Testing the Specificity of EEG Neurofeedback Training on First- and Second-Order Measures of Attention

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Abstract. During electroencephalography (EEG) neurofeedback training, individuals learn to willfully modulate their brain oscillations. Successful modulation has been shown to be related to cognitive benefits and wellbeing. The current paper addresses the specificity of three neurofeedback protocols in influencing first- (basic Stroop effect) and second-order (Gratton effect) measures of attentional control. The data come from two previously presented studies that included the Stroop task to assess attentional control. The three neurofeedback protocols were upregulation of frontal alpha, sensorimotor (SMR), and mid-frontal theta oscillations. The results show specific effects of different EEG neurofeedback protocols on attentional control and are modulated by the cognitive effort needed in the Stroop task. To summarize, in less-demanding versions of the Stroop task, alpha training improves first- and second-order attentional control, whereas SMR and theta training had no effect. In the demanding version of the Stroop task, theta training improves first-order, but not second-order control and SMR training has no effect on either. Using a drift diffusion model-based analysis, it is shown that only alpha and theta training modulate the underlying cognitive processing, with theta upregulation enhancing evidence accumulation. Although the current results need to be interpreted with caution, they support the use of different neurofeedback protocols to augment specific aspects of the attentional system. Recommendations for future work are made.

Keywords: EEG neurofeedback · Stroop effect · Gratton effect · Attention training

1 Introduction

Biofeedback is a paradigm in which individuals are trained to modulate their biological processes by providing them corrective feedback about the target biological variable. Commonly known target variables are the heart rate and heart rate variability. However, biofeedback of neuroelectrical signals as measured with electroencephalography (EEG) has also been shown in the clinical practice and in the research laboratories. Several clinical disorders have been purported to be ameliorated by specifically designed EEG neurofeedback training protocols (see for reviews, [1–4]). In the field of

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cognitive neurofeedback, the research focuses on cognitive enhancement and peak performance [5, 6]. For example, training the alpha band frequency has been associated with improved attentional control and working memory [7, 8]. Investigating attentional control is typically done with tasks such as the Stroop task, in which a color word is printed in a font color that is either the same (congruent) or different (incongruent) than what the word represents and the participant is required to name the font color. The slowed response time to naming incongruent compared to congruent stimuli is the Stroop effect and is the prototypical measure of attentional control. In addition to the simple difference of response times, recent theories of attentional control postulate that the amount of incongruency experienced on a preceding trial influences the amount of control exerted on the current trial [9, 10]. That is, the cognitive system reacts to the increase in cognitive conflict by increasing the attention paid to the task. This leads to an interaction effect whereby the Stroop effect is larger after congruent trials than after incongruent trials. This pattern, called the Gratton effect, is a marker of cross-trial fluctuations of attention and thus a more sensitive measure of how attention is distributed over time.

In a recent study, we showed that second-order measures of attentional control, i.e., the Gratton effect, was influenced by upregulation of frontal alpha oscillations [11]. In particular, the alpha training lead to a decrease in the Gratton effect, which was interpreted as a decreased need to exert reactive control. It was postulated that the increase in frontal alpha made the attentional control system more efficient, leading to less cognitive conflict and thereby to smaller Gratton effects.

An important consideration in neurofeedback research is the specificity of the results (see e.g., [12]). For example, it is yet unclear whether the effect observed with alpha neurofeedback is specific for that protocol or whether any other neurofeedback protocol produces the same result. To test this, we compare three neurofeedback protocols. The first is the frontal alpha protocol described above. The second and third are a mid-frontal theta and a sensorimotor (SMR) protocol, respectively. The latter two protocols were used in a large-scale study investigating their effects on a range of cognitive tests and phenomenological experiences. The study used two variants of the Stroop task that will be reanalyzed in this paper.

