Frontal alpha oscillations and attentional control: A virtual reality neurofeedback study

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In press in Neuroscience: https://doi.org/10.1016/j.neuroscience.2017.06.007
The content of this manuscript does not match the content of the published work.

Two competing views about alpha oscillations suggest that cortical alpha reflect either cortical inactivity or cortical processing efficiency. We investigate the role of alpha oscillations in attentional control, as measured with a Stroop task. We use neurofeedback to train 22 participants to increase their level of alpha amplitude. Based on the conflict/control loop theory, we selected to train prefrontal alpha and focus on the Gratton effect as an index of deployment of attentional control. We expected an increase or a decrease in the Gratton effect with increase in neural learning depending on whether frontal alpha oscillations reflect cortical idling or enhanced processing efficiency, respectively. In order to induce variability in neural learning beyond natural occurring individual differences, we provided half of the participants with feedback on alpha amplitude in a 3-dimensional (3D) virtual reality environment and the other half received feedback in a 2D environment. Our results show variable neural learning rates, with larger rates in the 3D compared to the 2D group, corroborating prior evidence of individual differences in EEG-based learning and the influence of a virtual environment. Regression analyses revealed a significant association between the learning rate and changes on deployment of attentional control, with larger learning rates being associated with larger decreases in the Gratton effect. This association was not modulated by feedback medium. The study supports the view of frontal alpha oscillations being associated with efficient neurocognitive processing and demonstrates the utility of neurofeedback training in addressing theoretical questions in the non-neurofeedback literature.

Keywords: neurofeedback, electroencephalography, virtual reality, cognitive control

Introduction

Biofeedback is a procedure aimed at teaching individuals to control their physiological processes by exposing them to real-time information about the respective activity (Niv, 2013). Once learned, the ability should persist beyond the training situation, providing individuals with a way to improve their health and performance without external interventions. Among the activities most susceptible to such feedback-based operant conditioning are skin temperature, heart function, and muscle activity. Training these responses has shown to alleviate the symptoms of disorders such as migraine and hypertension (Nestoriuc et al., 2008). While these effects appear to be established, feedback protocols focused on neural activity are more controversial. Summarised under the name of neurofeedback training (NFT), these protocols expose individuals to real-time information about their neural activity (Vernon et al., 2009). The latter can include the oscillations measured through electroencephalograms (EEG) or the blood-oxygen levels (BOLD) captured through functional magnetic resonance imaging (fMRI).

Although success has been reported in the treatment of Attention Deficit Hyperactivity Disorder (ADHD; meta-analysis: Arns et al., 2009), epilepsy (meta-analysis: Tan et al., 2009), insomnia (e.g., Schabus et al., 2014), and substance abuse (e.g., Scott et al., 2005), these results are not univocal, which may be due to methodological issues and lack of theoretical grounding (see for discussion Gruzelier, 2014a). Research with neuro-typical populations produced similarly mixed results (Niv, 2013). The areas explored include the effects of NFT on creativity (see Gruzelier, 2014b), sports performance (e.g., Landers et al., 1991), mood and affect (e.g., Moore, 2000) and cognitive performance (see Gruzelier, 2014a).

Despite the often-conflicting reports, or perhaps because of them, the past decade has seen a sharp rise of neurofeedback research in cognitive science (van Boxtel and Gruzelier, 2014), showing both functional (Ros et al., 2013) and structural (Ghaziri et al., 2013) changes due to NFT. Although much of the present literature is focused on validating NFT protocols, we consider that NFT in healthy participants can be used as a tool to address theoretical differences in other scientific domains. In particular, NFT allows the researcher to manipulate, in a within-subject design, the level of brain oscillations in order to ask the question whether a particular brain oscillation is causally linked with a cognitive outcome variable. Whereas much of cognitive neuroscience manipulates the cognitive task in order to observe changes in the brain, neurofeedback allows manipulations of the brain and observe changes in the cognitive performance. This makes NFT a very important research tool for the cognitive neuroscientist. In this paper, we demonstrate this utility by leveraging it to assess whether increasing prefrontal alpha oscillations enhances or decreases attentional control.

