Brain-Machine Interfaces: A Tale of Two Learners

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Abstract Brain-machine interface (BMI) technology has rapidly matured over the last two decades, mainly thanks to the introduction of artificial intelligence methods, in particular machine learning algorithms. Yet, the need for subjects to learn to modulate their brain activity is a key component of successful BMI control. Blending machine and subject learning, or mutual learning, is widely acknowledged in the BMI field. Nevertheless, we posit that current research trends are heavily biased towards the machine learning side of BMI training. Here, we take a critical view of the relevant literature and our own previous work, in order to identify key issues for more effective mutual learning schemes in translational BMIs, specifically tailored to promote subject learning. We identify the main caveats in the literature on subject learning in BMI, in particular lack of longitudinal studies involving end-users and shortcomings in quantifying subject learning, and pinpoint critical improvements for future experimental designs.

***Index Terms*—Brain-machine interface, machine learning, mutual learning, neurofeedback, sensorimotor rhythms**

I. Introduction: On the Need for Mutual Learning

BRAIN-machine interface (BMI) technology has rapidly matured over the last two decades to witness the first clinical evaluations of assistive or rehabilitation prototypes for people in paralysis [1]. Early BMI approaches mainly relied on the brain's ability to gradually learn to regulate its activity through feedback provision, a technique borrowing from neurofeedback research and applying operant conditioning principles [2–4]. This subject learning process is believed to be fueled by functional and structural plastic transformations within the brain itself [5–8], which is known to often require lengthy training. A breakthrough in BMI took place when Artificial Intelligence (AI) algorithms were introduced, enabling instead the machine to learn—in much shorter time scales—to decode the (high-dimensional) multivariate and noisy brain activity patterns of various mental tasks [9]. This state-of-the-art machine learning approach is based on the premise that different "thoughts" or "actions" must have unique, pre-existing neural substrates, which, if adequately captured by brain imaging technology, should be distinguishable thanks to the power of modern AI algorithms. Reconciling these competing practices, the opinion that future BMI should consider, facilitate and coordinate both learning agents involved in the BMI loop (i.e., the human subject and the machine) has been very early expressed and termed "co-adaptation" or "mutual learning" [10,11].

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Although the need for mutual learning is widely acknowledged in both invasive and non-invasive BMI [12–16], current research trends are heavily biased towards the machine learning side of BMI training. Here, we take a critical view of the relevant literature and our own previous work, in order to identify key issues for more effective mutual learning schemes in translational BMIs. Specifically, we put forward a line of reasoning promoting the reinstatement of subject learning as an equally important pillar in BMI training. We focus on non-invasive BMIs decoding sensorimotor rhythms (SMR) and invasive BMIs decoding kinematics, as the evidence supporting the possibility of learning to regulate evoked potentials is still limited [17].

II. The Place of Subject Learning in BMI

BMI literature is marked by a major contradiction. On the one hand, reference to subject learning, as the ability of subjects to modulate their brain activity through feedback towards optimizing BMI performance, is ubiquitous [4]. There seems to be a pervasive belief in the field that subject learning is a direct, "automatic" consequence of closing the loop between a user and a brain-actuated device. However, explicit experimental evidence is scarce, especially for human subjects. Also, literature providing support of human learning during BMI training and operation is based on small cohorts [2,8,18–20].

On the other hand, the literature (overall, and specifically on BMI training) is heavily dominated by studies oriented towards novel signal processing and machine learning methods applied to BMI [21]. The vast majority of these works entail open-loop ("offline") experimentation, which forthrightly exclude any role for subject learning. Closed-loop studies with real-time feedback ("online") conducted under the umbrella of "co-adaptation" are also mainly focused on issues pertinent to the machine learning side

[22]. In a survey conducted in 2010, it was found that less than half of reviewed neurofeedback and BMI publications in 50 years of relevant research, which were longitudinal enough to qualify as learning studies, actually reported some sort of learning effects [23]. Even in this minority subset, in most cases it is unclear to what extent BMI performance improvement can be attributed to subjects actually learning to better regulate their brain signals or other factors (e.g., machine learning interventions).

