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Measuring (Limitations on) Control Precision in BCI

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Abstract. To be useful for real-world neuroprosthetic applications, continuous BCI control will need to be much more accurate than the performance typically reported in contemporary studies. It is tacitly assumed that prolonged practice with a neuroprosthetic will allow a user to reach such levels of control, but it is not yet known whether current methods of BCI signal induction, measurement and signal processing will in fact allow this. Typical methods for demonstrating control do not scale easily to allow comparison of beginner-level and expert-level performance on the same axis, to allow this question to be addressed. Aiming to fill this gap, we developed a novel method for precise measurement of continuous control in BCI, based on a computer game in which the player moved a cursor left and right to catch descending targets. The game difficulty level (reflected in both the width of the cursor and the speed with which the targets moved) was adjusted using a weighted up-down psychophysical staircase procedure, configured to converge on a hit rate of 65%. This kept the level of challenge constant over a wide range of player ability levels. We validated the method by using it to evaluate the differences in performance, and possible learning effects, between four different types of control signal in an EEG experiment with 4 healthy subjects. We showed that the method was able to distinguish reliably between the four controller conditions: chance performance, motor-imagery BCI performance a little above chance, accurate direct control using digital input devices (Nintendo Wiimotes), and "pseudo-BCI" in which the input was mediated by the Wiimotes but processed using the same signal-processing pipeline as the EEG. In particular, the contrast between direct and pseudo-BCI controllers allowed us to expose and quantify the performance limitations imposed by the EEG signal-processing pipeline.

Keywords: EEG, Motor Imagery, Control, Performance Assessment, Computer Games

1. Introduction

Typically, BCI control is demonstrated by having the subject guide a cursor to hit targets that can appear in one of a number of discrete locations. By contemporary standards, if a subject were to use a BCI to hit a target in one of 16 locations with, say, 97% or 98% accuracy, this would be considered very impressive. However, this still falls far short of the level of control that the real world demands from humans every minute of every day. Imagine, now, using a neuroprosthetic device to drive a wheelchair along the edge of a busy road, or chop onions with a sharp knife: a control system that "only" misses 1 time in 40 or 50 would still clearly be inadequate. We generally hope and assume that *practice* with a long-term-fitted neuroprosthetic will fill this gap. But to establish whether this is true, let alone to quantify users' progress meaningfully, we will first need appropriate techniques for measuring control performance. Measuring the frequency of vanishingly rare errors is an inappropriate technique due to its low statistical power. Rather, we need a measurement system that presents a single adaptive scale on which beginners (barely above chance performance) and experts (close to real-world performance) can both be represented. This system must adapt rapidly, reliably and repeatably to these different levels of control, adjusting the difficulty of the task so that the user never approaches a performance ceiling, but also never feels frustrated by the appearance of no control at all (assuming their level of control is indeed above chance). Ideally, the system should also be presented in an engaging, motivating form, to encourage subjects to perform well over many repeated measurements. Here we present and validate such a system, which is based on one-dimensional computer-game control.

2. Materials and Methods

Four healthy subjects took part in the experiment, each subject attending for 10 sessions on separate days. **T**he game involved moving a cursor (in the form of a cart) left and right on the screen to catch falling targets. There were three active controller conditions, and one random baseline condition, as detailed below. In each 90-minute session, the subject played 3 games in each of the 3 active conditions, for a total of 9 games. The controller conditions were:

- *BCI Controller*: cart velocity was controlled by imagined hand movement (left hand to go left, right-hand to go right). The 16-channel EEG signal was translated via (1) surface-Laplacian spatial filtering; (2) buffering and detrending in 500 ms moving windows; (3) spectral amplitude estimation in 3 Hz bands via AR model of order

20; (4) differential linear weighting of amplitude features, chosen using BCI2000's OfflineAnalysis tool based on 20 left-hand and 20 right-hand cued motor imagery trials at the start of each session; (5) normalization to mean 0 and variance 1, calibrated using 20 further trials in which the moving cursor was visible.

