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PASSIVE BCI-BASED NEUROADAPTIVE SYSTEMS

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ABSTRACT: Passive brain-computer interfaces have been formally introduced and defined almost a decade ago, and have gained considerable attention since then. Here, we provide a new perspective on this field. We refer to *neuroadaptive* systems, and identify a key aspect with regards to which various passive BCI-based systems differ from each other: *interactivity*. With increased interactivity, the systems become increasingly responsive, autonomous, and capable to adapt to the user. We give an overview of four separate categories of interactivity using examples of past and current research. This categorisation of passive BCI-based neuroadaptive systems helps identify and pinpoint relevant human-computer interaction aspects and possibilities for future neuroadaptive technology and research.

INTRODUCTION

The term and concept of *passive BCI* was formally introduced at the 4th Graz BCI Conference in 2008 [1]. Although at that point, with hindsight, a number of previous works could be said to have already made use of passive BCI, e.g. [2-5], it was in the year 2008 that it was highlighted by two research groups, independently of each other, as a promising research endeavour of its own. BCI methodology that, up until then, was primarily aimed at clinical applications for direct communication and control, they argued, could also be used to provide *implicit input* [6-7] to a system to the benefit of any ongoing human-computer interaction without placing any additional demands on the user.

To that end, a passive BCI system [8] derives its output from automatic, involuntary, spontaneous brain activity, interpreted in the given context [9]. The brain activity in question is not expressly or voluntarily modulated in order to make use of the BCI system, but rather reflects aspects of the naturally present cognitive or affective state of the user. The system takes this context-sensitive interpretation of the user's state as implicit input, enabling it to adapt and support the user with their task.

This is contrasted with *active* BCI, where brain activity is consciously and purposefully modulated to achieve explicit BCI-based communication or control, and with *reactive* BCI, where the signal itself is not generated voluntarily, but its external elicitation is made possible by voluntary attention shifts [8]. For example, an active BCI may rely on imagined movements of the left and right hands to steer a prosthesis to the left or right [10], and a reactive BCI may use the evoked potentials resulting from presented stimuli to detect which stimulus was attended to [11].

The concept of passive BCI was ultimately included in the 2012 standard work on BCI [12], although the term "passive" was criticised for lacking a neuroscientific definition. Indeed both the concept and the terminology assume a perspective centred on the user experience, with the user remaining passive (i.e., undertaking no explicit actions) with respect to the BCI.

However, indeed care should be taken when presuming that user actions and mental states can be readily categorised as either "voluntary" (re/active BCI) or "spontaneous" (passive BCI). For example, the user's knowledge of the supposedly passive BCI system may still lead to certain voluntary changes in activity; or, a supposedly active BCI system may take into account brain activity that is not fully voluntarily modulated.

From the user-centred perspective, a thought experiment can clarify the issue. If the same user behaviour and brain activity would be observed if the user was not aware of their influence over a system, then we can say that this is "natural" behaviour and activity that in that moment does not depend on the presence of the system. In this article, when referring to passive BCI systems, we refer to systems that are—or can be—based on such natural brain activity.

Regardless, however, of these definitory issues, the concept of using BCI methodology to provide computer systems with a measure of its user's mental state as implicit input has endured and received increasing attention over the past decade.

The BCI Society categorises BCI systems based on the intended function of the output. They recognise five categories of applications: BCI systems can *replace, restore, enhance, supplement,* or *improve* the user's natural output [12-13]. The BNCI Horizon 2020 roadmap for the BCI community [13] lists a total of six future applications for the two categories *improve* and *enhance*, five of which rely on passive BCI as defined here. The category *supplement* is not included in the roadmap, but, as mentioned by Wolpaw and Wolpaw [12], this, too, is partially the domain of passive BCI.

Since its inception around a decade ago, passive BCI applications have thus come to represent a relatively large and promising area of BCI research.

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Among passive BCIs themselves, however, a further categorisation is possible. Whilst already focusing on the user's behaviour to define the scope of passive BCI, we propose to also focus on the BCI's behaviour, rather than its consequences. By focusing on the system's behaviour rather than its intended function, a clearer and more formal emphasis is placed on how the two adaptive agents (i.e. the human and the computer) cooperate and interact with each other. In BCI applications for communication and control (i.e. replace, restore), the intended division of labour between man and machine, and the feedback given from machine to man, is relatively clear. In passive BCI systems however, as they are intended to be unobtrusive and inconspicuous, the machine's influence can manifest in a number of different ways, with different implications for the human-machine system as a whole. It is important to take this into account when designing such systems.