Tackling BMI training as a purely machine learning problem stems from the great impact of AI on the field. Indeed, the introduction of multivariate brain feature processing algorithms for feature selection and decoding is the major distinction of BMI with respect to neurofeedback that makes it possible to control brain-actuated devices. This trend is stronger with the advent of advanced AI algorithms like deep learning [24,25]. Moreover, the view that ongoing developments in brain imaging techniques [26]—which promise to increase both the amount and quality of information extracted from the brain—will soon render the BMI problem a mere decoding issue, is popular.

Nevertheless, despite the benefits of machine learning, a large portion of prospective users is still unable to gain control of a BMI without adequate user training [22,27–30]. The situation seems to be even more critical with regard to people with disabilities [29], where lesions of the central and peripheral nervous systems might affect the natural sensorimotor apparatus that machine-learning-oriented BMI designs aim to exploit. The hope of deploying "big data" AI approaches, however, seems limited in BMI given the need for rapid deployment of decoders in closed-loop interaction to keep subjects engaged and motivated. Transfer learning approaches also seem so far unable to overcome this obstacle, largely due to the subject-specific nature of brain patterns that need to be employed for BMI [31].

In conclusion, the promise of "zero-training" BMI and universal access to the technology for all prospective users remain elusive. There is thus mounting evidence pointing to the need of shifting the focus of investigation towards subject learning and the interactions between human and machine adaptation [12,13,16,32,33].

III. Pitfalls in BMI Literature on Subject Learning

Research on subject learning in BMI is limited. Here, we identify the main caveats and pinpoint critical improvements for future experimental designs.

A. Lack of Longitudinal Experimentation

The practice in BMI closed-loop studies seems to involve a single, or rarely two or three training sessions [28,34–42]. A handful of works report 5-15 sessions [29,43–50], and only a few can be characterized as truly longitudinal studies [2,18–20,51–63] extending over many sessions and long periods of time. Assuming that BMI learning is—as mainly hypothesized—a form of operant conditioning and mainly falls under the category of implicit rather than explicit/declarative learning, it must be expected that it involves network and cellular level mechanisms akin to associative plasticity [64]. Such biological processes cannot possibly take effect in short training periods, at least as far as retained motor skills are concerned [65,66]. It can thus be said that the majority of BMI training literature has not yet fully explored the possibility to enable, observe and reliably evaluate subject learning effects.

B. Lack of End-User Studies

Another important pitfall is the lack of end-user studies. Although most longitudinal BMI experimentation has been done with people in paralysis, these works comprise an almost negligible percentage of the BMI literature. People with motor disabilities do not only represent the main target group of BMI technology, but might also be the user category where subject learning may prove to be particularly crucial. Pathologies of the central and even of the peripheral nervous system disrupt the normal action-perception loop of human-environment interaction and are known to often negatively influence the usual cortical activity patterns elicited by able-bodied individuals [29,34,39]. In other words, in this critical user group, machine learning alone seems unlikely to lead to universal access to BMI, since the "decodable" brain activity patterns that an AI model could learn to interpret, may no more be there at all; instead, subject learning and the accompanying plasticity might be needed in order to create "de novo" neuronal circuits that the BMI algorithm can later successfully translate into actions of an end-effector [12].

C. Shortcomings in Quantification of Subject Learning

Subject learning in BMI has not been properly assessed so far in the literature. A minimal quantitative piece of information that should be provided is the evolution of BMI proficiency metrics over time as, based on psychological studies and general learning literature, demonstration of learning curves is a "sine qua non" prerequisite to establish the existence and typology of learning effects. Yet, many works discuss subject learning without reporting such learning curves [19,27,29,36,54].