In the next section, the two studies are described to provide the context within which each study was conducted. Although the methods vary, they do use the same cognitive task. This is followed by two sets of analyses. The first set addresses first- and second-order measures of attention across the three protocols. The second set follows after an intermezzo about decomposition of response times in underlying latent cognitive processes and looks at cross-protocol differences in drift rate, boundary separation, and non-decision time. The paper closes with a speculative integration of the findings based on the conflict/control-loop theory.

2 Description of Studies

In the first study [11], participants were trained over 5 consecutive days to enhance the alpha oscillation over the prefrontal cortex (Fp2) using a virtual reality system. The task within the virtual world was to levitate a vase that rested on a table in a room. This study consisted of two groups: a 3D group and a 2D group. The aim of the study was to assess the effect of immersive feedback on the learning rate. It used the Stroop task to measure the attentional focus. The task required participants to respond to the strings RED, BLUE, and &&&& by pressing one of two keys denoting the font color of the string (red versus blue). This created three trial types: congruent, incongruent, and neutral. In each group, data from 10 participants were used in the analyses. The main results were that the immersion due to the virtual environment (3D vs 2D) lead to a higher rate of neural learning. The rate of enhancement of alpha over 5 training sessions was associated with the amount of decrease in the Stroop and Gratton effect.

The second study [13] had a different aim and experimental design. Participants were trained over 10 sessions to either enhance mid-frontal theta (Fz) oscillations or central sensorimotor rhythm (SMR). The choice of mid-frontal theta was based on the findings that the anterior cingulate cortex (ACC) is a critical neural component in the attentional control system [9, 10] and is the cortical source for theta oscillations. The SMR protocol was used as an active control condition, although in clinical practice, the SMR protocol is used to address symptoms associated with attention-deficit/hyperactivity disorder. Complete datasets were available from 10 and 16 participants in the SMR and theta group, respectively. Participants were given a standard feedback interface (not immersive) that provided visual and auditory (beeps) feedback every time the power in the target frequency was above threshold. A battery of cognitive tests was administered before and after the training period. Among these were two variants of the Stroop test. The first was the same version as used in the alpha study. The second, and more demanding, variant included an auditory beep that was present on 25% of the trials and signaled to the participant to withhold the response. Thus, in this variant, the participant had to keep two task goals in mind.

In sum, both studies included the Stroop task as the cognitive task to assess attentional control and the second study also varied the demand characteristics. We now turn to the results which are analyzed both across studies and for each training protocol separately.

Results: Stroop Effects

Although earlier reports presented the mean response times of all trials [11, 13], here the mean response times of congruent and incongruent trials that followed a neutral trial are presented. The rationale is that these trials are uncontaminated by the influence of reactive control. This also prevents confounding the first- and second-order measures, as data points will only contribute to one set of analyses.

Figure 1 presents the mean correct response times for all congruent and incongruent trials in the Stroop tasks for all training groups. Data from the two alpha groups were combined in the analysis to increase statistical power, but are shown separately for information. A 2 × 2 × 3 mixed factorial ANOVA crossing the factors trial type (congruent/incongruent), session (before/after), and neurofeedback group (alpha/SMR/theta) revealed a Stroop effect [$F(1,43) = 8.78$, $MSe = 1059.95$, $p < .01$, partial $\eta^2 = .17$], an overall speed up from pre- to post-training [$F(1,43) = 12.47$, $MSe = 4665.69$, $p = .001$, partial $\eta^2 = .23$], an interaction between session and trial-type [$F(1,43) = 8.90$, $MSe = 1431.11$, $p < .01$, partial $\eta^2 = .17$], which was part of the

