5–10% of accuracy lost to session shifts, demonstrating the power of leveraging unlabelled data for rapid recalibration.

Other methods exploit the temporal continuity of EMG signal, where adjacent segments are likely to belong to the same class [54], to generate pseudo-labels from the temporal context of predictions. One early approach to exploit this temporal context is the Multi-Vote (MV) algorithm introduced by Zhai et al. [53], where the network's softmax outputs are aggregated over a short window, and the gesture associated with the highest median value is assigned as the pseudo-label. This approach mitigates the influence of outliers and allows the model to update its parameters incrementally as new data arrives. However, for real-time control, such a majority vote strategy will increase latency, as transitions between gestures inevitably take longer to be detected. Additionally, trying to re-label every segment, even when there is no clear gesture detected by the classifier, will necessarily introduce undesirable noise in the pseudo-labels.

To overcome these limitations, [54] developed the Self-Calibrating Asynchronous Domain Adversarial Neural Network (SCADANN) algorithm. SCADANN extends the DANN framework by first reducing the domain gap between the labelled calibration data and continuously acquired unlabelled signals using a gradient reversal mechanism. It then refines pseudo-labelling by integrating a robust temporal aggregation strategy that detects gesture transitions via the derivative of prediction entropy and retrospectively adjusts pseudo-labels. By discarding unstable pseudo-labels and iteratively recalibrating with both original and refined labels, SCADANN has demonstrated consistent improvements in both offline and online multi-day evaluations—outperforming state-of-the-art algorithms such as MV, AdaBN, conventional DANN, VADA [97], and Dirt-T [97].

Another notable advancement is the Transferable Adaptive DANN (TADANN) [90] algorithm, which specifically addresses across-day adaptation in realistic settings. They introduced a large-scale dynamic EMG dataset recorded over 3–4 sessions spanning multiple weeks, in which users performed gestures under varying limb positions, effort levels, and with simulated electrode shifts in a VR environment. Using this as a testbed, TADANN was shown to significantly outperform standard fine-tuning for periodic recalibration. In fact, TADANN—which integrates the earlier multi-domain adversarial training (ADANN) with a continual transfer strategy—achieved superior across-day performance with no manual re-training, whereas naive fine-tuning on each new session was less effective. This highlights that domain-adversarial recalibration can be more data-efficient and robust than traditional supervised update techniques. Interestingly, even simpler unsupervised adaptation techniques have proven to be useful in this context. For example, Adaptive Batch Normalization (AdaBN) [96] adjusts only the batch normalization statistics of a network to match the target distribution. This method, applied to EMG by Li et al., assumes the network's weights capture gesture-discriminative information while the BN layers reflect domain-specific signal properties – by feeding unlabelled new-session data through the network to update BN means/variances, one can align feature distributions without any labels. AdaBN and similar lightweight strategies have shown meaningful gains (often restoring 5–10% accuracy) across session shifts, further attesting to the value of leveraging unlabelled data for quick calibration.

In summary, transfer learning and domain adaptation techniques are rapidly advancing the robustness of myoelectric control. Adversarial feature adaptation across users and sessions has proven effective at counteracting domain shifts, from inter-subject variability to day-to-day signal drift. By exploiting large pools of previously unusable data—whether other subjects' EMG recordings or the continual stream of unlabelled signals from the end-user—these methods attain high accuracy with minimal new supervision. This not only eases the upfront training requirements (making calibration once or rarely sufficient) but also enables controllers to self-calibrate over time, maintaining stable performance in the long run. Such advancements not only address day-to-day signal drift but also pave the way for myoelectric systems that maintain personalized, robust performance over extended periods, thereby making these interfaces more practical for everyday use.

B. The Role of Self-Supervised Regression in Simultaneous & Proportional Myoelectric Control

1) Regression-Based Myoelectric Control and Challenges: The complexity of mapping sEMG signals to simultaneous & proportional (s/p) myoelectric control outputs requires capturing the non-linear dynamics inherent in muscle activity while ensuring that the system is robust to uncertainties and nonidealities. Influencing factors include muscle

