An Adaptive Approach for Task-Driven BCI Calibration

Heskebeck, Frida; Bergeling, Carolina

2021

Document Version:
Publisher's PDF, also known as Version of record

Link to publication

Citation for published version (APA):
Heskebeck, F., & Bergeling, C. (2021). *An Adaptive Approach for Task-Driven BCI Calibration*. Abstract from BCI meeting 2021. https://bcisociety.org/wp-content/uploads/2021/05/vBCI-Abstract-Book-.pdf

Total number of authors:
2

An Adaptive Approach for Task-driven BCI Calibration

Frida Heskebeck[1,*] and Carolina Bergeling[1]
[1]*Department of Automatic Control, Lund University, Lund, Sweden*
[*]Email: frida.heskebeck@control.lth.se

Introduction One of the most significant obstacles for the every-day use of systems based on Brain-Computer Interfaces (BCIs) is the tediousness of calibration. Successful improvements on calibration, particularly the time needed and the user-experience, have been made with, e.g., transfer learning, gamification, and task estimation [1, 2, 3]. In this work, we present an adaptive approach to BCI systems' calibration with a model that evaluates if more calibration is needed. We inspect the model in its simplest form to showcase its versatility.

Material, Methods, and Results The model is built as a Markov Decision Process (MDP) with actions in each state and transition probabilities after each action (see Figure 1) [4]. The states s_{si} and s_{di} represent if the user is satisfied or dissatisfied with the BCI system's outcome. The number of updates of the classification algorithm is denoted through the index i. Two actions are possible: a_e - listen to the user intent and respond accordingly, and a_u - update the classification algorithm. Transition probabilities reflect the accuracy of the classification algorithm. In the case of model analysis, these can be estimated from data. There is an associated reward for each state transition: positive if reaching any of the states s_{si} and negative otherwise. Moreover, action a_u is considered expensive since it includes collecting more training data and training the classification algorithm.

Based on this model, the aim is to construct a policy (choice of action in each state) by which the system reaches any of the states s_{si} with maximum total reward. The best action to take will depend on the rewards and the expected value for the transition probabilities. Given the simplest model (opaque in Figure 1), one reaches inequality (1) with γ denoting the discount factor. Action a_u is best in state s_{d0} if (1) is true. The results from this analysis are intuitive. Given the rewards as stated above, (1) is true if $q > p$, i.e., action a_u is best if the classification algorithm is better at classifying the user intent after an update.

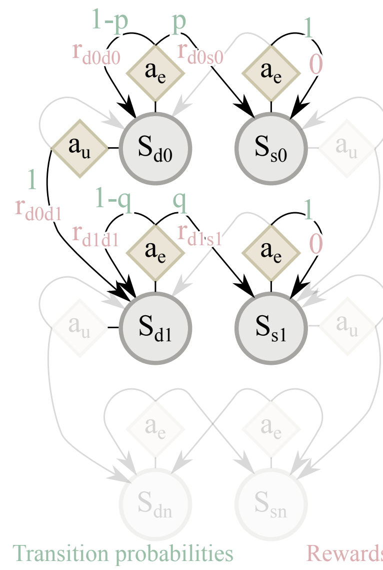

Figure 1: *Graphical outline for the model. The opaque parts are the simplest form of the model.*

The model description is independent of the task to be solved, the BCI paradigm, and the classification method. A more tailored model could be constructed if these aspects were accounted for. The model is not intended to choose the best classification algorithm or preprocessing methods for the BCI system. Instead, it adapts the calibration to the current situation.

$$\frac{(1-p)r_{d_0d_0}+pr_{d_0s_0}}{1-\gamma(1-p)} < r_{d_0d_1}+\gamma\left(\frac{(1-q)r_{d_1d_1}+qr_{d_1s_1}}{1-\gamma(1-q)}\right) \quad (1)$$

Discussion The simplest model can be extended in several ways (see transparent parts in Figure 1). For instance: 1) the user can change their mind, 2) the classification accuracy is not improved after the action a_u, 3) action a_u is possible also from a state s_{si}, and 4) n number of classification algorithm updates are possible (more states). Finally, it is not necessarily true that the BCI system knows the current state. This can be addressed through the theory of Partially Observable MDPs [5, 6]. The approach of reinforcement learning is also compelling for the extended model [7].

Significance The model facilitates the decision of when to use the BCI system and when to calibrate it. We believe that it can be combined with other calibration approaches to create the next-generation autonomous BCI systems.

References

[1] Ahmed M Azab et al. "A review on transfer learning approaches in brain–computer interface". In: *Signal Processing and Machine Learning for Brain-Machine Interfaces* (2018), pp. 81–98.

[2] David R Flatla et al. "Calibration games: making calibration tasks enjoyable by adding motivating game elements". In: *Proceedings of the 24th annual ACM symposium on User interface software and technology*. 2011, pp. 403–412.

[3] Jonathan Grizou et al. "Calibration-free BCI based control". In: *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 28. 1. 2014.

[4] Richard J Boucherie and Nico M Van Dijk. *Markov decision processes in practice*. Springer, 2017.

[5] Karl Johan Åström. "Optimal Control of Markov Processes with Incomplete State Information I". eng. In: Journal of Mathematical Analysis and Applications 10 (1965), pp. 174–205. issn: 0022-247X. doi: 10.1016/0022-247X(65)90154-X.

[6] Michael L Littman. "A tutorial on partially observable Markov decision processes". In: *Journal of Mathematical Psychology* 53.3 (2009), pp. 119–125.

[7] Aurélien Géron. *Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow: Concepts, tools, and techniques to build intelligent systems*. O'Reilly Media, 2019. Chap. 18.

Acknowledgements This work was partially supported by the Wallenberg AI, Autonomous Systems and Software Program (WASP) funded by the Knut and Alice Wallenberg Foundation.