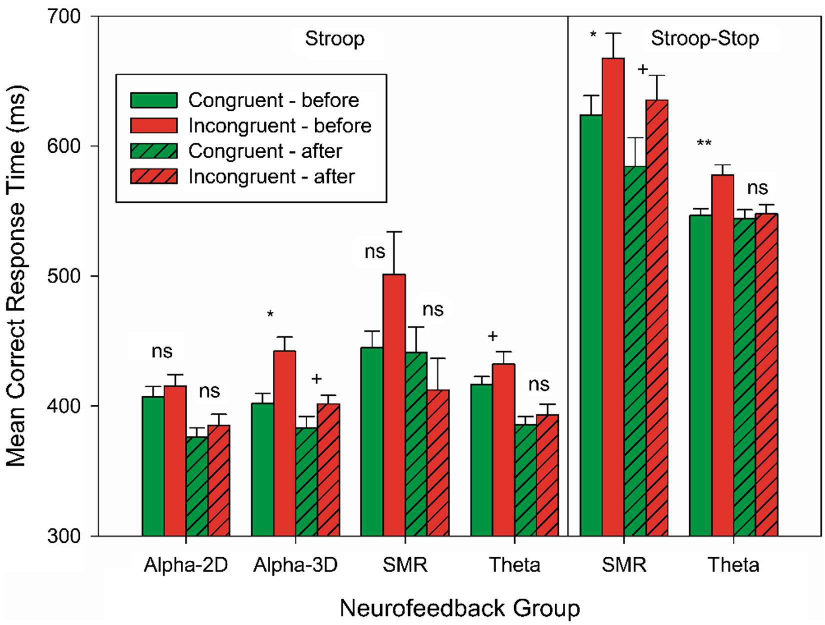

Fig. 1. Mean correct response times for congruent and incongruent trials (following neutral trials) before and after neurofeedback training. Error bars represent standard error of the within-subject mean. Simple effects comparing pre- and post-training scores are indicated: ** p < .01, * p < .05, + p < .10, ns = nonsignificant.

three-way interaction [$F(2,43) = 3.96$, $MSe = 1431.11$, $p < .05$, partial $\eta^2 = .16$]. The interaction was due to the SMR group not showing any Stroop effects.

For the Stroop-Stop task, a 2 × 2 × 2 factorial ANOVA revealed a marginal speed up across sessions [$F(1,24) = 3.74$, $MSe = 4450.61$, p .065, partial $\eta^2 = .14$] and a significant Stroop effect [$F(1,24) = 17.55$, $MSe = 1480.10$, $p < .001$, partial $\eta^2 = .42$].

Results: Gratton Effects

Figure 2 presents the mean correct response times for all congruent and incongruent trials in the Stroop tasks for all training groups as a function of the previous Stroop trial type.

The overall Gratton effect was present [previous x current trial type interaction $F(1,43) = 9.38$, $MSe = 2225.25$, $p < .01$, partial $\eta^2 = .18$], as was the across-session speed up [$F(1,43) = 12.24$, $MSe = 9236.23$, $p = .001$, partial $\eta^2 = .22$] and Stroop effect [$F(1,43) = 9.08$, $MSe = 2071.59$, $p < .01$, partial $\eta^2 = .17$]. However, the Gratton effect differed across groups [$F(2,43) = 4.73$, $MSe = 2225.25$, $p < .05$, partial $\eta^2 = .18$] and across sessions [$F(1,43) = 5.06$, $MSe = 1085.20$, $p < .05$, partial $\eta^2 = .11$], due to absence of the effect in the theta group.

For the Stroop-Stop task, the Stroop effect was significant [$F(1,23) = 8.79$, $MSe = 2271.61$, $p < .01$, partial $\eta^2 = .28$], but the Gratton effect was marginally significant [$F(1,23) = 3.69$, $MSe = 3350.13$, $p = .067$, partial $\eta^2 = .14$] and failed to reach statistical significance in the interaction with session and group ($p = .21$).

