It's Easy as ABC Framework for User Feedback

Alexandra Fischmann(✉) and Sydney Levy

Swarthmore College, Swarthmore, PA 19081, USA
{afischm1,slevy1}@swarthmore.edu

Abstract. Improving the interface and training provided to users during data collection could present an important step to solving the reliability issue of Brain-Computer Interfaces (BCIs). We incorporate design principals from human-computer interaction (HCI) and educational research to create an interface for future researchers. Our interface is based on being **A**ttuned to the user (A) by providing **B**iased user feedback (B) and **C**lassification algorithm descriptions (C). This interface can serve as a framework for providing users with feedback according to the experience level and emotional state of the user. Additionally, the interface provides example descriptions of common classification algorithms to better inform users of how their data is being utilized.

Keywords: Human-computer interaction · User feedback design · Brain-computer interfaces · Education

1 Introduction

1.1 Problem Statement

A brain-computer interface (BCI) is a computer system that communicates with a user in an interactive method that translates brain signals into instructions for an application to execute [12]. The common method for receiving these brain signals is the use of electroencephalography (EEG). An online BCI system begins by taking an EEG signal from the user and records the signal being measured [12]. After this, the EEG signals are processed using a variety of filters which extract the important features from the EEG signal [12]. The next step includes classification methods that interpret the EEG features and translate them into the command for the application [12]. Finally, users are informed whether or not the EEG signals were successfully translated into the command for the computer [12]. Machine Learning and Deep Learning algorithms have been implemented in many EEG-based BCI experiments and research [2,6,13,23,27].

Current brain-computer interfaces are not reliable enough to be used consistently outside of laboratory environments [7,14,22,24]. Most BCI research that aims to solve this reliability issue focuses on improving the classification step of

A. Fischmann and S. Levy—Contributed equally to the paper.

M. Kurosu et al. (Eds.): HCII 2022, LNCS 13519, pp. 429–441, 2022.
https://doi.org/10.1007/978-3-031-17618-0_30

translating the EEG signals effectively into commands for the computer. This has primarily been done through implementing new machine learning techniques.

While this research presents an important step in the right direction for BCI classification algorithms, there has been a lack of research attention devoted to improving the user interface for engaging with BCI systems. Improving the interface and training provided to users could present an important step to solving the reliability issues of BCIs [14].

1.2 Literature Review

The ability to interact with BCIs is not one that comes immediately to the user. The user needs to learn how to operate the BCI while the system simultaneously learns to classify the user's EEG signals [17]. Lotte et al. describe this ability as one that needs to be taught to a user and practiced often [14]. Specifically, the user needs to be able to provide the EEG with consistent and clear brain activity patterns. Without the ability to successfully interpret the user's brain activity, even effective classification algorithms are rendered useless [14]. Current teaching approaches often provide users with uni-modal feedback which fails to adhere to well-known pedagogical design principles [14].

Mladenovic emphasizes the need for a standardization of protocol designs among researchers for how best to train users of BCIs [18]. One attempt to outline effective BCI feedback was created by Kübler et al. [10]. They provide a framework which emphasizes effectiveness, efficiency, and satisfaction [10]. Other frameworks have prioritized motivational factors such as: user's curiosity, relevance to user's values, confidence, and intrinsic and extrinsic rewards [14]. Lotte et al. argue that by focusing on these factors, BCI performance can improve for novice users [14]. Schumacher et al. have explored the potential for providing users of BCIs with explanatory feedback during training [28] and found no deteriorating performance as a result of incorporating multiple forms of feedback. The effective use of feedback has also been studied extensively within educational research. For example, Narciss et al. outline the value of providing learners with details regarding not only the errors they made, but also the flaws in the strategies they used [20].

In addition to these frameworks, Roc et al. provide a review of the feedback, environment, and methods for mental task-based BCI user training [25]. Similarly, Lotte et al. highlight more practical suggestions for the content and type of feedback specific to BCIs [15]. Lotte et al. propose that BCI instructions include both the goals of the training as well as explanations for classifier output [15]. Additionally, Lotte et al. opt for providing the user with detailed information regarding the beneficial or detrimental qualities of their EEG patterns [15].