co-contraction, fatigue, and anatomical specificities, necessitating advanced techniques to compensate for such variabilities and maintain accuracy and reliability [98]. Traditional supervised regression techniques, which rely heavily on meticulously labelled datasets, offer modest performance but are constrained by their reliance on high-quality, temporally synchronized data labelling. As such, collecting such data has traditionally been considered labour-intensive, often requiring prolonged sessions that are impractical for real-world scenarios or clinical applications where user comfort and time efficiency are critical [86]. Recent studies, however, have demonstrated that minimal calibration can still yield functional real-world control. Notably, Hahne et al. [99] reported that a prosthetic user was able to operate a regression-based control system at home for two months following only an initial fitting of 40 seconds, highlighting the promise of lightweight calibration protocols for practical deployment. Unsupervised methods could also offer a low-overhead solution by eliminating the need for labelled data entirely. For example, methods based on factorization algorithms assume that sEMG signals can be decomposed into a set of basis vectors that can be interpreted as muscular/myoelectric synergies and corresponding activation coefficients [100]. However, these approaches frequently rely on restrictive assumptions, such as orthogonality or sparsity of muscle synergies, which are not ensured to hold in practice. The presence of cross-talk between muscles and the complex interplay of multiple motor units complicates the regression's reliability. Consequently, unsupervised methods often exhibit suboptimal performance, particularly in scenarios involving multiple simultaneous grasping or movement tasks [46], [98].

2) Self-Supervised Regression Via Neural Architectures: Self-supervised regression introduces a hybrid approach that combines the strengths of both supervised and unsupervised learning while addressing some of the weaknesses related to challenges in sEMG data labeling. This method leverages indirect supervision derived from the data itself, eliminating the need for explicit, temporally aligned labels. For example, self-supervised systems can utilize information from sEMG signals paired with asynchronous movement data, generating pseudo-labels or exploiting intrinsic temporal relationships to guide the learning process.

One of the critical challenges in datasets involving myoelectric signals is the temporal misalignment between inputs (sEMG signals) and outputs (desired motions or forces). Physiological delays, asynchronous muscle activations, and variations in the timing of user intentions contribute to this misalignment, which complicates the regressor's performance. Through the application of advanced loss functions like soft-Dynamic Time Warping (soft-DTW) [98], self-supervised models can learn mappings between inputs and outputs without being constrained by the exact timing of their occurrence. Unlike conventional loss functions that penalize discrepancies in a pointwise manner, soft-DTW measures similarity between time series in a phase-invariant manner, allowing the alignment of inputs and outputs dynamically during training. This flexibility greatly simplifies the learning process while enabling regression models to either maintain or enhance their performance.

In implementing self-supervised regression, neural network architectures can play a pivotal role, and Deep Neural Networks (DNNs), in particular, can be highly effective in processing multi-dimensional signals [101]. A notable innovation in this context is the integration of unsupervised decomposition techniques, such as Non-Negative Matrix Factorization (NNMF), with DNNs [102]. In this combined approach, NNMF is employed to extract latent muscle synergies from sEMG signals, providing pseudo-labels that represent simplified patterns of muscular activation and are used to train the DNN. This process capitalizes on the strengths of both methods, with NNMF providing a low-dimensional representation of the data and the neural network offering non-linear mapping capabilities required for enhanced regression.

Self-supervised regression can be particularly advantageous in scenarios where labelled data are scarce or less practical to obtain, such as, for example, in clinical applications, where a rapid deployment without extensive data collection and annotation can be essential. In prosthetic control, these models can be further investigated to achieve adaptation to individual users by leveraging their unique sEMG patterns, enabling more personalized and intuitive control systems.

C. Intent Detection at the Neural Level via High-Density EMG Interfaces

Traditional low-density or bipolar surface EMG-based neural interfaces have historically been limited in their ability to capture high-fidelity neural information. As they rely on low-pass filtered versions of the EMG signals, the number of degrees of freedom that can be decoded in real-time from these interfaces is therefore inevitably limited. The recent increase in computing power in compact devices opens the feasibility of using advanced electromyographic sensing technology, in particular High-Density surface EMG (HD-sEMG), for applied myoelectric control. These systems rely on several tightly spaced surface electrodes to provide multi-focal observation of the underlying neural sources, capturing the full physiological information on the motor unit action potential level within the 20–500 Hz bandwidth [103]. This approach has evolved EMG interfaces, allowing the recorded muscle activity to be treated as a gateway to the behaviour of the driving alpha motor neurons embedded in the spinal cord [104] (Fig. 4).

The activation of muscle fibers, regulated by alpha motor neurons and reflected in EMG signals, can provide accurate information about user intentions when decomposed into individual neuronal contributions [105]. Hence, HD-sEMG has been used in conjunction with mix source separation (MSS) (f.k.a., blind source separation) techniques to conduct motor unit decomposition and identify individual motor units as sources while treating EMG channels as observations [106].

