How much learning is involved in BCI-control?

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Introduction

Experiments with animals and humans starting in the late sixties demonstrated that physiological functions that were believed to be autonomous, such as glandular responses, blood pressure, and the electrical activity of the brain (EEG) could be brought under voluntary control via operant conditioning (1,2). After it has been repeatedly shown that subjects could produce clearly distinguishable brain responses on command the idea was at hand to use this ability for communication in people who are in the so-called locked-in state with only residual muscular movement left for communication (3,4). In contrast to the neurofeedback approach which involves learning to control a component of the EEG, the machine learning approach aims at detecting patterns of activation in the brain that can be readily produced by the individual (5). Several authors claim that BCI control constitutes a skill (6,7), but a skill requires learning and improvement with practice (8).

Data Selection

We have selected 212 papers reporting neurofeedback results and control from the 60’s until today using keywords ‘brain-computer interfaces, neurofeedback, self-regulation, slow cortical potentials, P300, SMR, SSVEP and SSSEP’ in various combinations. Also included was data from EEG studies, single unit studies, microelectrode arrays, ECoG, fMRI, MEG and mNIRS studies in human and animal models.

Criteria for Learning

Our criteria for studies that were designed to allow for learning were as follows:

Online (real time feedback) studies, consisting of 5 or more sessions in which control using neural or muscular movement was excluded.

We expected learning to be revealed in significant linear or power trends. The power trend indicates rapid improvement at the beginning and asymptotic performance after automatically has been achieved.

Examples of Learning

Fig. 1 Demonstration of a hybrid approach, where learning follows the expected curve, this approach relies both on subject brain plasticity and on assisted machine learning techniques.

Fig. 2 Learning to move a paralysed hand in chronic stroke with the MEG BCI. Performance of two chronic stroke patients with no residual hand movement over 20 sessions (170 runs). Online performance is shown in blue and the significant linear trend in red.

Fig. 3 Rapid learning in ECoG 2D control. The movement level is rated at 25%. Epilepsy patients were told to imagine movement.

Fig. 4 (left). Learning to regulate slow-cortical potentials (SCP) in healthy subjects and those with ALS. Linear and power trends were significant. While healthy subjects learned quickly at the beginning of training and plateaued after 3 sessions, ALS patients needed more time and did not show asymptotic behaviour after 12 sessions, indicating that more time for learning is required in this patient group.

Fig. 5 (top). (a) Successes (mean percent) in meeting the criterion amplitude of a specified evoked potential component over 12 days. The letter R with the arrow indicates the end of the extinction period and beginning of reinforcement each day. Animals are reinforced for increased amplitude at 170 to 193 ms after the light flash. (b) Acquisition (percentage of successes) in meeting the criterion response for the first day of extinction and training.

Findings

After the filtering process we found 72 (~34%) papers with the appropriate criteria, in which:

Non-invasive:

47 (~65%), SCP and SMR based recording studies, of which 27 reported learning, 15 lacked details and 5 reported no learning, of which were already dealing with experienced learners, leading to a suspected plateau effect.

Invasive:

Of 16 of 12 studies reporting ECoG and intracortical recording methods, 10 reported learning. Most learning reported in these studies relied upon the support of a significant amount of machine learning. 13 studies did not apply to specifically declare results that could constitute as subject learning (due to evoked response paradigms rather than feedback based paradigm), or contained incomplete data leading to an inconclusive analysis.

Results pre-criteria

Fig. 7 (left) Breakdown of learning evidence in BCI before screening. criteria were applied from 212 journal articles.

Fig. 8 (right) Once our filtering criteria have been applied, our literary review has shown that most online SMR, SCP and invasive studies present clear evidence of subject learning.

Discussion and Conclusion

We conclude that many BCI studies or BCI approaches do not involve human learning. Those which do, rely on neurofeedback and operant conditioning to achieve self-regulation mainly of the SMR or SCP amplitude. In some of those studies performance followed a power trend indicating strong improvement of performance at the beginning of training followed by asymptotic performance with practice. In further studies with human subjects, specifically those in the locked-in syndrome it could be investigated whether control of such BCIs that rely mainly on pattern recognition could be improved with more practice.

References


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