In terms of the relationship between user characteristics and feedback, a recent study has found that a user's level of tension affects mean BCI performance [21]. Mladenovic et al. found that a user experiencing low initial workload or low anxiety provides the best results when given feedback with a negative bias as opposed to no bias [19]. Research has further suggested providing positive feedback for inexperienced users and more honest feedback for experienced users

[14,15]. This positive feedback can be accomplished through either making the user believe they did better than they actually did, or only providing feedback when the user successfully completed the task [14].

Both interactive visual and tactile forms of user feedback have been explored for BCI training. Lotte et al. advocate for a game-like process for the user to engage with during training and testing for BCIs [15]. Further, researchers have discussed the interplay between EEG-based BCIs and video games [3,9]. Research by Ron-Angevin & AntonioDíaz-Estrella even suggests the use of virtual-reality for increasing user motivation during BCI user training [26]. Additionally, research conducted by Cincotti et al. 2007 explores the potential for vibrotactile user feedback during BCI training [5].

1.3 Purpose of Study

Through our research we hope to bridge the gap between advanced classification methods for BCIs and the feedback that users receive while providing EEG data for these applications. We hope to utilize design principles from human-computer interaction research as well as educational research to improve training protocols for users, increase the effectiveness of communication utilizing BCIs, and improve user motivation during training and testing.

This research has the potential to impact a multitude of user groups who could rely on BCIs [1]. For example, BCIs can serve as a pivotal piece of technology for assessing neurological disorders, providing stroke rehabilitation [16], acting as a communication device for locked-in patients [29], and as a way to detect human drowsiness [8].

1.4 Research Questions

The main research questions that motivate this paper are:

1. What is the most effective interface for providing user training and feedback for BCIs?
2. How can one incorporate pedagogical methods into beneficial feedback for users of BCIs?

2 Experiment

2.1 Experiment Design

Many popular BCI datasets, such as BCI IV Competition 2a dataset, are collected without providing feedback to the users [4]. Although we cannot alter this, we would suggest that to improve EEG data collection, this should have been done. Thus, we will create an interface to provide example feedback for different situations the users might encounter during data collection.

This feedback will be based on the design principles we outline in Table 1. Within our user interface, in order to abide by principle 1, we plan to base feedback on user experience level. For inexperienced users, we will provide feedback

Table 1. Design principles to guide research.

Design principles	Source	Implementation
(1) Positive feedback for inexperienced user and more honest feedback for experienced users	Lotte and Jeunet (2015), Lotte et al. (2013)	Ask the user for their level of experience - provide differing feedback accordingly
(2) Low-anxiety users provide the best result when given feedback with negative bias	Mladenovic et al. (2021)	Ask the users for their anxiety levels and provide biased feedback accordingly
(3) Learners benefit from actively thinking about the strategies they are implementing	Narciss et al. (2004)	Inform users about the classification methods being used for them to better understand the strategies they need to employ during training

with a positive bias whereas feedback for more experienced users will be more honest. To implement design principle 2 from Table 1, we will ask users about their levels of anxiety during training in order to boost confidence for high-anxiety users and provide feedback with a negative bias for low-anxiety users. For design principle 3 from Table 1, we provide classification algorithm descriptions so that users can better understand how their data is being processed and thus come up with improved strategies for providing clear EEG signals. We hope that including these descriptions will make users feel that they are truly a part of the training process and not isolated from the data they provide.

Finally, in order to test the effectiveness of our interface, we had 21 participants answer survey questions as they interacted with our interface and read our classification algorithm descriptions. Users reported their answers via selecting options from a 4-point or 5-point scale via a Google Form.

The questions that made up our survey are:

1. What is your past experience with computer science?
2. What is your past experience with machine learning?
3. What is your past experience with brain-computer interfaces?
4. Are you motivated to learn about machine learning/brain-computer interfaces?
5. Do you get stressed out by computer issues?
6. What is your current understanding of Linear Discriminant Analysis?
7. Here is our description of Linear Discriminant Analysis... After reading this description how would rate your new understanding of Linear Discriminant Analysis?
8. What is your current understanding of Support Vector Machine?