In the literature on attentional control, the conflict/control loop theory (Botvinick et al., 2001) is a widely cited theory that accounts for an impressive range of findings in such tasks as the Stroop task. Classic Stroop analyses focus on the differences in response times (RT) to incongruent and congruent stimuli. The effect is, however, modulated by the word that was presented on the previous trial: the Stroop effect is smaller if the preceding trial presented an incongruent compared to a congruent stimulus. This effect is known as the Gratton effect (Gratton et al., 1992) and provides a window in the temporal deployment of attentional control. According to the conflict/control loop theory (Botvinick et al., 2001, 2004), an incongruent stimulus elicits cognitive conflict, which is monitored by the anterior cingulate cortex (ACC), a mid-frontal brain region. The ACC sends input to the prefrontal cortex (PFC) which then exerts more top-down control. This results in a smaller interference effect after incongruent compared to congruent trials. In behavioural terms, the need to exert cognitive control is observed as an interaction between previous and current stimulus type. The sequence of previous and current trial type is labelled with a lowercase letter for the previous trial (i = incongruent, c = congruent) and an uppercase letter (I = incongruent, C = congruent) for the current trial. The Gratton effect is therefore calculated as $RT_{cI} - RT_{cC} - (RT_{iI} - RT_{iC})$.

Alpha oscillations have been linked to cognitive processing with two competing theoretical viewpoints that make opposite predictions with regard to the Gratton effect. The first view is that large alpha oscillations over a cortical region reflect inactivity of the underlying neural substrate. This "cortical idling" hypothesis has its origins in Berger's observation of decreasing alpha amplitudes over occipital areas when participants shifted their attention to a visual stimulus (Berger, 1929). Recent theories, however, explore a more active role of alpha in cognition (e.g., Doppelmayr et al., 2005; Klimesch, 1999; Klimesch et al., 2007). Cooper et al. (2003) observed that alpha amplitudes were greater on internally directed tasks, such as mentally visualising a stimulus. Attending to a stimulus presented externally, however, led to a drop in alpha amplitudes. The researchers concluded that alpha plays a role in inhibiting internal information, thus linking it to task-related attention. According to this "neural efficiency" hypothesis, increase in alpha oscillations reflects more efficient cognitive processing.

Whereas most of the above-cited references focus on alpha oscillations at posterior electrodes or do not deal directly with the Stroop task, the role of alpha oscillations could be in the same direction over other cortical areas. To test this, we vary the frontal alpha amplitude by means of NFT and observe the concomitant change in Gratton effect. Increase in the effect would mean that the prefrontal cortex is unable to exert sustained attentional control and the cognitive system becomes reliant on the trial-to-trial variation in cognitive conflict to refocus attention. Decrease in the effect reflects a stronger sustained attentional control. Whereas the former pattern provides evidence for the idling hypothesis, the latter supports the neural efficiency hypothesis.

It is well-known in the NFT community that there exists a large variability in the speed of learning to control one's brain oscillations. Whereas in prototypical NFT studies this added variance frequently leads to failure in validating NFT protocols, in our research question regarding covariation of brain oscillations and cognitive performance, this variability is necessary to estimate the effect size. Thus, instead of excluding "non-learners" from the statistical analyses (cf. Zoefel et al., 2011), these participants provide important data for the overall regression analysis. In order to further spread the learning rates in our sample, we provide feedback to individuals in either a 3D or a 2D environment. Gruzelier et al. (2010) observed that learning was faster when feedback was delivered in a 3D virtual reality environment compared to a 2D control situation. The precise mechanism by which a 3D feedback environment speeds up the learning is yet unclear, but in the context of this study the manipulation provides a tool to induce differential learning rates that is critical to assess the alpha-control association.