Extrapolating from Other Fields

A reason for claiming subject learning in BMI without hard evidence is its affinity to human neurofeedback experimentation. While such similarity arguably exists [67], there are good reasons why these arguments fall short. First, neurofeedback has recently received a lot of criticism regarding its real efficacy [67,68]. Second, the extrapolation from neurofeedback to BMI learning is a fairly far-fetched one. As already noted, the main difference is that neurofeedback requires users to learn to regulate univariate brain activity, for example, the amplitude or the power in some frequency band of a single EEG channel; conversely, a modern BMI is driven by the output of a classification or regression model that combines several spatio-spectro-temporal features of brain activity—even if the actual controlled effector is unidimensional (i.e., a visual feedback

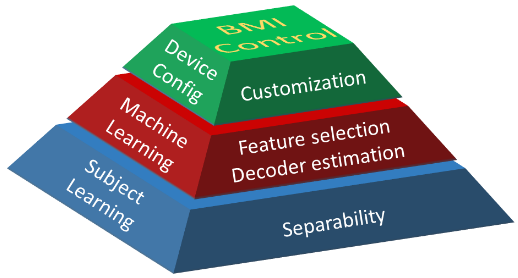

Fig. 1. Pyradimal nature of BMI control and co-adaptation.

bar moving left/right or up/down). Hence, the learning burden in a BMI seems to be much heavier [66]. It is currently unclear how humans can cope with this situation, whether they may be overwhelmed and give up, they can subconsciously focus and gain control over a learnable manifold [69], or prove able to gradually exploit the whole available multivariate feature space. In addition, even multimodal neurofeedback studies are simplistic when compared to the complex end-effectors and surrounding environments (and the interactions therein) a user must learn to master a BMI, especially in real-world conditions [20]. Under this perspective, BMI learning seems to be much closer to natural motor and skill learning [6,8] rather than neurofeedback.

Another overstated extrapolation derives from well substantiated subject learning effects shown in invasive BMI studies with animal models [3,5–7,13]. Despite the great value of these works in understanding BMI learning and control, especially taking into account the seminal and holistic manner in which the issue of subject learning has been quantified for regular [6] and co-adaptive [13] BMI systems, the translational value of subject learning in BMI must be experimentally verified: the need to transition from animal model studies to human clinical trials in order to prove the effectiveness of a therapy or medical device is a concept well established in the medical world; yet, somewhat overlooked in the engineering-oriented BMI field. Even the recent longitudinal studies with end-users that sparked a renewed interest in BMI and can be thought to be the natural successors of the aforementioned previous efforts with non-human primates or rodents, still largely neglect the issue of subject learning [53,56,59,61,62], save a few notable exceptions [57]. Moreover, the great differences in hardware, brain signals or features and control paradigms employed in this line of research make it unclear whether subject learning occurs similarly in other types of BMIs.

Flaws in Quantification of Subject Learning

Although there exist studies providing quantitative evidence for the emergence of human learning effects during BMI training and operation, their methodologies are open to criticism. The most typical weakness is reporting only learning curves of either BMI application performances [50,70] or output of the BMI decoder [29,35,36,45,47,52,56]. The problem is that such "high-level" metrics cannot disentangle the individual contributions of the subject and the BMI decoder to the overall performance, effectively ignoring the presence and individual roles of the two learning agents in the BMI loop.

We suggest that BMI control emerges in a vertical/hierarchical—rather than horizontal—fashion (see Fig. 1). The subject is at the base of the pyramid (first level) and must necessarily be able to generate distinct patterns of brain activity in some physiological brain feature space. Subjects will subsequently learn to improve these brain patterns with practice and the support of the other two levels above. In the second level, machine learning techniques identify the brain activity feature space where subjects' intentions are optimally distinguishable (feature extraction and selection) and build an optimal multivariate decoder (classification/regression). In the third level, the output of the decoder is mapped to actions of the brain-controlled device. This mapping can benefit from shared control approaches in order to increase the reliability of the device and reduce the subject's workload, thus facilitating subject learning [58,71,72].