9. Here is our description of Support Vector Machine... After reading this description how would you rate your new understanding of Support Vector Machine?
10. What is your current understanding of Random Forest (classification method)?
11. Here is our description of Random Forest... After reading this description how would you rate your new understanding of Random Forest (classification method)?
12. How would you rate the clarity of our classification algorithm descriptions?
13. If you were providing data for a brain-computer interface, would you find our feedback helpful?
14. How would you rate the ease of use of our interface?
15. How motivated are you to continue learning about brain-computer interfacesmachine learning?
16. Imagine you are providing data for a study involving brain-computer interfaces... After reading the descriptions above and receiving the tailored feedback, would you be more motivated to try your best on the tasks asked of you during the study?

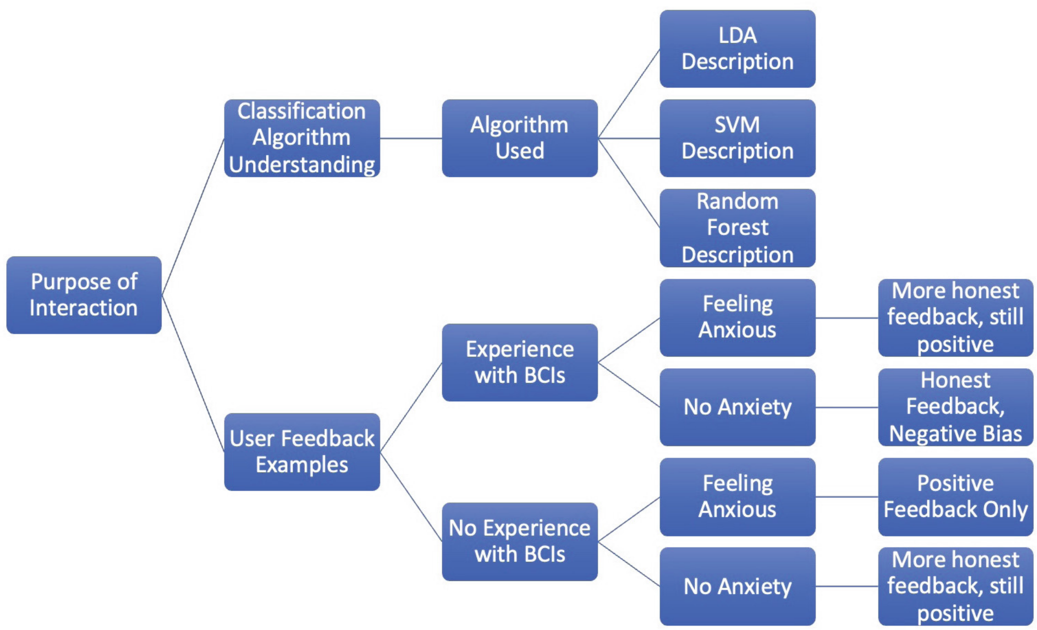

Fig. 1. Interface design flow chart

3 Result

We created an interface that we hope will improve the data that users provide during BCI EEG data collection. Our interface is based on being **A**ttuned to the user (A) by providing **B**iased user feedback (B) and **C**lassification algorithm descriptions (C). Our interface has two main capabilities: (1) Classification Algorithm Descriptions and (2) User Feedback Examples. The code for our interface is publicly available[1].

If a user wants to better understand the classification algorithm that is being used on their data, they can select this option and choose which classification algorithm they are interested in (as shown in Fig. 1). They will then be given a short description of the algorithm they have chosen. To motivate our choice of LDA, SVM, and Random Forest we note that a prominent BCI researcher, Yann LeCun, began his research by focusing on Linear classifiers, K-nearest neighbors and SVMs [11]. Thus, we believe it is important for users of BCIs to begin by understanding the most basic algorithms and can then move onto more advanced and complex algorithms.

The second capability of our interface is to gauge a user's level of anxiety and experience during data collection. In accordance with the design principals noted in Table 1, we provide appropriate feedback tailored to the user. Further, Table 2 shows the feedback we recommend giving to users of brain-computer interfaces during training based on their anxiety, experience level, and the strength of their EEG signal. For experienced users feeling no anxiety during data collection, we will provide more honest feedback depending on the quality of their EEG signal. For inexperienced users with some anxiety, we will provide positive feedback only. For inexperienced users with no anxiety or experienced users with some anxiety, we will provide more honest feedback with slight positive bias. A flow chart for how one might engage with our interface is provided in Fig. 1.