We expect learning rates to be faster with a 3D compared to a 2D feedback environment. In addition, based on the cortical idling hypothesis we expect learning rates to be negatively associated with sustained attentional control. If, however, prefrontal alpha signals more efficient processing, a positive association is expected.

Method

Participants

Twenty-two participants (eight females; mean age = 35.2, SD = 8.8) were recruited among friends and colleagues of the experimenter. Eleven participants were randomly assigned to each of the feedback groups. There were no significant age differences between the two genders (males: M = 34.7, SE = 2.8; females: M = 36, SE = 2), or between the feedback groups (2D: M = 32.5, SE = 3; 3D: M = 37.8, SE = 2.1).

The subjects were recruited by word of mouth and received a book upon completion. Prior to participation, subjects filled out an online screening questionnaire which served to exclude participants prone to motion or VR sickness. Other exclusion criteria were susceptibility to migraines, a diagnosis of ADHD or epilepsy, prior psychiatric treatment, current pharmacological treatment (especially benzodiazepine-based), and high levels of anxiety and stress. Out of an initial 30 candidates, four were excluded on the basis of their screening answers. An additional four participants dropped out due to scheduling conflicts.

Materials

VR-neurofeedback set-up

The neurofeedback training protocol was run from an Apple MacBook Pro with OS X Yosemite, version 10.10.4. The computer had a 2.5 GHz processor to ensure smooth and fast running of the VR environment. The computer's native monitor had a display of 15.4 inches and served as a control screen used by the experimenter. Participants in both feedback group viewed the test environment through a VR headset. This was connected to the computer via HDMI and USB cables and was configured as an extended monitor. The VR headset was an Oculus Rift Development Kit 2.

The EEG data were recorded using a MyndPlay BrainBand XL with the signal electrode over Fp2, one ground electrode over Fp1, and a reference electrode clipped to the left ear. The data were sent to a computer via a Bluetooth transmitter in the battery pack. For the purpose of the experiment, the electrodes and the battery pack were taken out of the elastic headband and fixed directly to the Oculus Rift. The device held the electrodes on participants' foreheads.

The BrainBand XL records EEG data using a NeuroSky chip. We used the raw EEG data and created two bespoke software applications: the first was a control application (control.app), used to extract, transform and integrate the data from the chip, with a bespoke VR environment through the second application (oculus.app). Both applications were created using the Unity game engine, with the data transforms written in C++. The control application collected the data from the chip and decomposed them into a frequency spectrum using a Fast Fourier Transform. A one-second sliding window was used with data snapshots refreshed every 250 milliseconds (ms). Power values were then extracted from within the alpha frequency band of 8 - 12Hz, an average of which was computed to help filter out the effects of eye blinking. This filter identified data with an average above 2.5 times the mean power within the alpha spectrum and the respective data was excluded from later calculations. The programme then computed the baseline measure used as a threshold. This was calculated as the 70th percentile of all power values of alpha measured within a baseline trial. During neurofeedback trials, the programme compared all amplitudes within alpha and awarded a point each time the threshold was passed, excluding blinks.

The second application, oculus.app, controlled the VR environment. The two programmes were connected through the network and ran in parallel. Oculus.app ran the two visual environments participants would see through the VR device. In the 3D environment, participants were placed in the middle of a room, whereas in the 2D environment, participants watched a cinema screen. Videos of the environments can be found at https://youtu.be/sqolLshyaFQ (3D) and https://youtu.be/E3-O6VfMTzM (2D). The oculus.app received the points above threshold from the control.app. Each point would cause an object to float: a blue vase (positioned on a table) in the 3D group and a blue square in the 2D group. To ensure the smooth movement of the objects, a sliding window of 100ms was exponentially averaged.

Stroop set-up

The Stroop test used to capture behavioural outcomes was programmed in ePrime 2.2 and ran from a Dell Latitude 2100 laptop with a 10-inch monitor and a Windows XP operating system. Participants were required to respond to the colour of a colour word or a set of coloured ampersands (neutral condition) by pressing the "z" or "m" key on the keyboard. There were 75% neutral trials and 25% colour words.