As becomes apparent in this abstraction, reporting only the BMI performance (2nd level) or the application performance (3rd level) cannot isolate and assess subject learning (1st level). For instance, a random classification outcome could be either attributed to the subject not being able to produce separable patterns or to the BMI decoder being outdated: classification accuracy or application-dependent metrics will be unable to identify these different situations. Consequently, also a reported increase or an overall "learning curve" on such metrics cannot be used to claim subject learning effects beyond reasonable doubt, certainly not in the case where parallel interventions on the BMI algorithm (i.e., periodic or real-time recalibration or feature re-selection) may account for the performance enhancement. Our previous work provides evidence of this potential mismatch [42]: the increase in classification accuracy exhibited by the majority of 10 participants during spelling with an online adaptive SMR-based BCI was not followed by the anticipated strengthening in the separability of their brain patterns; conversely, an average discriminancy decrease was observed. In that case, we were able to show that performance boosting was solely attributed to better fitted classifiers thanks to their adaptation. In another of our studies [49], several end-users exhibited, on average, improvements in BCI command accuracy over a maximum of 10 sessions before proceeding to control a telepresence robot. However, further inspection revealed that this increase did not correlate with enhancement in discriminancy of the power spectral density features used in the decoders, and seemed to mainly derive from better parametrization of the BMI telepresence device and the BMI hyperparameters. It is noteworthy to mention that, for the exact same reasons, metrics like classification accuracy are insufficient to isolate improvements on the machine learning side. To address this problem, we have previously introduced a "classifier precision" metric, suitable for decoders that belong to or can be represented by generative modeling [42].

Using classification accuracy or regression fitness metrics has prevailed in the BMI field following the introduction of machine learning. Most machine learning is grounded on assumptions like stationarity and "independent identically distributed" data. When these assumptions hold, an increase in performance of a fixed, trained model seems reasonable to be attributed to the underlying class-dependent distributions getting more separable. However, neural signals (and the features computed on those) are notorious for violating such assumptions. Non-stationarity effects have been well described [16,37,42]. Violation of the independence assumption, and a potentially varying degree of it over time, may invalidate classification performance estimation through techniques like cross-validation and training-testing split [73], explaining potential "spurious" performance improvements that in fact do not represent subject learning. The "identically distributed samples" assumption may also be violated when subjects (often, subconsciously) employ different mental strategies over time, which can be viewed as another case of non-stationarity not necessarily manifesting simply as "shifts" in the feature space [37]. Importantly, even with a fixed model, the estimation of metrics like classification accuracy is known to be sensitive to a number of factors such as class-wise balance of samples, cardinality of the dataset and tendency of the used model to overfit [74]. There is thus still no guarantee that an increase in accuracy (especially, if small in magnitude, as it is usually the case) actually corresponds to better brain signal modulation.

Given that the common machine learning evaluation metrics employed are insufficient to assess the existence and magnitude of subject learning effects, we advocate to use metrics that directly measure improvements in brain activity modulation; i.e., metrics directly computed at the feature level. Additionally, in order to uphold the operant conditioning nature of subject learning, still thought to be the dominant learning model in BMI, these feature-based metrics should be either computed on the same features giving rise to BMI control or, at least, on directly dependent ones. Indeed, the theory of instrumental learning dictates that learned regulation should necessarily reflect the variable fed back to the user during closed-loop control—although one cannot exclude the case that a change could occur in a related physiological variable; e.g., increase in brain connectivity as a result of SMR-based BMI training [75]. Such metrics have been already proposed in the literature and largely pertain to different ways to measure the separability of the distributions of the different mental classes, like r^2 [37], Fisher Score [20], or Kullback-Leibler divergence [42]. Metrics inspired by basic neuroscience research that effectively describe the same brain phenomena giving rise to the features used for control can also serve the same purpose adequately [38,43,48,55]; for instance, a demonstrated increase of ERD/ERS in a SMR BMI based on power spectral density (PSD) features.

IV. Open Issues in BMI Mutual Learning

So far only a handful of studies with able-bodied users [43,48] and end-users [18,20,49,55,57] adequately comply with what we have identified as essential prerequisites for a reliable evaluation of subject learning effects during BMI training: longitudinal monitoring, evaluation at the BCI feature level and, ideally, inclusion of end-user participants. There is thus considerable room for improvement which, we strongly believe, will also help reveal the true potential of subject learning for bringing people in control of BMI-based applications. Below, we discuss the most important open issues emerging from the study of BMI learning and co-adaptation literature with reference to lessons learned from our own previous work.