After conducting a survey with 21 participants, we found that respondents with less experience with computer science, machine learning, and brain-computer interfaces improved more in their understanding of the classification algorithms than those with higher experience levels (as shown in Fig. 2). We measured survey respondents understanding of the 3 classification algorithms through their responses to questions 6–11. Respondents first selected their understanding on a 5-point scale, then read our classification algorithm description, then rated their new understanding on the same 5-point scale.

Figure 2 displays the improvement in user understanding on the y-axis. Thus, all survey respondents improved in their understanding of the classification algorithms, but the magnitude of improvement varied according to the participant's experience level with computer science, machine learning, and BCIs. We found that users with less experience had similar improvement levels regardless of classification algorithm type, while users with more experience appeared to have higher increases in understanding for LDA and SVM. Thus, we feel that it is of the utmost importance to provide users who have less experience with ML and

[1] https://github.swarthmore.edu/slevy1/ABCUserFramework.

Table 2. Feedback provided to users.

Anxiety level	Experience level	Bias framework	Feedback given
Feeling anxious	Experience with BCIs	Honest feedback, positive bias	**Strong signal**: Your signal looked great. Keep doing what you're doing. **Weak signal**: Your signal wasn't quite right. Good try and keep going
Feeling anxious	No experience with BCIs	Positive feedback only (positive bias)	**Strong signal**: Your signal looked great, fantastic job! Keep doing what you're doing. **Weak signal**: Good try. We think you will improve with practice
No anxiety	Experience with BCIs	Honest feedback, negative bias	**Strong signal**: Good job, your signal is strong but can always be improved. Keep focusing on the task at hand. **Weak signal**: Your signal wasn't clear. Try changing up your strategy
No anxiety	No experience with BCIs	Honest feedback, positive bias	**Strong signal**: Your signal looked great. Keep doing what you're doing. **Weak signal**: Your signal wasn't quite right. Good try and keep going

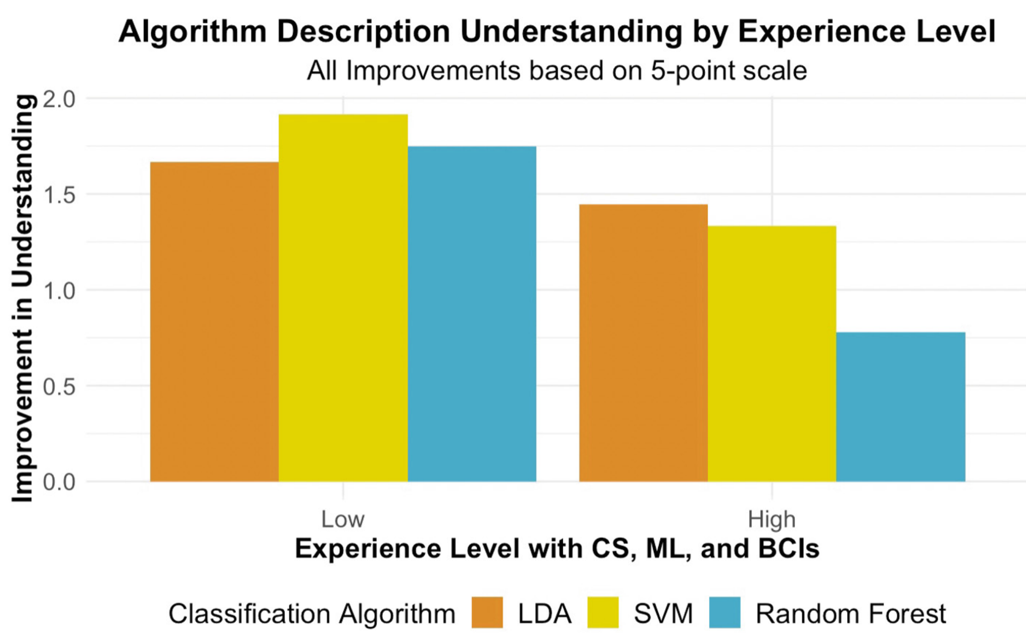

Fig. 2. Improved algorithm understanding

BCIs with classification algorithm descriptions. According to the design principles we outline in Table 1 and our survey results, we believe that an improved classification algorithm understanding could result in increased user motivation during BCI data collection.