It has been demonstrated that using motor neuron discharge timings to establish proportional control can outperform conventional methods [107]. Similarly, machine-learning based decoders that leverage these motor unit characteristics show signs of outperforming traditional myoelectric control

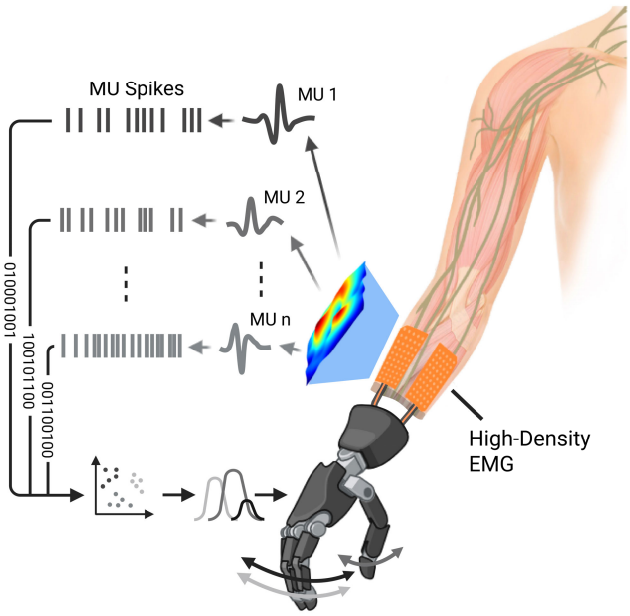

Fig. 4. Concept of using High-Density configurations of sEMG electrodes for myoelectric control: Exploitation of single motor unit activation patterns, extracted in real-time from High-Density sEMG, for user intent detection and assistive device control.

strategies for nuanced control of finger motions, muscle force prediction, and low contraction intensity motions [107], [108], [109]. Because the constituent motor unit action potentials are embedded within the EMG, full decomposition may not always be necessary or may, at least in part, be learned by a neural network trained to predict kinematics using the full bandwidth of the HD-sEMG signal (20–500 Hz, [110], [111]).

Motor unit decomposition interfaces have also been effective in detecting precise finger motions [112], as recent research indicates high task specificity in motor unit recruitment during hand movements [113], [114]. For example, motor unit activation patterns extracted using offline and online decomposition algorithms accurately predicted digit motion in patients with chronic cervical spinal cord injury, despite the patient's inability to produce observable hand motion [115], [116]. A recent approach using the synergistic activity of spinal motor neurons extracted through real-time decomposition combined with postural synergies to control a prosthesis shows promising results, outperforming control based on muscle synergies only [117].

Ultimately, the use of motor unit action potentials is trending towards incremental learning like conventional myoelectric control. Conventional motor unit decomposition techniques assume consistency in surface motor unit action potentials, which are influenced by factors such as fatigue, contraction intensity, and joint position [118], [119], [120], [121]. Decoding algorithms that adapt to new data have been developed to address these variations [122], [123]. However, these methods have been designed for specific conditions and have yet to be evaluated against the gold standard of iEMG-decomposed spike trains. A recently proposed real-time motor unit (MU) decoding algorithm [124] updates the MU filter and signal preprocessing transforms as new action potentials emerge. Although this algorithm has yet to be fully tested, initial benchmarking against invasive systems and other adaptive decomposition approaches suggests it is a promising candidate for further development.

D. The Role of End-Effector Design

For several years, myoelectric control limitations represented a bottleneck for the effective usage of multi-articulated upper limb prostheses; however, incremental learning may change this. Historically, complex prostheses have relied on unnatural control techniques. The inability to control single finger movements naturally encouraged the adoption of underactuated mechatronic architectures, combined with direct myoelectric control or simple pattern recognition-based control systems. These approaches have demonstrated adequate performance in terms of strength and speed, as well as robust grip capabilities, maintaining anthropomorphic form factors and reasonable battery life [26]. As an example, the Hannes prosthetic hand [125], allows human-like grasping using just a single motor, providing naturalness in daily life activities and simplifying remarkably the control. In parallel to this mechatronic development trend, recent technological advances in co-adaptive control opened new opportunities for motor intent detection. Innovations, such as high-density EMG sensing [36], neuromusculoskeletal models, artificial vision systems [126], and sensor fusion of kinematic and incremental learning based approaches [41], [44] have paved the way for the intuitive control of multiple degrees of freedom, and justified the realization of more advanced prosthetic systems, adding, for instance, poly-articulated wrist control [127].