Nature of Subject Learning

Subject learning in BMI has been mainly discussed in the contexts of operant conditioning (instrumental learning), motor learning (especially regarding systems involving motor-related mental tasks like invasive BMI decoding kinematics and non-invasive SMR-based BMI) and general skill learning. Given the very broad definitions of all these frameworks, the abundance of different methodologies each one of them encompasses and the variety of different BMI paradigms, these categorizations should rather be viewed as complementary and overlapping, not as mutually exclusive. For instance, the role of feedback contingent to entrained brain activity is regarded as crucial under all these schemes.

One of the most important questions regarding the nature of subject learning in BMI pertains to whether it is mostly an implicit/procedural or an explicit/declarative process. Implicit learning suggests that subjects may gain control over BMIs gradually, in a largely subconscious manner through feedback observation, as shown to occur in neurofeedback studies. This mode of learning is more compatible with the instrumental and skill learning theories [67]. On the other hand, explicit learning relies on declarative knowledge passed on to the subject verbally or schematically, i.e. through instructions, examples and illustrations. Delineating the implicit and explicit aspects of learning in BMI is crucial for a number of reasons. First, it is a critical factor in training protocol design. For example, the explicit learning approach calls for more "explanatory" protocols that better take into account educational theories of learning, or instructional and motivational designs [32], whereas implicit learning could more likely be boosted by interventions like the establishment of more natural feedback provision strategies [75–77]. Second, the expected timescales of learning (and as a result, the required training times) should heavily depend on the degree of its explicit or implicit nature. Specifically, declarative learning paradigms are more likely to induce abrupt changes in performance and in the elicited task-dependent brain patterns, which are coupled to the onset of adopting a new successful (i.e., separable) mental task or strategy. These changes should probably reflect the preexisting engrams of the newly employed mental tasks rather than any functional plasticity and cortical reorganization. On the contrary, implicit learning is thought to rise from plastic effects encoding a newly acquired skill and thus should more likely manifest with smooth and gradual emergence of brain patterns and performance improvements that follow some associated functional and/or structural plasticity. The only principled investigation conducted so far on the issue of the (procedural or declarative) nature of learning in SMR-based BMI has argued in favor of the implicit learning model [78]. Also, the fact that proficient BMI users often report reaching a state of "automaticity" after long-term use, where they no longer explicitly employ the instructed "surrogate" mental task (e.g., motor imagery of some limb) but instead directly command the control of the BMI actuator [10,19,20,44,54,55], also supports an implicit learning process.

Time Scales of Subject Learning

Although most studies imposing 5-15 training sessions [29,43–50] (including our own work with end-users [29,46,49]) have mostly failed to show clear indications of subject learning, our recent study involving two users with spinal cord injury has shown that people with severe disabilities can learn to operate an SMR BCI in real-world conditions with a slightly higher number of 15-20 sessions [20]. Importantly, they started training with a poor ability to spontaneously modulate SMRs and outperformed other participants with similar disabilities in an international competition. While our subjects relied on a mutual learning approach that explicitly elicited subject learning, all other participants seemed to follow a conventional machine learning approach—including multiple feature re-selection and classifier re-calibration rounds. It thus seems that BMIs adequately supported by machine learning and also fostering subject learning may deliver better long-term outcomes. The few longitudinal studies where BMI subjects received only sparse or parsimonious machine learning interventions have led to comparable conclusions [55,57]. These are approximately the derived timescales of learning also in early animal studies [3,5].

Assuming that this amount of training sessions is a minimum to induce subject learning, the question is raised whether claiming BMI learning within a single or a couple of sessions merits any scientific grounding. It is well established that acquisition of motor and general skills evolves with an initial "fast learning" (even intra-session) phase followed by a "slow learning" (multi-session) one [67,79–81]. Both stages have been linked with functional synaptic plasticity in animal models and humans [80]. Hence, some form of BMI learning taking place in short time scales cannot be excluded. However, neural circuit changes in the fast learning phase have been thought to reflect short-term plasticity; i.e., effects tend to return to baseline in a matter of minutes or hours. Furthermore, motor skill consolidation and, eventually, retention has been shown to require long-term training and leads to larger cortical reorganization or even structural plasticity.

