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Towards Faster Startup of Brain-Computer Interfaces

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Popular science summary of the PhD thesis *Source Data Selection for Brain-Computer Interfaces*, October 2026. The thesis can be downloaded from: <http://www.control.lth.se/publications>.

A brain-computer interface (BCI) is a device controlled by brain signals. Brain signals are measured using an electroencephalography (EEG) cap placed on the user's scalp as shown in the figure. BCIs can be used for medical applications such as controlling a prosthetic arm or for entertainment applications such as controlling video games.

For a BCI to work, it needs to be fine-tuned to the user's brain. This fine-tuning is performed in a process called calibration. During calibration, the user performs specific mental tasks while EEG data is recorded. The BCI then learns to recognize the patterns in the EEG data for each mental task. The mental tasks are mapped to commands for the application, for example, moving the cursor on a screen to the left when the user imagines moving the left hand. For the BCI to fully recognize the patterns in the EEG data, the user must repeat the mental tasks multiple times. This results in calibration times of around 20 minutes before the BCI can be used. Doing this calibration is tiresome and boring for most users.

For medical applications, long calibration times are generally acceptable, as the additional time is worth it to achieve good BCI performance. In entertainment applications, on the other hand, a short calibration time is often more important than perfect final performance, since few want to use an entertainment device with a 20-minute startup time. For both applications, reducing calibration time is important to improve the user experience. Thus, much research focuses on this.

One approach to reduce the calibration time is to reduce the number of times the mental tasks need to be repeated. This can be done by using already recorded data



A person wearing an EEG cap that measures the brain signals used in BCIs.

from someone else. Using data from one person to train the BCI for another is a form of so-called transfer learning. Formally, data from a new BCI user is called target data, and preexisting data is called source data. A problem with transfer learning is that the source and target data must be sufficiently similar for it to work. The question is then: How can we identify which source data is similar to the target data? In this thesis, two methods for source data selection are presented. One is the transfer performance predictor method, which is particularly useful in settings with a lot of available source data. The other is the pole ratio method, which evaluates how well source and target data are aligned. The thesis also studies so-called multi-armed bandits for source data selection. To understand why data from some source users work better than data from others, the thesis also studies the limitations of transfer learning for two well-known transfer learning methods for BCIs: the Riemannian Procrustes analysis and the tangent space alignment.

Another approach to reduce the number of times the mental tasks need to be repeated is to identify which mental tasks yield good performance and collect data only from those. For example, some users may perform better when imagining right-versus left-hand movements, while others may perform better when imagining foot versus hand movements. The thesis presents two methods for task selection: the direct prediction band and the mean-difference approach. Multi-armed bandits are also investigated for task selection.

With the methods and results of the thesis, source data and mental tasks can be selected more efficiently, thereby reducing calibration times while maintaining good BCI performance. This will allow for faster BCI startup and, in the long run, we will likely see improvements in both medical and entertainment applications.