Nevertheless, these techniques have so far been validated primarily in offline settings or virtual tests, due to the lack of prosthetic devices with both high levels of dexterity and advanced control capabilities. This highlights the necessity of a realistic clinical-grade prosthetic platform, with enhanced sensory capability and computational power, seamlessly integrated with a dexterous prosthetic hand. In the field of high-DoF prosthetics, the literature indicates a limited number of prosthetic systems capable of natural, simultaneous, and biomimetic movements. Existing solutions often fail to achieve human-like dexterity, due to their inability to control all joints synergistically. Most clinically available systems rely on medium to low-density electromyography, enabling only limited simultaneous joint control. Specifically, commercial prosthetic hands such as the iLimb Ultra, Bebionic, Ability Hand, and Taska offer multiple motorized fingers, but typically rely on sequential selection of pre-programmed grips or wrist actuation modes. Even when interfaced with modern pattern recognition systems (e.g., Myo Plus TR, Coapt Gen2, IBT Sense), control is generally limited to actuating one predefined grip or wrist function at a time — albeit via more intuitive muscle pattern decoding — thus still constraining the naturalness and flexibility of control. Dexterous robotic hand research platforms, such as the Shadow Hand, offer up to 24 controllable DoFs for hand and wrist, but their complexity and reliance on external systems, such as artificial vision and motion capture, make them unsuitable for prosthetic applications. Therefore, despite the availability of commercial

and research prototypes, a significant gap remains in achieving natural control of multiple movements.

One promising direction to address this gap is integrating dexterous wrist mobility with underactuated hands. The wrist has a crucial role in positioning the hand for optimal grasping: interestingly, in a recent study from Montagnani et al. [129], a simple hand with only grasp functionality, paired with a two degrees of freedom wrist, has been demonstrated to be as effective as the intact hand with wrist flexion blocked. This sheds light on the importance of having a controllable, dexterous, and active wrist joint in prostheses. However, active commercial wrists have developed more slowly than hands, with just two powered wrist rotators (Electric Wrist Rotator [130], the Fillauer MC Wrist Rotator [131]) and one powered wrist flexor (Fillauer Powered Flexion Wrist [132]) available on the market.

In prosthetic research, Boccardo et al. [127] proposed a wrist design incorporating two active DoFs for flexion-extension and pronation-supination, closely approximating the biomechanical range of motion of a healthy human wrist. The wrist design is seamlessly integrated with the anatomical shape of the underactuated Hannes hand, with a very small impact on anthropomorphism (Fig. 5 B and C). A comparative study was conducted to assess the proposed design, evaluating the range of motion and task performance of the prosthetic wrist against healthy participants' natural wrist movements. Key performance metrics included motion range, execution speed, and the ability to perform common daily tasks. Initial results indicate that the prosthetic wrist's biomechanical range closely matches that of a human wrist. Preliminary assessments with amputee users demonstrated enhanced task performance, particularly for activities involving complex hand positioning. The inclusion of active wrist movements resulted in more intuitive control, reducing the cognitive load associated with performing tasks and improving the overall functionality of the prosthetic system. Another study by Miller et al. [128], compared functional outcomes of five participants with transradial limb absence with and without wrist flexion and extension, combining an Ottobock transcarpal hand with a custom two DoF wrist system (Fig. 5 A). The functional tests showed very similar results between the two conditions, but the authors acknowledge that the results may have been limited by the inability to complete patient-related training activities due to COVID-19 delays. This research has enabled the possibility of testing new control algorithms and neuromuscular interfaces in a clinically realistic scenario, investigating the integration of neuromuscular interfaces to further bridge the gap between biological and prosthetic limb capabilities.