Procedure

The study was approved by the local ethics committee. Participants were tested individually in meeting rooms at the experimenter's workplace or a testing room at Birkbeck College. They would sit on a chair or sofa with the Oculus and the electrodes positioned on their head. The experimenter would sit next to them with the control computer on a nearby table. The Stroop tests were administered in the same settings. Whenever possible, participants would be tested in the same location across all sessions. Where this was not feasible, the experimenter would ensure that the environments are matched as far as possible with regards to seating position, noise level, and room temperature.

Participants who passed the initial screening were randomly assigned to one of the two experimental groups. They were instructed about the purpose and structure of the experiment, received an information sheet and signed a consent form. Participants were then asked to provide basic demographic information, including their age, and handedness. They were assigned a unique subject number, which was used as an anonymous identifier across all tests. Each participant was tested in five sessions, one session per day. Where possible, these sessions were scheduled on consecutive days, though in a few instances, the schedule was interrupted by a weekend. Figure 1 provides an overview of the entire experiment and the structure within each training session.

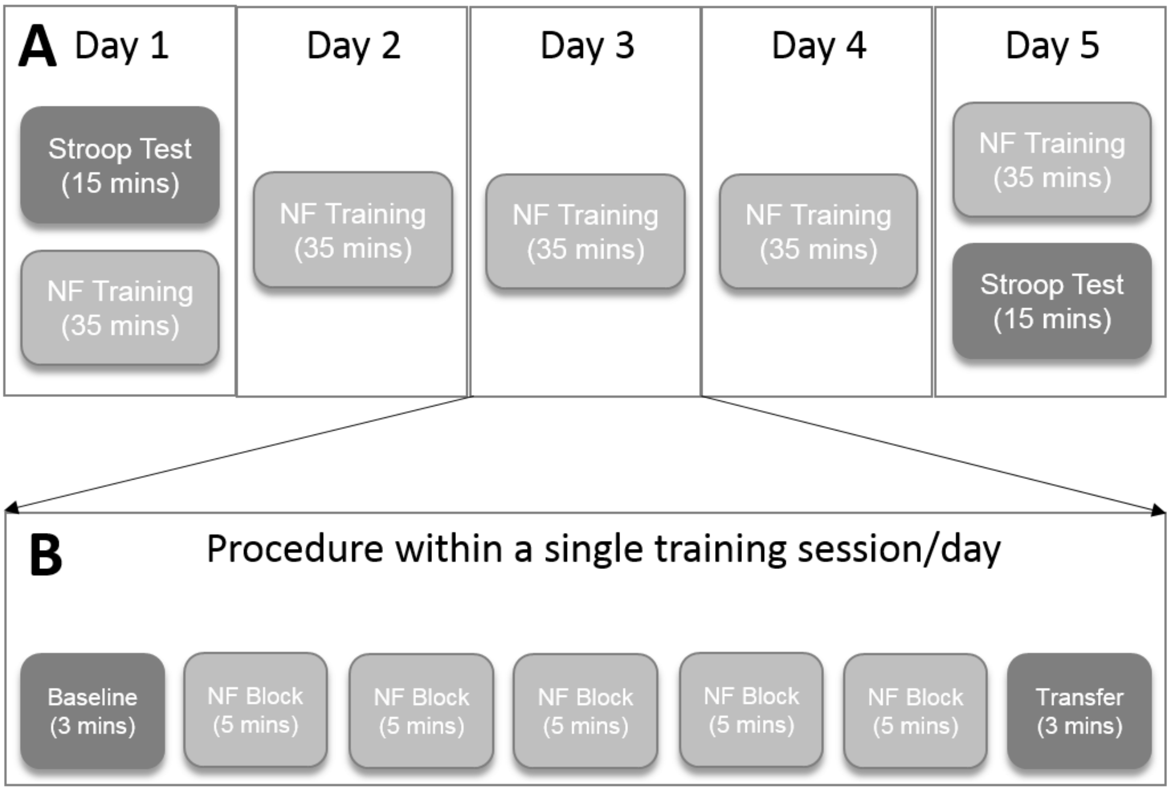

Figure 1. Overview of the experimental procedure: Box A shows the structure of the entire experiment, spanning 5 days. NF denotes neurofeedback training. Each neurofeedback session lasted approximately 35 minutes and was divided into 7 blocks, as visualised in box B. The session started with a baseline block, followed by 5 training blocks of 5 minutes each. The session was closed with a transfer block. Between each block, participants rested for approximately 1 minute.

The Stroop task was administered at the start of the first and at the end of the last session. Written test-specific instructions were given on-screen, followed by two practice blocks of 12 and 16 trials. The first practice block required participants to respond to the words "blue" and "red" written in blue and red font respectively. The second practice block also included incongruent and neutral trials (ampersands). The practice trials were accompanied by performance feedback. A sound was played when participants failed to answer within the specified time frame of 1 second. Additionally, each practice trial was followed by an on-screen notification informing participants about the accuracy of their answer and the response time. No feedback was given during the actual test, which consisted of four blocks with 96 trials each. Between each block, participants took short breaks.