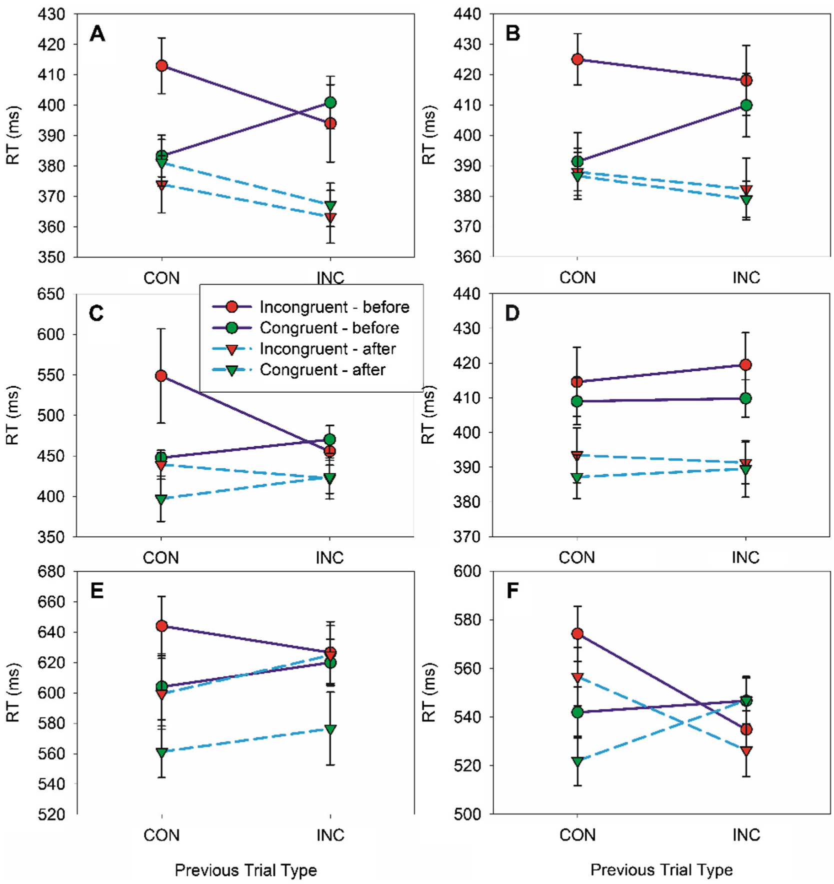

Fig. 2. Mean correct response times for congruent and incongruent trials before and after neurofeedback training broken down by previous trial type. Error bars represent standard error of the within-subject mean. A = alpha 2D (Stroop), B = alpha 3D (Stroop), C = SMR (Stroop), D = theta (Stroop), E = SMR (Stroop-Stop), F = theta (Stroop-Stop).

3 Decomposition of Response Times

The results in the previous section focused on response times, which are the main data of interest for most, if not all, of the Stroop literature. However, a particular response time is the result of a series of cognitive events that can be roughly broken down into a decision and a non-decision component. An influential theoretical explanation of response times is the drift diffusion model (for a recent review see, [14]). According to this theory, response times are a linear combination of the two components, with the decision component being governed by two further parameters: drift diffusion and boundary separation. The latter dictates the threshold at which a particular decision is made, whereas the former reflect the speed at which the system approaches this threshold. Fast responses can therefore be due to short non-decision times, fast drift rates, or lower boundary separations. In order to adjudicate among these possibilities, the drift diffusion model takes into account the accuracy level. For example, lowering the boundary separation will not only decrease the response time, but also increase the error rate. Increasing the drift rate will decrease response time and increase accuracy. Finally, decreasing non-decision time speeds up response times, but has no effect on accuracy. In order to obtain parameter estimates of the drift diffusion model, Wagenmakers et al. [15] developed the EZ diffusion model which