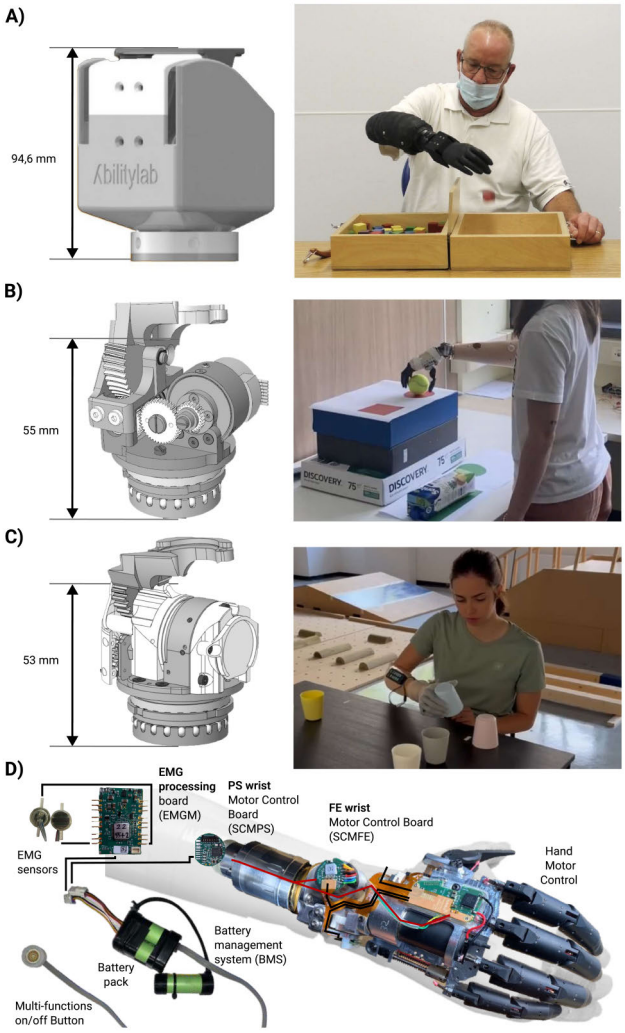

Fig. 5. Wrist design examples seamlessly integrated with prosthetic hands. A) [128] Ottobock transcarpal and B-C) [127] Hannes hand both integrated with custom two DoF wrist systems and D) mechatronic architecture of the Hannes multi-DoF prosthetic system.

E. Human-Device Co-Adaptation: A Dual Learning Approach

Recent improvements in sensing, actuation, and computation have changed the landscape upon which myoelectric control innovation takes place. Notably, incremental learning and domain adaptation in myoelectric control provide new opportunities for co-adaptation on the part of both the human and the machine. We here think of co-adaptation as learning-related change (e.g., to behaviour or internal configuration) on the part of both a person and their prosthesis. Joint learning processes are now possible in the prosthetic setting thanks to powerful instances of *model formation*—the ability of an animal or machine system to create an internal representation of the external world that it can use to perform or improve its acts of computation. More than ever before, machine learning systems in human-prosthesis interaction have the potential to build and maintain models of their user, their environment, and their own operation continually and during ongoing interaction. Models are argued to be central to coordination and communication between agents [133]. As such, users of myoelectric control solutions can perhaps now begin to engage in *human-prosthesis joint action* [134]—the shared, goal-directed pursuit of desired spatial and temporal change in an environment shared by distinct agents [135], [136], [137].

Substantial work has been done to study the way humans build models of their own action (and their interaction with others) as they carry out sensorimotor tasks [135], [136], [137], [138], [139], [140], [141]. As reviewed by Kalinowska et al.

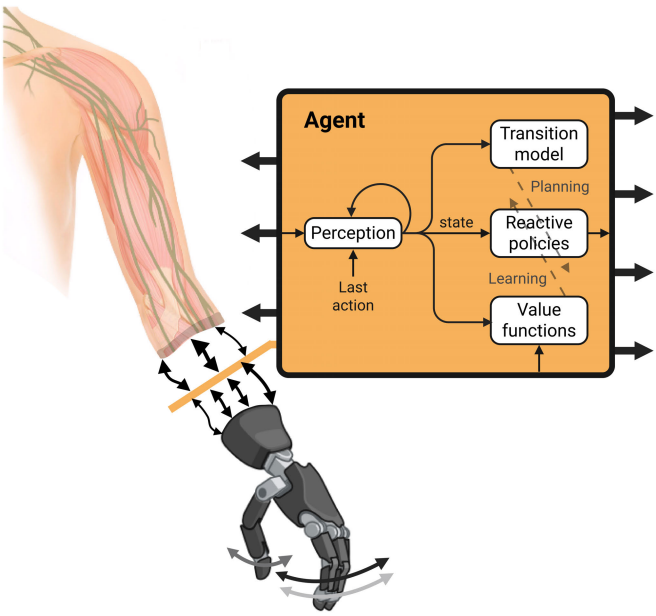

Fig. 6. A multi-agent view on neuroprosthesis use: Co-adaptation as facilitated by a machine with advanced model-forming capabilities. An agent here effects communication via processes of ostension and inference [142], leveraging its learned models to act as the mediator of signals flowing from a human body (left) and the robotic machinery of a myoelectric prosthesis (right). Shown here, the interface includes a standard view of an agent that comprises the ability to continually learn, perceive, act, predict, and plan (cf., [134], [159]).