The neurofeedback training consisted of 7 blocks. At the start of the first training session on day one, participants in the 3D group were encouraged to look around the entire virtual room. This was to ensure that they felt comfortable in the environment and also deepened their immersive experience. The training session started with a three-minute baseline block during which the participants' EEG was recorded without any neurofeedback. Once completed, the baseline measure appeared on the experimenter's control screen and the value was set as a threshold for that day. In the subsequent training blocks, each time the participants' alpha levels exceeded the threshold a point was awarded, causing the stimulus object (vase in 3D or square in 2D) to levitate.

Between each block, participants took breaks of approximately one minute. They were encouraged to move in their chair and stretch, without taking off the VR headset. The final block in each session was a transfer block during which the participants' EEG was again recorded without any feedback. Like the baseline block, the transfer was three minutes long. Following the last session on the fifth training day, participants were debriefed.

Data analysis and statistics

The neural data were analysed using 2 x 5 factorial ANOVAs crossing the factors feedback group and session/block. Learning scores were based on the points awarded for exceeding the threshold levels. Because these were likely to interact with the baseline (lower baselines will lead to more points and vice versa), a "learning score" was computed using the product of baseline and points (see also, Pineda et al., 2014). Both within- and between-session learning was analysed. The behavioural data were analysed with mixed ANOVAs including group and pre/post-NFT factors. Response times for correct trials were used in the basic Stroop analysis, while the preceding needed to be correct as well for the analyses of the Gratton effect. Finally, to assess our main hypothesis, we conducted a multi-level regression in which change in learning score was used to predict change in the Gratton effect. For this analysis, for each individual in each group the regression slope of the learning score across sessions was computed. This formed the predictor variable. Second, for each individual, the Gratton effect, $(RT_{cI} - RT_{cC}) - (RT_{iI} - RT_{iC})$, before and after NFT was computed. The difference between the two Gratton scores, the Gratton difference, was the dependent measure in the regression analysis.

Results

Neurofeedback learning

The learning curves for between- and within-session learning are shown in figures 2 and 3.

Between-session baseline measures

A 2 x 5 mixed factorial ANOVA on the baseline values across sessions revealed no significant main or interaction effects. Within-subject contrasts showed a quadratic trend in the session x group interaction [$F(1, 20) = 4.7$, $p = .042$, $\eta_p^2 = .19$], which was the result of the quadratic trend in the 2D group (see figure 2).