We identify four categories of systems, listed ordinally by increasing degree of *interactivity*. Interactivity denotes "the ability of a computer to respond to a user's input" (Oxford English Dictionary, Oxford University Press, 2016). By the proposed measure, most past and current research into passive BCI as well as suggested future applications, including all those mentioned in the BCI roadmap, provide relatively little interactivity and fall into the lower categories. We found only two recent examples for the final identified category. We believe that a lot can be gained by focusing on increased interactivity when designing new passive BCI systems.

This categorisation suggests a new way to think about passive BCI systems, and highlights BCI-based opportunities for increased human-computer synergy. A more detailed review and discussion of these categories can be found in our contributed chapter for the BCI Handbook (in press), of which this conference submission is a summary aimed more at current BCI researchers.

The following four sections will describe one category each: mental state assessment, open-loop adaptation, closed-loop adaptation, and automated adaptation. The paper concludes with a discussion and outlook.

MENTAL STATE ASSESSMENT

The first category encompasses systems the sole purpose of which is the measurement of mental states, without providing any feedback. Because feedback is lacking, these are not BCI systems, nor is there any interactivity. This category of *mental state assessment* [14-15] is still included, however, to serve as a theoretical zero point on the interactivity scale, and because mental state assessment does provide the basis for all higher systems.

The measurement and quantification of mental states can be helpful and informative by itself in various fields where no interactivity is required. Instead, user state information is gathered to be analysed and studied afterwards, to answer different questions.

For example, mental state assessment based on BCI methodology is being used in the field of *neuroergonomics*, "the study of brain and behaviour at work" [16]. One mental state that is highly relevant to ergonomics and human factors research is the state of high workload [17]. Whilst there are disagreements as to its precise definition and measurement in theory [18], BCI can offer a data-driven approach based on reference measurements. For example, Gevins and Smith [19] simulated controlled working conditions of three different load levels. Based on differences they found in frontal theta and parietal alpha, they constructed a cognitive workload index that could then be used to analyse other, less controlled recordings.

Using such pre-calibrated indices, mental state assessment can be used, for example, to compare alternative graphical user interface designs with respect to the workload they induce. See [20] for a review.

Such an approach has a number of advantages compared to traditional methods to obtain information, such as questionnaires. Brain activity provides a continuous source of data, and its recording does not interfere with the state that is measured. The method can be individually calibrated, side-stepping intersubjective reference issues as well as conceptual conflicts. Certain mental states may not even be possible to ascertain otherwise.

All this, however, hinges on the ecological validity of the recordings and corresponding interpretations. Special care must be taken to validate the measurements, ideally cross-context. See e.g. [21-22] for a discussion of pitfalls and lessons learned in mental state assessment research, which also applies to (passive) BCI research more generally.

OPEN-LOOP ADAPTATION

Interactivity denotes the computer's ability to respond to a user's input. In the case of passive BCI applications, this input is the *implicit input* [6-7] gathered by the system by analysing the user's natural brain activity in real time. In BCI terminology, the system's response to this interpreted input is generally termed *feedback* [12], denoting an action and/or piece of information resulting from the input that is subsequently "fed back to" (i.e. perceived by) the user.

As mentioned above, passive BCI systems can be unobtrusive and inconspicuous, and their responses to user input may thus be similarly hidden. It is for this reason that we refer to *adaptation* as a more generic term for the system's response to input. Traditional feedback—e.g. a cursor moving on a screen or a prosthetic limb moving—can be one form of such adaptation, but, as this categorisation will also highlight, the nature of passive BCI enables other meaningful types of adaptations as well. When adaptation is based on (natural) brain activity, we refer to these systems as *neuroadaptive* [23].

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It is through the system's adaptations in response to user input that different levels of interactivity can be achieved. The first level of interactivity—the second category overall—consists of *open-loop adaptations*. Systems from this category of applications apply mental state assessment to obtain a measure of a mental state on-line, and respond to certain states with specific pre-programmed actions in an open-loop fashion.

"Open loop" refers to the absence of any direct or intended coupling of the adaptation back to the input.