[142], humans are able to leverage their own learned models to form novel control and feedback interaction conventions with an assistive robot such as a prosthesis, with notable examples in practice [143], [144], [145], [146]. Schofield et al. [147] suggest that these internal models are useful in building user embodiment and trust of a body-attached device. Crandall et al. [148] discuss more generally the way human adaptability facilitates emergent interactions with machine partners, and the benefits this provides to the interacting human and machine parties in achieving a shared goal. Similarly, models formed via modern machine learning techniques have well demonstrated their capacity to represent not just task elements but also the presence of other agents [149], [150], [151], [152]. A survey by Lazaridou and Baroni [149] highlights the true utility and power of such models in emergent machine-machine and machine-human communication and coordination. In addition to the domain adaptation and environment-dependent learning innovations noted above in this manuscript, the capacity for prosthetic-related models and architectures to respect and represent deployment context has increased notably in recent years [7], [66], [95], [153], [154], [155]. Model building by machines is now something that can occur continually, and not only before deployment [156], including prediction models in the prosthetic domain [157], and there is substantial recent progress towards truly long-term continual learning of machine models [158].

These developments, and those other advances surveyed in this manuscript so far, present a new and important opportunity for co-adaptation—moving from fixed human-designed interaction paradigms to emergent or fully learned signalling between a person and a prosthesis. As suggested by the review of Crandall et al. [148], such a change could be expected to increase the flexibility and adaptability of myoelectic control systems, further reduce the design effort needed to sculpt solutions to individual users, and most importantly, put the user front and center in terms of how they want their device to perform and how they wish to interact with it.

Following this view on co-adaptation, a next-generation prosthesis could perhaps become closer to a partner than a tool, with the relationship between a person and their device brokered not by engineered channel coding, but instead by more advanced processes of ostension and inference that leverage learned models [81], [134], [142], [146], [160]. We here refer the reader to the foundational work on ostensive-inferential communication by Scott-Philips [133]. This opportunity to deploy powerful dual-learning interfaces has as its foundation the concepts highlighted in the preceding paragraphs, most notably understanding human internal models of myoelectric prosthesis use, along with developments in our ability to create high-capacity machine models—especially those that can continually and incrementally learn predictions and behaviours during deployed use (cf., [159]).

It is now possible to move beyond our field's legacy of encoding and decoding information on Shannon-style code channels, and to *consider a truly multi-agent view on continual human-prosthesis co-adaptation*. We suggest that pursuing this opportunity will open up new avenues to explore novel and resilient prosthetic solutions that are driven by and sculpted to end-user needs.

VI. User Acceptability and User-Centered Design

Incremental learning fosters the transition of a prosthetic system from a tool to a life-long companion by enabling the user to update the myoelectric control system on demand. This can mean adding new data (both to improve the existing control and add new actions), deleting previous data (to correct for wrong updates), changing the emphasis on existing data, and more; potentially, the user can control each observation in the model dataset. At the same time, the system can call for updates, e.g., if the confidence in its prediction is deemed insufficient or if the sensors aboard the prosthesis report instability in the grasp, etc. While this can lead to improved performance, this process can be demanding for the user, leading to frustration and, potentially, rejection. Alternatively, if these updates happen completely autonomously, these strategies can potentially reduce the user's feeling of agency with the system. It is thus crucial that incremental learning solutions are designed to account for these factors.

Many solutions exist to overcome the training burden that could potentially be associated with incremental learning. For example, serious games, which have had success in skill acquisition of myoelectric control [161], [162], could be used as arenas for calibration. This is particularly interesting because these environments can use gamification elements (e.g., difficulty level, target size, cursor speed, etc.) to capture different user behaviours that are often not accounted for during typical screen-guided training [60], [163]. More

importantly, however, these games can improve motivation and adherence to training protocols [164]. Coapt [37], for example, has built-in games for user training that are being extended to arenas for incremental learning [42]. Alternatively, the training burden can be eliminated by leveraging autonomous incremental learning through additional sensors or other forms of context. In both cases, however, the user should always maintain agency over the system by being able to revert to older models or updating a model that is not behaving as they want.