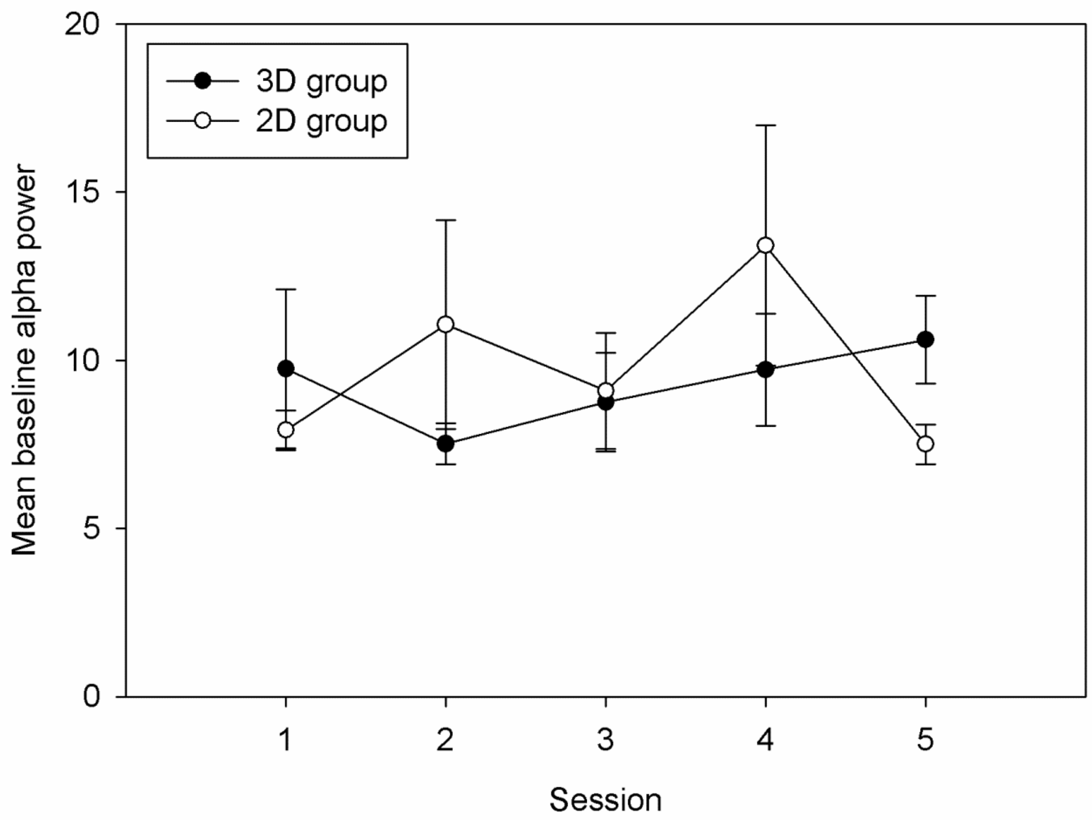

Figure 2. Mean baseline values (in μV^2) as a function of training day and feedback type. The error bars indicate standard error of the means.

Between- and within-session learning

As can be seen in figure 3A, both groups show a strong uplift from session 1 to 2 and another one from session 4 to 5. In between, the 3D group appears rather stable, while the 2D experiences a steep drop from M = 3684.31 in the second session to M = 1827.68 in the fourth. A 2x5 mixed factorial ANOVA did not show a significant main effect of group. Within-subject contrasts showed a significant cubic trend for session [$F(1, 20) = 8.07$, $p = .01$, $\eta_p^2 = .29$] and a significant linear trend for the session x group interaction [$F(1, 20) = 7.97$, $p = .01$, $\eta_p^2 = .28$]. Linear regressions were carried out on each group separately to determine the locus of this interaction. The regression was significant for the 3D group [$R^2 = .06$, $F(1, 53) = 4.35$, $p = .04$]. For every additional session, the learning scores increased by 376.1. With a baseline and raw point score of 9.74 and 326.5 respectively, this means an 11.8% points increase per session. In other words, participants stayed 9.65 seconds longer in an alpha state with each additional session. This effect was not found in the 2D group, which explains the above interaction.