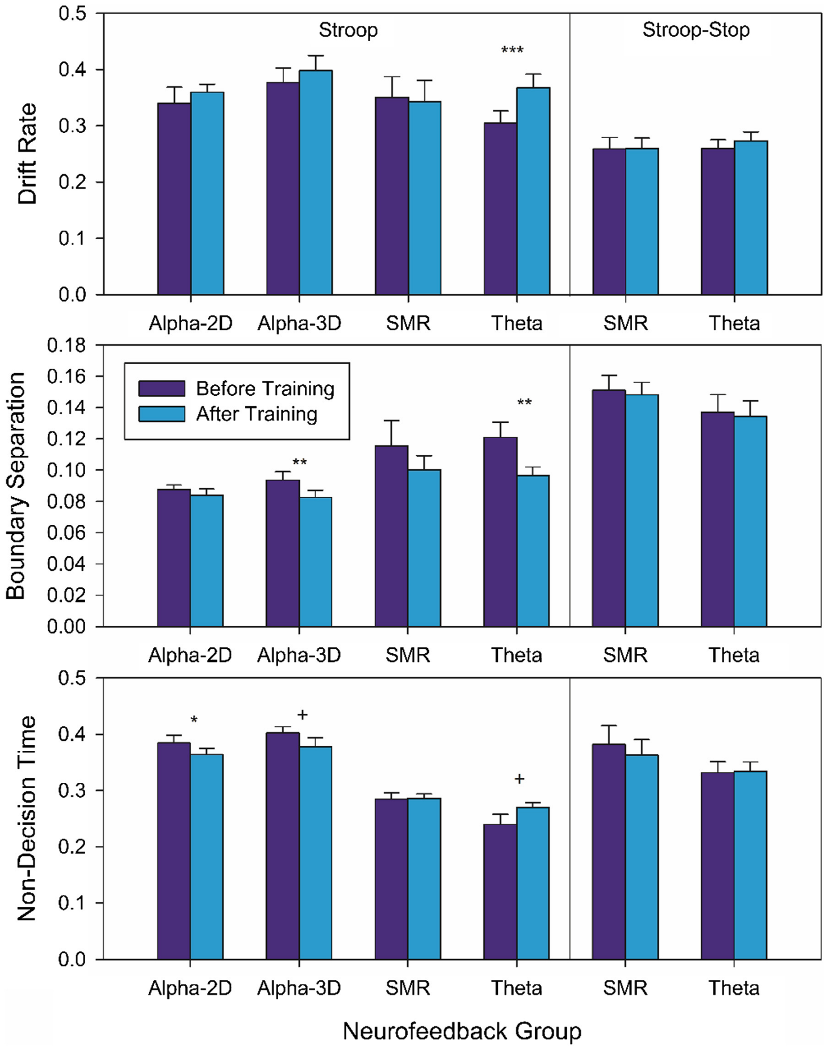

Fig. 3. EZ diffusion parameter estimates for each neurofeedback training group. *** p < .001, ** p < .01, * p < .05, + p < .10

simplifies the original diffusion model[1] to a closed-form expression. In order to obtain estimates of the drift rate, boundary separation, and non-decision time, all that is needed are the mean correct response time (in seconds), the variance (in seconds^2), and the proportion of correct trials.

EZ Diffusion Model Decomposition
In order to obtain the parameter estimates, only the neutral trials in the tasks were used. The rationale for this selection was that the congruent and incongruent stimuli are invoking additional processes that warrant the diffusion model inappropriate as a reasonable model for extracting cognitive parameter estimates.

Results: Diffusion Model Parameter Estimates
Figure 3 shows the parameter estimates for each group in each task. For the Stroop-Stop task none of the parameter estimates changed due to neurofeedback training. For the Stroop task, only alpha and theta training modified parameter estimates. Alpha training decreased non-decision time [session x group interaction $F(1,43) = 6.45$, $MSe = 0.001$, $p < .01$, partial $\eta^2 = .23$] and boundary separation [session x group interaction $F(1,43) = 2.70$, $MSe < 0.001$, $p = .079$, partial $\eta^2 = .11$], whereas theta upregulation lead to an increase in non-decision time, a decrease in boundary separation, and a strong increase in drift rate [session x group interaction $F(2,43) = 2.76$, $MSe = 0.003$, $p = .074$, partial $\eta^2 = .11$]. No effects were observed for the SMR group.