Compelling evidence exist that myogames can help to improve the myocontrol algorithm, but it remains unclear to what extent they can train the user and thereby foster both sides of the co-adaptation [165], [166]. A growing body of literature has shown that a skill transfers from a virtual to a real environment, so long as care is taken in the game design [162], [167], [168]. Therefore, environments which are physically accurate and contain a realistic robotic simulation and interaction could be beneficial to train and assess future co-adaptive myocontrol paradigms. In all cases, the *user interface* needs to be carefully designed to provide friendliness of use and motivation, leading to a tighter and tighter co-adaptation and, ultimately, to optimal user control. Visualization of the user's own data in real-time is paramount, together with a way of quantifying the quality of the provided data. Moreover, the timing of data gathering must be targeted to avoid gathering noise or irrelevant signals. Both these requirements can be fruitfully tackled using, e.g., principles of *Interaction Design* [169] and constructivist psychology [170], [171]. Steps forward to simplify this situation are being made, for instance in the system provided by *Infinite biomedical technologies* [172], which enforces selective action data gathering and several ways of graphically representing a user's data in real-time.

VII. Discussion

Building on the taxonomy of incremental learning strategies for myoelectric control, the following discussion explores open challenges and limitations that span these categories. Key topics include the ability to distinguish between signal changes caused by non-stationarities versus those reflecting genuine changes in user behaviour, the quality and quantity of data required for different strategies to function robustly, and user adaptation versus model adaptation.

A. Sensitivity to Noise Vs. User-Behaviours

A key limitation across many incremental learning approaches for myoelectric control is the inability to explicitly distinguish between meaningful shifts in user behaviour and non-stationarities arising from noise or sensor drift. Predictor-dependent incremental learning (PDIL) and unsupervised incremental learning (UIL) rely on their own predictions or latent representations to update the model, and because they lack any external guidance for class labels, they can easily mistake transient noise, drift, or other non-stationarities as genuine behavioural change and end up selecting for this variation as they adapt. While forgetting mechanisms [56] offer one means to mitigate the accumulation of noise-selective updates, few methods actively attempt to attribute signal changes to behaviour versus noise. Nonetheless, this challenge underscores the importance of carefully selecting adaptation mechanisms and incorporating safeguards—such as confidence thresholds, regularization, or controlled forgetting—especially in unsupervised or predictor-dependent frameworks. Other methods also offer stronger implicit safeguards. Environment-dependent incremental learning (EDIL) and dedicated on-demand recalibration (DODR), for example, draw on external information (e.g., environmental pseudo-labels, reward signals, or explicitly supervised calibration data) to verify that each update is functionally beneficial without needing to attribute the change as either noise or behavioural. This additional validation layer offers more robust guarantees that learning remains directed to meaningful control improvements.

B. Model Complexity Vs. Data Requirements

The quantity of data required for effective incremental learning is influenced more by the underlying intent recognition model and control complexity than by the incremental learning strategy itself. For instance, simple linear models can converge with minimal training data, while more expressive architectures such as transformers typically require orders of magnitude more data to perform reliably, regardless of which incremental learning strategy is deployed. Additional factors such as the number of degrees of freedom being controlled and the variability in user behaviour further impact data requirements. Nevertheless, learning paradigms that rely on externally validated updates, such as environment-dependent incremental learning (EDIL) and dedicated on-demand recalibration (DODR), tend to be more data-efficient due to their access to high-quality labels or reward signals. In contrast, predictor-dependent incremental learning (PDIL) models rely on their own predictions to generate pseudo-labels. While this allows them to function with limited data, it also makes them highly sensitive to sudden perturbations in recording conditions. To mitigate erroneous updates, these methods often use filtering techniques (e.g., high-confidence or margin-based filters) that deliberately reduce the number of training samples to prioritize their reliability. Similarly, unsupervised incremental learning (UIL) approaches do not require extensive data but depend heavily on consistent collection conditions. For instance, if a low-dimensional representation is learned using an incremental form of NNMF, the emergence of a new, more separable muscle potential during operation could shift the loading vectors, thereby disrupting the control mapping that the user has already internalized. Despite ongoing efforts to improve sample efficiency and robustness, the field still lacks comprehensive benchmarks for understanding how data quantity, quality, and distribution impact real-time adaptation. Addressing this gap is vital for deploying adaptive myoelectric systems that are both reliable and user-friendly in practice.