For example, in the above example of a workload index, open-loop adaptation could be used to assess the load level in real time, and give a warning every time a certain threshold is exceeded [24].

Prominent in the literature is the use of the error-related negativity as indicative of the mental state "error perception" [25]. Once the system learns that its user perceived an error, the system adapts, for example by correcting the error in case of a binary decision [3]. Note that such input corrections can also *induce* errors, rather than correcting them, when the initial mental state was not correctly detected.

Other examples include the detection of an "intention to interact" mental state to replace an explicit selection command in hybrid gaze/BCI systems [26-27]. Once such an intention is detected upon fixating an interactive on-screen element, a "mouse click" can be automatically executed.

In a gaming context, Van de Laar et al. [28] showed how, once a certain threshold of "relaxation" (versus "tension") is passed, the user's in-game character would switch from one set of abilities to another.

Open-loop adaptive systems, based on passive BCI, use a measurement of the user's state as implicit input. The user states of interest can be transient, such as error perception, or more constant and continuous ones such as moods or workload. As such, the former ones need to be clearly linked to the context (e.g., *what* was perceived to be in error?) for the adaptation to be effective [9]. This implicit input can then be used as a basis to execute timely adaptations. Continuous mental states are better suited to control an application's mode.

As mentioned above, it is important to validate that the mental state that is intended to be measured is indeed the one that is measured. Real-time adaptation in response to these measurements can provide an indirect validation that at least the system *functions* as intended.

Open-loop adaptation reflects simple stimulus-response logic: single, independent state detections result in single, fixed actions. More interactivity can be achieved when the system's adaptations have an influence that reaches beyond the single responses, affecting further input and future actions; for example, when interactive applications exhibit closed-loop control, discussed next.

CLOSED-LOOP ADAPTATION

In closed-loop systems, the system's output is fed back to the system as new input, or otherwise influences the next input cycle. In our present context, the ultimate source of input is the human user, and the input given to the adaptive system constitutes a measure of their mental state. In a closed-loop passive-BCI system, the initiated adaptation must thus influence the mental state that is being measured. Closed-loop adaptive systems apply mental state assessment to obtain a measure of a mental state on-line, and adapt to certain states—or changes in states—by means of actions that influence that same mental state.

The adaptations can be either discrete or continuous. For example, sounding an alarm bell to call to attention someone who has been detected to doze off is a discrete countermeasure, aimed at promoting the state being monitored: vigilance.

Kirchner [29] used a sequence of discrete events of increasing saliency: if an initial alarm was not perceived (as detected by the passive BCI), the alarm was repeated with a higher intensity.

Continuous adaptation can provide a more fine-grained approach. For example, *adaptive automation* [30] attempts to match task demands to the current capacity of the user, in real time. When workload increases, certain tasks are automated in order to keep the user in a productive state of engagement. As more capacity becomes available again, task control is gradually handed back to the user, keeping the equilibrium.

For example, Kohlmorgen et al. [31] implemented a form of passive BCI-based adaptive automation in the car. During highway driving, one of the participants' tasks would be automatically suspended and unsuspended depending on measured workload levels.

Similarly, Yuksel et al. [32] demonstrated closed-loop adaptation of educational material. The pacing of the learning process was adjusted dynamically in real time in order to sustain the student's performance, based on a measure of workload.

In a gaming context, [33] applied the concept of closed-loop adaptation to Tetris, adjusting the game's speed in order to maintain a level of optimal engagement.

These examples show how closed-loop feedback mechanisms can increase interactivity and human-computer synergy. The system's adaptations enable it to respond purposefully, as well evaluate the effect of each adaptation, such that the system obtains a qualitative participation in the ongoing interaction. The system not merely adapts to given input, but influences the next input and with that, its next adaptation. The implicit input is now part of a more interactive *implicit dialogue* between a user and the system.

Closed-loop systems go beyond open-loop systems by influencing the next interaction cycle. They can thus have a continuous, dynamic effect on their users and the interaction as a whole. The logic of a single closed loop, however, is still a limited one, usually reflecting the limited amount of input gathered by the system. Coupling adaptation directly to a limited range of input necessarily limits the range of the adaptation. By

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distancing the adaptation itself from the input, a further step can be made beyond closed-loop systems towards increased interactivity, discussed next.