4 Discussion

The current analyses addressed the specificity of EEG neurofeedback protocols on measures of attentional control obtained in the Stroop task. The numerical results (and simple effects analyses) showed that training theta leads to decrease in the Stroop effect, while not affecting the Gratton effect. This pattern was only observed in a version of the Stroop task that was made more cognitively demanding by including a stop-signal on 25% of the trials. In the less-demanding version, Stroop and Gratton effects did not reach statistical significance.

In the SMR group, the Gratton effect in the less-demanding version was marginal before training and non-significant after training with no influence on the Stroop effect. In the more demanding Stroop version, Stroop effects were present before and after SMR-training and a Gratton effect was absent. Finally, Stroop and Gratton effects decreased with alpha neurofeedback.

The results on alpha oscillations supports theories claiming that alpha is associated with the inhibition of distracting information. Enhancing the power of alpha oscillations would thus lead to decrease in Stroop effects and of the Gratton effect. The

[1] The diffusion model contains many more parameters, most of which are variance parameters, in order to account for complete response time distributions. In order to fit the full model to empirical data, many data observations are needed and a complex fitting procedure be employed. The EZ diffusion model has been shown to be reasonably accurate in estimating the underlying model parameter values. Its simplicity lends itself to application to cognitive data obtained from the neurofeedback studies.

mid-frontal region, the cortical source of theta oscillations, has been associated with monitoring cognitive effort and triggering top-down control. Enhancing theta power specifically affects the incongruent stimuli, leading to a decrease in Stroop effect. However, the Gratton effect, an interaction effect, is not affected. The absence of a training effect with SMR underscores its use as an active control condition.

Strength and Limitations
Although the current analyses provide insights into the specificity of neurofeedback protocols, there are some limitations that should inspire further empirical work. First, Stroop effects were not always observed in the pre-training session, making it difficult to infer any improvement in attentional deployment. This was inevitably due to the small sample size from which data was available. It is recommended that the pre-training test session be used to select for neurofeedback training those participants who show initial cognitive effects. Although this would require a larger sample size from the outset, it would prevent a situation where the number of completers is insufficient to observe cognitive effects at the group level, as is the case here for the SMR group. Second, the analyses compared data from two studies that varied in methodology. It is not impossible that some of the observed differences can be attributed to these. Future work could therefore aim to use the same methodology and vary only the neurofeedback protocol in a large multi-protocol study. This would also allow the opportunity for replication to assess whether any of the reported findings were statistical anomalies. The nature of EEG neurofeedback requires multiple training sessions to observe learning and as individuals vary in their rate of learning this will inevitably lead to datasets that include this uncontrolled variance.

Despite these methodological issues, the current paper demonstrates two data-analytic directions for neurofeedback research that can lead to understanding the cognitive mechanisms underlying neurofeedback success. First, the second-order measure, the Gratton effect, is a theoretically articulated pattern coming from an understanding of the cognitive processes involved in the Stroop task. The use of theory-driven analyses can ground neurofeedback results in an existing theoretical framework, from which new testable predictions can emerge. Second, the use of the EZ diffusion model presents an example in which a computational model is used to extract latent cognitive parameters to allow evaluation of the impact of neurofeedback on these parameters. Model-based data analyses like this provides insights beyond the dependent measures observed and speak directly to the question of which cognitive processes are influenced by neurofeedback training. It should be noted that both types of data-analytics can be applied to any cognitive and brain training program to evaluate its efficacy. In doing so, the analyses bridge the theoretical literature with the literature on cognitive enhancement.

5 Conclusion

EEG neurofeedback training has been shown to influence first- and second-order measure of attentional deployment. Three training protocols demonstrate different impact profiles on the Stroop task, evidencing that the protocols influence specific components in the cognitive system supporting attentional control. Whereas frontal alpha enhances efficient deployment of top-down attention, mid-frontal theta leads to faster conflict resolution.

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