C. User Vs. Model Adaptation

In co-adaptive prosthetic learning paradigms, the interaction between user and model forms a two-learner problem. Prior work has shown that users can compensate for model

errors [173], and even adapt to arbitrary motor mappings [49]. An interesting future research direction could be to prevent premature convergence to a suboptimal state, e.g., when a user adapts quickly to a poorly performing model, leading to input patterns that further reinforce the model's unwanted behaviour. It remains unclear which co-adaptation protocols best guide both learners toward global convergence. Previous research has shown that the model's learning rate plays a critical role. Müller et al. [174] demonstrated that while overly slow learning rates lead to stagnation and overly fast rates destabilize user learning, there exists a broad intermediate range that supports stable co-adaptive convergence. These findings were supported by findings from [175], who additionally describe that a matching adaptation between user and system supports the fastest and most stable convergence. Users then interact with the prosthesis based on internal expectations of system behaviour. Whether and how they adapt depends on how well the (visual) feedback aligns with these expectations [176]. Following this line of thought, human behaviour is not static or deterministic in response to a given feedback. Rather, it can be actively managed by providing instructions and information that influence expectations and behaviour. For example, during the early training stages of a model with a higher data requirement and slow adaptation, the user could be asked to persist in performing the intended behaviour even given unsatisfactory feedback to avoid prematurely adapting to poor mappings. Similarly, the right balance between open-loop training (e.g., screen-guided training without feedback) and closed-loop co-adaptation remains an open question. Open-loop phases may allow for data collection without human adaptation and compensation, while testing sessions with static models could support dedicated human adaptation and expectation management. Similarly, actively instructing users or injecting small perturbations into the model could promote exploration and help escape local optima. The applicability and necessity of curated training protocols may vary by incremental learning learning category. In DODR, model and user adaptation are inherently staged sequentially, limiting the option of co-adaptation phases where both learners are active at the same time. Whereas, in some of the UIL models (e.g. iNNMF), the user could be instructed to either reinforce muscle synergies discovered by the model or explore new activation patterns. PDIL, since it is self-referential, would converge promptly without much risk of destabilizing. EDIL could inherently reduce the risk of local optima by providing external context or task success as neutral guidance.

While co-adaptive strategies have shown promise in improving long-term performance, model updates can also degrade control or lead to unintended movements if applied naively. Therefore, protocols should not only consider how to co-adapt users and models, but also how to rigorously evaluate the safety and reliability of these updates. One option could be to perform updates in dedicated sessions, where performance can be evaluated before deploying changes to the user's prosthesis, such as in a virtual, physically accurate simulation environment with minimal risk. Alternatively, online validation strategies could serve as model safety checks in continuous adaptation scenarios. These strategies could include approaches such as evaluating data separability or model performance on representative sample batches. While changes in the control mapping can influence the sense of agency [147], [177], it remains unclear how frequent incremental changes to myoelectric control affect the user's sense of agency, ownership and trust in the system.

VIII. Conclusion

This review shows that incremental learning offers a transformative framework for advancing myoelectric control systems. By categorizing approaches into dedicated on-demand recalibration, unsupervised, predictor-dependent, and environment-dependent strategies, this taxonomy shows how different adaptive methods can address the inherent challenges of signal non-stationarity, frequent recalibration, and variability in user behaviour. This work also establishes another taxonomy of types of incremental learning studies, namely domain-incremental, task-incremental, and class-incremental continual learning. Emerging themes such as transfer learning or domain adaptation, and self-supervised regression further enhance system robustness by leveraging real-time data and reducing the need for extensive initial calibration. Innovations in sensor modalities and end-effector design could complement these adaptive algorithms by capturing richer neural information and enabling more biomimetic movements. Additionally, the integration of human-device co-adaptation highlights the importance of mutual learning, where both the prosthesis and the user evolve their control strategies to improve performance and usability. Finally, a focus on user-centred design ensures that these technological advancements translate into practical, user-friendly solutions that maintain agency and comfort. Collectively, these insights pave the way for next-generation myoelectric prostheses that are not only more intuitive and resilient but also closely aligned with the dynamic needs of end users, setting a promising course for future research and clinical application.

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