AUTOMATED ADAPTATION

Purely closed-loop systems are restricted by their respective loops in that the adaptations directly follow the input signal. In case of input derived from neurophysiological signals, such as EEG, its bandwidth and dimensionality are generally limited. It gives insight into momentary mental states, but not into likely causes, or appropriate responses. The adaptive systems mentioned thus far are embedded in fixed, known contexts. As such, it is reasonable to assume that, for example, an increase in workload is caused by the task demands of that same environment, and can be counterbalanced by increased automation. These interactive functions however are constrained by this logic that is predetermined by known contexts.

In this next category, the adaptive logic itself is adaptive, such that a system can support its user across different and changing contexts. To that end, the system needs access to context information as well as the user's mental state. By collating and co-registering these, the system can learn its user's behaviour and responses in different scenarios. Based on that, it can then decide how and at what times to give support. Automatically adaptive systems apply mental state assessment alongside other methods of information gathering in order to build a model to represent aspects of the user's cognitive or affective responses. This model then serves as a basis for the system's own autonomous behaviour.

Zander et al. [7, 23] detected error- and satisfaction-related brain activity not in order to immediately correct perceived errors, but to learn, over time, the user's preferences. To that end, the system exhibited different behaviours and registered which system actions led to negative evoked responses and which led to positive ones, depending on the given context.

Specifically, this approach was applied to two-dimensional cursor control. The system moved to the cursor autonomously, whilst registering the evoked responses to the movements in different directions. Over time, the system could learn the pattern behind these responses and as such, learned where the user wanted the cursor to go. Already during the learning process, the system adapted its behaviour to steer the cursor towards the suspected target.

Iturrate et al. [34] demonstrated a similar principle using a robotic arm. Participants observed its movements whilst their error-related responses to certain movements were tracked and remembered. The robotic arm was guided based on the inferred information.

In automated adaptation, the gathering of information is the primary system adaptation in lieu of direct actions, with action to follow only once the system autonomously determines it to be appropriate. The parameters of adaptation are learned automatically by the system itself. This increased autonomy also translates into increased interactivity, as the system learns to respond in different ways even to input that was given in the past, or not even given at all.

DISCUSSION AND OUTLOOK

We propose a categorisation of passive BCI-based *neuroadaptive* systems based on the behaviour of that system in terms of its interactivity.

The category of *mental state assessment* systems represent a base category. These systems provide no interactivity, but by registering natural brain activity that is not influenced by the system itself, they lay the foundation for passive BCI and interactive neuroadaptive systems.

The most basic way to implement interactivity is to enable *open-loop adaptation*, giving systems the ability to respond to given input in an open-loop fashion: simple input-output response logic connects a mental state to a specific action, with no further dependencies between them.

In *closed-loop adaptation*, the system's output influences its upcoming input. The system now purposefully attempts to influence the user's mental state. Interactivity is increased as the system's actions do not merely inform, but purposefully *act upon* the user and thus influence the interaction as a whole.

Automated adaptation, finally, refers to the category of systems that learn to adapt and act autonomously based on (implicit) information gathered previously. Increased interactivity is due to the system's increased autonomy with respect to its adaptations and adaptive strategies.

These three adaptive behaviours are, of course, not mutually exclusive. An automated adaptation system might predict what a user intends to do and execute that action in advance, but then, in an open-loop fashion, undo the action when it is detected that the prediction was in error.

Note also that whether the above error-correction example should be considered open-loop or closed-loop depends on the exact state that is being targeted. Error perception, as a transient state in the form of e.g. an error-related potential, cannot always or necessarily be used as such in closed-loop systems. A more persistent state, perhaps reflecting general dissatisfaction (initially caused by the error), however, *can* be influenced in a closed loop.

It is important in general that researchers and designers pay close attention to exactly define the user state they are targeting. This categorisation also helps in formalising that.

Four out of five future scenarios suggested in the BCI roadmap under the relevant categories fall into the open-loop adaptation category. The one remaining example of passive BCI systems in the BCI roadmap

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uses closed-loop adaptation.

We would thus encourage researchers to also look further afield. Human-computer synergy can only be achieved by close cooperation between the two agents. Human-human communication is a dynamic, continuous process, and hinges on a shared understanding of the world and informative as well as empathic models of the conversation partner [35]. Human-computer interaction can be improved by mirroring such processes: by dynamic, responsive adaptation, and by having the system learn autonomously how to optimise that behaviour. Passive BCI methodology in particular can help us attain such close human-computer cooperation, as it can give systems access to an individually calibrated, real-time source of subjective and personally relevant information concerning the user.