We then utilized question 5 as a proxy for a user's anxiety level during BCI data collection. Survey respondents ranked the amount of stress they often feel while using technology on a 5-point scale. We found that respondents with higher anxiety levels found our user feedback more helpful relative to those with lower anxiety surrounding new technology as per Fig. 3. Thus, users with very high anxiety would likely benefit from the more positive feedback we utilize in our interface. Further, these results suggest that users with low or very low anxiety levels would respond well to more negatively biased feedback.

Moreover, users with all levels of experience with computer science, machine learning, and BCIs exhibit a clear increase in motivation after interacting with our interface as per Fig. 4. We measured the survey respondents' motivation to continue learning about machine learning and BCIs as a proxy for their motivation to provide clear EEG signals during BCI training and testing. We based the user's motivation before and after using our interface from questions 4 and 15 in our survey. Thus, users with higher experience levels with CS, ML, and BCIs showed a larger improvement in motivation, on average than respondents with lower experience.

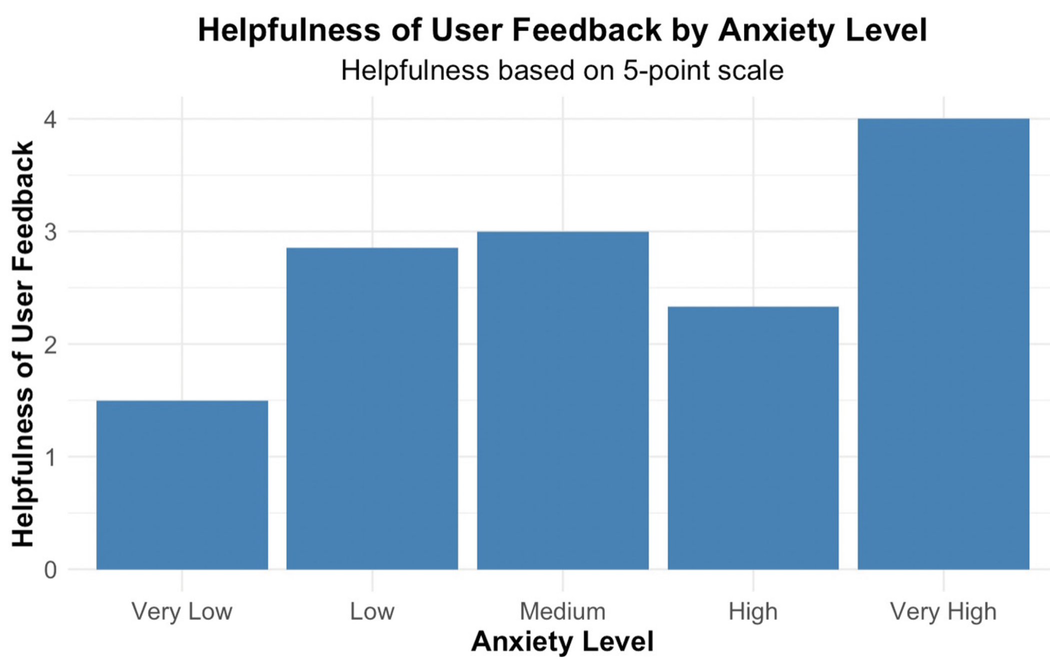

Fig. 3. User feedback helpfulness

Additionally, in question 16, users were asked if they were more motivated to try their best on a BCI data-related task after reading our descriptions. Survey respondents reported an average score of 2.857 (median 3) on a 4 point scale where 1 represented motivation would not change and 4 represented that they were much more motivated. Thus, we believe that users of our interface would have a higher motivation to provide clear EEG signals than users who did not receive biased user feedback and classification algorithm descriptions.