- *Direct Controller*: the player held a Nintendo Wiimote controller in each hand: shaking the left Wiimote caused the cart to move left, and shaking the right Wiimote caused it to go right.
- *Pseudo-BCI Controller*: the player held the Wiimotes and shook them as in the Direct condition. However, translation into cart velocity was different: the accelerometer power in each Wiimote inversely modulated the amplitude of an artificial white noise signal, which was then passed through exactly the same signal-processing pipeline as the BCI signal, starting with stage (2) and ending with a separately-calibrated normalization stage (5).
- *Random Baseline*: the same as the BCI condition, except that the control signal was derived from a replay of the subject's EEG from each game, with a 3-minute time-shift. The shift abolished all meaningful control of the cart.

Each game concluded with an adjustment phase in which a game-difficulty variable d was adjusted according to the procedure of [Kaernbach, 1991]. $\exp(d)$ was proportional to the speed of the falling targets, and inversely proportional to the width of the cursor; d increased by an amount S_{up} every time the player hit a target, and decreased by an amount S_{down} every time the player missed. We set $S_{up} = 1.0$ and computed S_{down} according to Kaernbach's formula $S_{up}/S_{down}=p/(1 - p)$, where p is the target hit rate on which the procedure converges (we used $p = 0.65$). The staircase procedure continued until the change in d reversed direction 8 times. The final d value was computed as the median of the last 6 reversals: this value was used as the starting difficulty level in the next game.

3. Results and Discussion

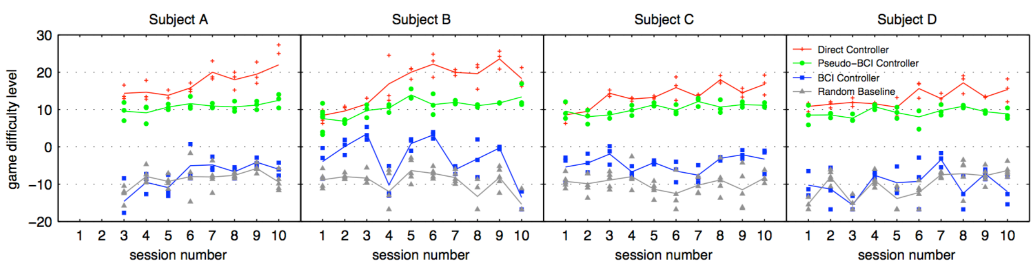

Figure 1: *Performance levels are plotted as a function of number of sessions, for each subject (panels left to right), in each of the four controller conditions (different symbol shapes/colors). Each point marks the result of the adjustment phase at the end of a game. Solid lines show the session means. Subject A's first two sessions were discarded due to changes in the game framework.*

Spearman correlation analysis showed that Direct-Controller performance improved significantly over time for all 4 subjects ($p < 0.0005$ in all cases). This shows that our method is sensitive enough to track improvements in control even when the starting level is very much better than beginner-level BCI control as measured on the same scale. Furthermore, Fig. 1 reveals that the individual measurements overlap very little between the four controller conditions (although clearly only subjects B and C achieved BCI control above chance). This shows that the method is sensitive and precise enough to distinguish at least these four levels of control on a session-by-session basis. Finally, the difference between Direct and Pseudo-BCI performance was significant overall for every subject, and on a single-session basis in 24 out of 37 individual two-tailed two-sample t-tests. This shows that the EEG signal-processing pipeline alone imposes a performance ceiling below the maximum that can be achieved in this game. Pseudo-BCI control also appears to improve more slowly than subjects' Direct Controller performance, suggesting that the pipeline may be a limiting factor on subjects' rate of learning as well as on their absolute level of control.

We conclude that a simple computer game of this kind, in combination with the weighted up-down adaptive procedure, is a promising approach for tracking BCI performance at both high and low levels of control. It seems suitable for probing the extent to which specific aspects of current BCI systems, such as the temporal integration performed in the signal-processing pipeline, impose limits on the performance levels that users are able to reach.

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References

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