A formalisation of passive BCI-based neuroadaptive systems helps identify and pinpoint relevant human-computer interaction aspects during the design and development of such systems, and aids the design of and discourse about future neuroadaptive technology.

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REFERENCES

[1] Zander TO, Kothe CA, Welke S, Rötting M. Enhancing human-machine systems with secondary input from passive brain-computer interfaces. In Proc 4th Int Graz, Graz, Austria, 2008, 144-149.

[2] Blankertz B, Schäfer C, Dornhege G, Curio G. Single Trial Detection of EEG Error Potentials: A Tool for Increasing BCI Transmission Rates. In: JR Dorronsoro (Ed.), Artificial Neural Networks – ICANN 2002 (Vol. 2415, pp. 1137–1143). Berlin, Germany: Springer 2002, pp 1137-1143.

[3] Parra LC, Spence CD, Gerson AD, Sajda P. Response error correction—a demonstration of improved human-machine performance using real-time EEG monitoring. IEEE Trans Neural Syst Rehabil Eng, 11(2), 2003, 173–177.

[4] Ferrez PW, Millán JdR. You Are Wrong!—Automatic Detection of Interaction Errors from Brain Waves. In Proc Int Joint Conference on Artificial Intelligence. San Francisco, CA, 2005, 1413–1418

[5] Zander TO, Kothe CA, Jatzev S, Dashuber R, Welke S, De Filippis M, Rötting M. Team PhyPA: Developing applications for brain-computer interaction. In Proc BCI for HCI and Games Workshop at SIGCHI CHI, 2008.

[6] Rötting M, Zander TO, Trösterer S, Dzaack J. Implicit interaction in multimodal human-machine systems. In CM Schlick (Ed.), Industrial engineering and ergonomics, Berlin Heidelberg, Germany: Springer, 2009, pp 523-536.

[7] Zander TO, Brönstrup J, Lorenz R, Krol LR. Towards BCI-based Implicit Control in Human-Computer Interaction. In SH Fairclough, K Gilleade (Eds.), Advances in Physiological Computing, Berlin, Germany: Springer, 2014, pp. 67–90.

[8] Zander TO, Kothe CA. Towards passive brain-computer interfaces: applying brain-computer interface technology to human-machine systems in general. J Neural Eng, 8(2), 2011, 025005.

[9] Zander TO, Jatzev S. Context-aware brain-computer interfaces: exploring the information space of user, technical system and environment. J Neural Eng, 9(1), 2012, 016003.

[10] Wolpaw JR, McFarland, DJ. Brain-computer interface operation of robotic and prosthetic devices. Computer, 41, 2008, 52–56.

[11] Farwell, LA, Donchin, E. Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. Electroencephalography and Clinical Neurophysiology, 70(6), 1988, 510–523.

[12] Wolpaw JR, Wolpaw EW. Brain-computer interfaces: something new under the sun. In Brain-computer interfaces: Principles and practice. Oxford, UK: Oxford University Press, 2012, pp 3-12.

[13] Brunner C, Birbaumer N, Blankertz B, Guger C, Kübler A, Mattia D, Millán JdR, Miralles F, Nijholt A, Opisso E, Ramsey N, Salomon P, Müller-Putz GR. BNCI Horizon 2020: towards a roadmap for the BCI community. BCI Journal, 2015.

[14] Müller KR, Tangermann M, Dornhege G, Krauledat M, Curio G, Blankertz B. Machine learning for real-time single-trial EEG-analysis: From brain-computer interfacing to mental state monitoring. J Neurosci Methods, 167(1), 2008, 82–90.

[15] van Erp JB, Lotte F, Tangermann M. Brain-Computer Interfaces: Beyond Medical Applications. Computer, 45(4), 2012, 26-34.

[16] Parasuraman R. Neuroergonomics: Research and practice. Theoretical Issues in Ergonomics Science, 2003, 4(1–2), 5–20.

[17] Wickens CD, JG Hollands, S Banbury, R Parasuraman. Engineering psychology and human performance. New York, NY: Routledge, 2016.

[18] Young MS, Brookhuis KA, Wickens CD, Hancock PA. State of science: mental workload in ergonomics. Ergonomics, 58(1), 2015, 1–17.