Overall, we did find a statistically significant increase in motivation among all survey respondents after using our interface. When conducting a paired t-test between the motivation of each participant before and after reading our classification algorithm descriptions and using our interface, we found a statistically significant improvement in motivation ($p = 0.008$, $t = 2.65$, $df = 20$).

We recognize that our measure of user motivation before and after using our interface is not a perfect proxy as our survey respondents did not actually use a BCI or provide EEG data. However, we believe our results serve as preliminary evidence of the importance of providing BCI users with feedback based on human-computer interaction as well as educational design principles.

Further, we asked users how easy they found interacting with our interface in question 14. When reporting the ease of use of our interface, the average reported score was 4 (mean 3.905) on a 5 point scale where 1 represented very difficult to use and 5 represented very easy to use. Thus, we believe that the overall framework of our interface can serve as a guide for future researchers.

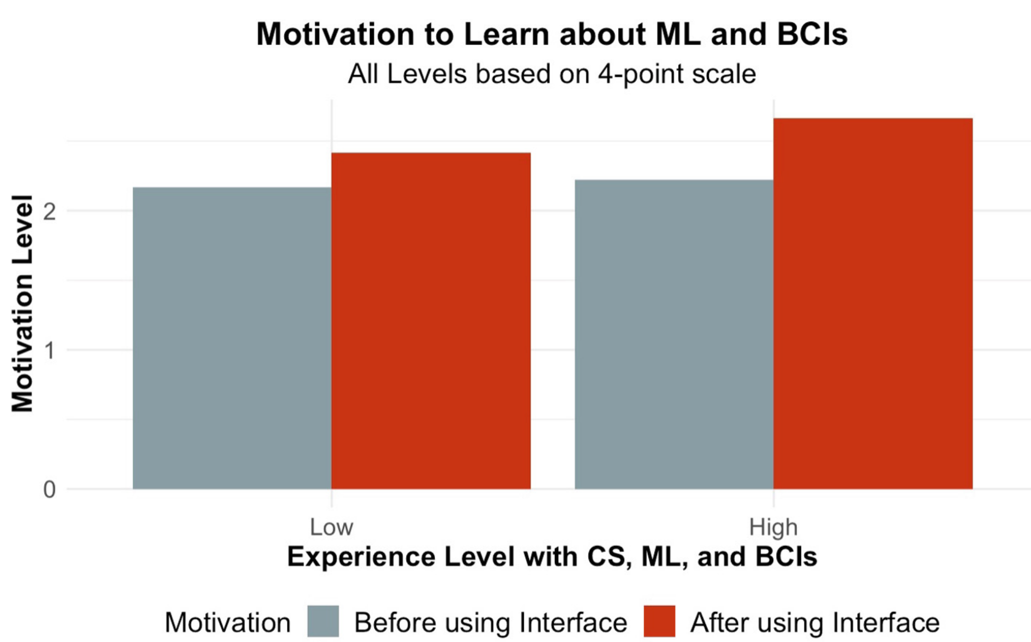

Fig. 4. Motivation before and after utilizing interface

4 Discussion

4.1 Limitations

As our research was conducted during a one-semester undergraduate course, our work was subject to time and complexity limitations. We note that the classification algorithm descriptions provided within our interface give a simplified version of the methods of these algorithms. We implemented the most basic classification algorithms descriptions as a means of demonstrating our interface's algorithm descriptions, but we recognize that future work should implement more advanced classification strategies and more detailed descriptions. Further, we recognize that future researchers may want to further customize these descriptions to their particular work. These descriptions are meant as a sample framework for future research.

Additionally, we provide very brief user feedback that represents the tone and bias that should be implemented for users. We based this biased feedback on the pedagogical and human-computer interaction principles outlined in Table 1. Thus, future researchers should implement more descriptive feedback tailored to their work.

Our research was limited by a lack of time and funding to be able to collect EEG data for a BCI application. Thus, with additional time and resources, we would gather EEG data for users that received feedback based on our interface as compared to no feedback or standardized feedback and measure whether the clarity of the EEG signal or the accuracy of the classification algorithms improved.

4.2 Future Work

In the long term, we would collect data with both users using and not using our interface. We would compare the quality of the data collected as well as user ratings of their experience during the collection process.