V. Redefining Co-Adaptation: When and What Machines and Humans Learn

As with the rest of the BMI literature, the studies introducing co-adaptation in BMI have also almost exclusively focused on the machine learning challenges of this new framework. Efforts have mainly concentrated on the algorithmic modifications needed to solve the mathematical optimization problem associated with parameter estimation of each decoder type during real-time BMI operation (instead of the traditional batch and offline approach). But, can subject learning happen under the dynamics generated by an adaptive BMI decoder? Since adaptive BMIs inevitably result in the situation where a given neural activity pattern can lead to different BMI outputs within short amounts of time and thus to an unstable, confusing feedback, the concern has been sensibly raised [12,66] whether it is reasonable to expect that subjects can learn such an "ever changing" task.

Given the absence of longitudinal studies of truly BMI co-adaptation in humans, the answer to this question remains largely speculative. Nevertheless, gleaning evidence from the ensemble of relevant literature converges towards the following conclusion: BMI decoder adaptation during closed-loop control should only be enabled in the beginning of new BMI (training or operation) sessions until non-stationarity effects are alleviated and BMI performance restored; subsequently, stable—or, at least, only smoothly adapting—decoders should be preferred, so as to foster and exploit subject learning capacities. Partial support to this view comes from the few longitudinal studies with humans that have showcased subject learning effects with BMIs involving no or only parsimonious decoder adaptation [18,20,57]. Collinger et al. [57] adopted the methodology of previous works on primates with daily, session-wise re-recalibration; however, parameter re-estimation happened only in the beginning of sessions and decoders were kept fixed for the remainder of each session, in full accordance with our proposition. Perdikis et al. [20] modified the decoders only if the new one outperformed the current decoder—something that happened sporadically. McFarland et al. [55] is the only case where subject learning effects seem to accompany continuous decoder adaptation. Nevertheless, it is not clear whether the learning rate hyperparameter led to intensive or mild decoder modifications: in the latter case, it can be assumed that an adaptive, but, still "approximately stable" decoder, may not have disturbed the subjects' learning efforts.

Several BMI studies on animals are particularly supportive of the ability of stable decoders to foster subject learning [3,6]. In particular, Orsborn et al. [13] have presented the only study explicitly designed to answer the question whether consolidated subject learning is possible during BMI adaptation. The authors highlight the risk of the "moving target" problem commenting that the performance variability in previous studies employing online or recurrent BMI adaptation may be due to the unsuitability of these approaches for inducing permanent neuroplasticity and consolidated skill formation, in spite of the average performance improvement. Furthermore, they identify the study of the interactions between subject and machine as key to resolving these issues. They also suggest that decoder adaptation is certainly beneficial only in terms of coping with non-stationarity of neural signals and the need to track changes in neural ensembles (e.g., dying cells—the equivalent in non-invasive BMI would be changes in the optimal feature subset). Ultimately, they show the possibility of BMI skill acquisition with simultaneous decoder adaptation; however, the latter was "infrequent, minimal and interspersed with long periods of fixed decoders". Hence, continuous adaptation may not prevent subject learning as long as parameter update is mild, as shown in earlier work of this and other groups [59,82]. Lastly, the only recent work that has attempted a generic mathematical model of co-adaptation [16] has also found in simulations that mild learning rates yield stable, converging systems and should promote subject learning effects.

In conclusion, we suggest that machine learning should identify the optimal brain feature space, decode the brain patterns therein and track their shifts once non-stationarity effects occur; while subject learning should be responsible for increasing separability within this brain manifold—a process that strongly relies on implicit/procedural mechanisms and requires substantial practice. We consequently advocate to put more emphasis on exploring novel paradigms that promote implicit subject learning of BMI skills. This view on how to foster and unfold BMI co-adaptation, or any alternative one, can only be probed through longitudinal and comprehensive experimental assessments involving end-users.

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