[19] Gevins A, Smith ME. Neurophysiological measures of cognitive workload during human-computer interaction. Theoretical Issues in Ergonomics Science, 4(1–2), 2003, 113–131.

[20] Frey J, Mühl C, Lotte F, Hachet M. Review of the use of electroencephalography as an evaluation

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Graz University of Technology

 DOI: 10.3217/978-3-85125-533-1-46

method for human-computer interaction. In Proc Int Conference on Physiological Computing Systems. Lisbon, Portugal, 2014, 214–223.

[21] Gerjets P, Walter C, Rosenstiel W, Bogdan M, Zander TO. Cognitive state monitoring and the design of adaptive instruction in digital environments: lessons learned from cognitive workload assessment using a passive brain-computer interface approach. Front Neurosci, 8, 2014, 385.

[22] Brouwer AM, Zander TO, van Erp JBF, Korteling JE, Bronkhorst AW. Using neurophysiological signals that reflect cognitive or affective state: six recommendations to avoid common pitfalls. Front Neurosci, 9, 2015, 136.

[23] Zander TO, Krol LR, Birbaumer NP, Gramann K. Neuroadaptive technology enables implicit cursor control based on medial prefrontal cortex activity. Proc Natl Acad Sci U.S.A. (PNAS), 113(52), 2016, 14898-14903.

[24] Zander TO, Shetty K, Lorenz R, Leff DR, Krol LR, Darzi AW ... Yang GZ. Automated task load detection with electroencephalography: Towards passive brain-computer interfacing in robotic surgery. J Medical Robotics Research, 2(1), 2017, 1-10.

[25] Gehring WJ, Liu Y, Orr JM, Carp J. The error-related negativity (ERN/Ne). In SJ Luck, ES Kappenman (Eds.), Oxford handbook of event-related potential components. New York, NY: Oxford University Press, 2012, pp 231-291.

[26] Protzak J, Ihme K, Zander TO. A passive brain-computer interface for supporting gaze-based human-machine interaction. In C Stephanidis, M Antona (Eds.), Universal Access in Human-Computer Interaction. Design Methods, Tools, and Interaction Techniques for eInclusion (8009). Berlin Heidelberg, Germany: Springer, 2013, pp. 662– 671.

[27] Shishkin SL, Nuzhdin YO, Svirin EP, Trofimov AG, Fedorova AA, Kozyrskiy BL, Velichkovsky BM. EEG negativity in fixations used for gaze-based control: Toward converting intentions into actions with an eye-brain-computer interface. Front Neurosci, 10, 2016, 528.

[28] van de Laar B, Gürkök H, Bos DPO, Poel M, Nijholt A. Experiencing BCI control in a popular computer game. IEEE Trans Comput Intell AI in Games, 5(2), 2013, 176–184.

[29] Kirchner EA, Kim SK, Tabie M, Wöhrle H, Maurus M, Kirchner F. An intelligent man-machine interface—multi-robot control adapted for task engagement based on single-trial detectability of P300. Front Human Neurosci, 10, 2016, 291.

[30] Byrne EA, Parasuraman R. Psychophysiology and adaptive automation. Biological Psychology, 42(3), 1996, 249–268.

[31] Kohlmorgen J, Dornhege G, Braun M, Blankertz B, Curio G, Hagemann K, ... Kincses W. Improving human performance in a real operating environment through real-time mental workload detection. In G Dornhege (Ed.), Toward Brain-Computer Interfacing. Cambridge, MA: MIT Press, 2007, pp 409-422.

[32] Yuksel BF, Oleson KB, Harrison L, Peck EM, Afergan D, Chang R, Jacob RJK. Learn piano with BAch: An adaptive learning interface that adjusts task difficulty based on brain state. In Proc CHI, 2016, 5372-5384.

[33] Ewing KC, Fairclough SH, Gilleade K. Evaluation of an adaptive game that uses EEG measures validated during the design process as inputs to a biocybernetic loop. Front Human Neurosci, 10, 2016, 223.

[34] Iturrate I, Chavarriaga R, Montesano L, Minguez J, Millán JdR. Teaching brain-machine interfaces as an alternative paradigm to neuroprosthetics control. Scientific Reports, 5, 2015, 13893.

[35] Fischer G. User modeling in human-computer interaction. User Modeling and User-Adapted Interaction, 11(1-2), 2001, 65-86.

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