As we did not have survey respondents interact with a real brain-computer interface, our survey will primarily be used as a proof of concept for whether user feedback and classification algorithm descriptions can have a positive impact on user's motivation and feelings of anxiety.

Our preliminary results support the findings of Lotte et al. that suggest that BCI instructions include both the goals of the training as well as explanations for classifier output. By providing users with classification algorithm descriptions, we believe they will be better-equipped to provide clear EEG signals to the BCI [15]. Our results further suggest that Mladenovic et al. are correct in distinguishing between users with low and high levels of anxiety, and more specifically providing users with low anxiety feedback with a negative bias [19]. Additionally, Lotte et al. (2015) reviewed a series of studies noting that only providing positive feedback can be beneficial for inexperienced users. By attuning the user's feedback to their level of anxiety and experience, we believe that users will experience higher motivation and enjoyment of the BCI data collection process.

Questions we would like to pose to future researchers include:

1. Does accuracy of classification algorithms improve depending on whether users are provided with biased feedback during data collection?
2. Does accuracy of classification algorithms improve depending on whether users are provided with classification algorithm descriptions before data collection?
3. Does attuning user feedback to the user's emotional state and experience level result in clearer EEG signals and improve user motivation when compared to the same feedback being provided to all users?

5 Conclusion

We created an interface that is **A**ttuned to the user (A) by providing **B**iased user feedback (B) and **C**lassification algorithm descriptions (C). We created an interface where users can better understand classification algorithms that aid in their understanding of how their BCI data will be utilized. Further, this interface provides a framework for how to give biased feedback based on the user's experience and anxiety level. This framework is based on well known pedagogical and human-computer interaction principles that suggest that a user's motivation increases as they better understand the goals of the task at hand. Our interface provides an important step in the direction of improving human computer interaction within the field of machine learning and brain-computer interfaces.

References

1. Allison, B.Z., Wolpaw, E.W., Wolpaw, J.R.: Brain–computer interface systems: progress and prospects. Expert Rev. Med. Dev. **4**(4), 463–474 (2007). https://doi.org/10.1586/17434440.4.4.463. pMID 17605682
2. Bashivan, P., Rish, I., Yeasin, M., Codella, N.: Learning representations from EEG with deep recurrent-convolutional neural networks. arXiv preprint arXiv:1511.06448 (2015)
3. Benaroch, C., et al.: Long-term BCI training of a tetraplegic user: adaptive Riemannian classifiers and user training. Front. Hum. Neurosci. **15** (2021). https://doi.org/10.3389/fnhum.2021.635653. https://www.frontiersin.org/article/10.3389/fnhum.2021.635653
4. Brunner, C., Leeb, R., Müller-Putz, G., Schlögl, A., Pfurtscheller, G.: BCI competition 2008-Graz data set A. Institute for Knowledge Discovery (Laboratory of Brain-Computer Interfaces), Graz University of Technology **16**, 1–6 (2008)
5. Cincotti, F., et al.: Vibrotactile feedback for brain-computer interface operation. Comput. Intell. Neurosci. **2007** (2007)
6. Craik, A., He, Y., Contreras-Vidal, J.L.: Deep learning for electroencephalogram (EEG) classification tasks: a review. J. Neural Eng. **16**(3), 031001 (2019)
7. Ienca, M., Haselager, P., Emanuel, E.J.: Brain leaks and consumer neurotechnology. Nat. Biotechnol. **36**(9), 805–810 (2018)

8. Kastrati, A., et al.: EEGEyeNet: a simultaneous electroencephalography and eye-tracking dataset and benchmark for eye movement prediction. arXiv preprint arXiv:2111.05100 (2021)
9. Kerous, B., Skola, F., Liarokapis, F.: EEG-based BCI and video games: a progress report. Virtual Real. **22**(2), 119–135 (2018)
10. Kübler, A., et al.: The user-centered design as novel perspective for evaluating the usability of BCI-controlled applications. PLoS ONE **9**(12), e112392 (2014)
11. LeCun, Y., Cortes, C., Burges, C.J.: The MNIST database of handwritten digits. http://yann.lecun.com/exdb/mnist/
12. Lotte, F., et al.: A review of classification algorithms for EEG-based brain-computer interfaces: a 10 year update. J. Neural Eng. **15**(3), 031005 (2018)
13. Lotte, F., Congedo, M., Lécuyer, A., Lamarche, F., Arnaldi, B.: A review of classification algorithms for EEG-based brain-computer interfaces. J. Neural Eng. **4**(2), R1 (2007)
14. Lotte, F., Jeunet, C.: Towards improved BCI based on human learning principles. In: The 3rd International Winter Conference on Brain-Computer Interface, pp. 1–4. IEEE (2015)
15. Lotte, F., Larrue, F., Mühl, C.: Flaws in current human training protocols for spontaneous brain-computer interfaces: lessons learned from instructional design. Front. Hum. Neurosci. **7**, 568 (2013)
16. Mane, R., Chouhan, T., Guan, C.: BCI for stroke rehabilitation: motor and beyond. J. Neural Eng. **17**(4), 041001 (2020)
17. McFarland, D.J., Wolpaw, J.R.: Brain-computer interface use is a skill that user and system acquire together. PLOS Biol. **16**(7), 1–4 (2018). https://doi.org/10.1371/journal.pbio.2006719
18. Mladenović, J.: Standardization of protocol design for user training in EEG-based brain-computer interface. J. Neural Eng. **18**(1), 011003 (2021)
19. Mladenovic, J., Frey, J., Pramij, S., Mattout, J., Lotte, F.: Towards identifying optimal biased feedback for various user states and traits in motor imagery BCI. IEEE Trans. Biomed. Eng. **69**, 1101–1110 (2021)
20. Narciss, S., Huth, K.: How to design informative tutoring feedback for multimedia learning. Instruct. Des. Multimedia Learn., 181195 (2004)
21. Pillette, L., Roc, A., N'Kaoua, B., Lotte, F.: Experimenters' influence on mental-imagery based brain-computer interface user training. Int. J. Hum.-Comput. Stud. **149**, 102603 (2021). https://doi.org/10.1016/j.ijhcs.2021.102603. https://www.sciencedirect.com/science/article/pii/S1071581921000215
22. Portillo-Lara, R., Tahirbegi, B., Chapman, C.A., Goding, J.A., Green, R.A.: Mind the gap: state-of-the-art technologies and applications for EEG-based brain-computer interfaces. APL Bioeng. **5**(3), 031507 (2021)
23. Qu, X., Liu, P., Li, Z., Hickey, T.: Multi-class time continuity voting for EEG classification. In: Frasson, C., Bamidis, P., Vlamos, P. (eds.) BFAL 2020. LNCS (LNAI), vol. 12462, pp. 24–33. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-60735-7_3
24. Qu, X., Mei, Q., Liu, P., Hickey, T.: Using EEG to distinguish between writing and typing for the same cognitive task. In: Frasson, C., Bamidis, P., Vlamos, P. (eds.) BFAL 2020. LNCS (LNAI), vol. 12462, pp. 66–74. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-60735-7_7
25. Roc, A., et al.: A review of user training methods in brain computer interfaces based on mental tasks. J. Neural Eng. **18**(1), 011002 (2021)

26. Ron-Angevin, R., Díaz-Estrella, A.: Brain-computer interface: changes in performance using virtual reality techniques. Neurosci. Lett. **449**(2), 123–127 (2009). https://doi.org/10.1016/j.neulet.2008.10.099. https://www.sciencedirect.com/science/article/pii/S0304394008015176
27. Roy, Y., Banville, H., Albuquerque, I., Gramfort, A., Falk, T.H., Faubert, J.: Deep learning-based electroencephalography analysis: a systematic review. J. Neural Eng. **16**(5), 051001 (2019)
28. Schumacher, J., Jeunet, C., Lotte, F.: Towards explanatory feedback for user training in brain-computer interfaces. In: 2015 IEEE International Conference on Systems, Man, and Cybernetics, pp. 3169–3174. IEEE (2015)
29. Vansteensel, M.J., et al.: Fully implanted brain–computer interface in a locked-in patient with ALS. N Engl. J. Med. **375**(21), 2060–2066 (2016). https://doi.org/10.1056/NEJMoa1608085. pMID 27959736