Within-session learning was marginal for the 3D group [$F(4,40) = 2.17$, $p = .09$, $\eta_p^2 = .18$], but not the 2D group [$F(4,40) = 0.66$, $p = .61$, $\eta_p^2 = .06$], explaining the marginal interaction between group and within-session block [cubic: $F(1,20) = 3.30$, $p = .08$, $\eta_p^2 = .14$] revealed by a significant interaction between group and training block (see figure 3B).

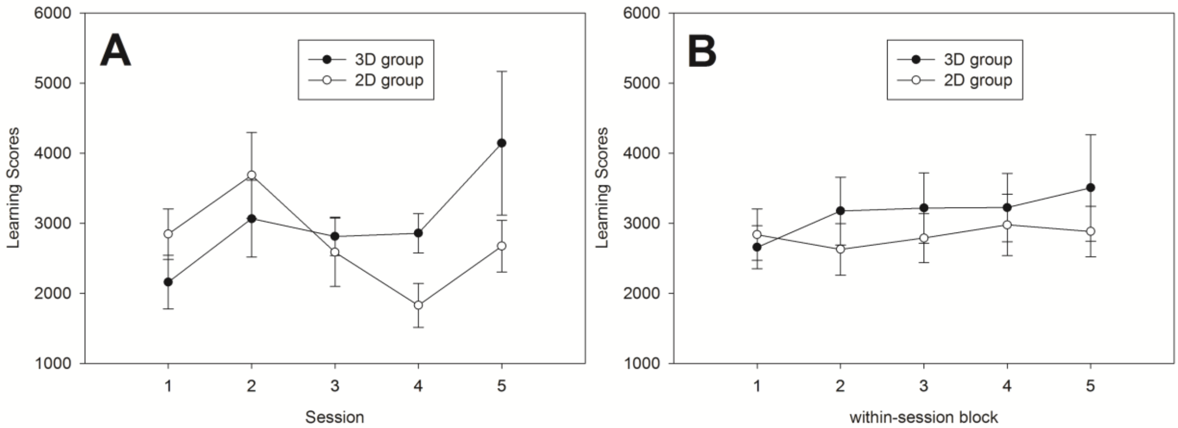

Figure 3. A. Mean learning scores as a function of training session and feedback type. B. Mean learning scores as a function of training block within sessions and feedback type. The error bars indicate standard error of the means.

Stroop effect

The mean response times for correct trials and the accuracy for the Stroop task are shown in table 1. One person from each group had to be excluded due to high error rates.

Table 1. Mean correct response times (in ms) and accuracy (in brackets) for the Stroop task

Group	Session	Stroop condition		
		Congruent	Incongruent	Neutral
2D	Pre-NFT	403 (.95)	417 (.90)	393 (.94)
	Post-NFT	376 (.96)	381 (.93)	369 (.95)
3D	Pre-NFT	409 (.96)	434 (.95)	406 (.96)
	Post-NFT	384 (.95)	397 (.96)	379 (.96)

Accuracy

A 2 x 2 x 3 mixed ANOVA revealed a main effect of condition [$F(1.5, 26.7) = 7.37$, $p < .01$, $\eta_p^2 = .29$], which was qualified by a condition x group interaction [$F(1.5, 26.7) = 6.33$, $p = .01$, $\eta_p^2 = .26$]. This interaction was due to an effect of condition in the 2D group [$F(2,18) = 8.47$, $p < .01$, $\eta_p^2 = .49$], but not in the 3D group ($p > .8$), showing lower accuracy for incongruent compared to congruent and neutral trials. No other comparisons were significant.

Response times

A 2 x 2 x 3 mixed ANOVA on correct response times only revealed a main effect of session [$F(1, 18) = 16.45$, $p < .01$, $\eta_p^2 = .48$], condition [$F(1.4, 25.6) = 11.88$, $p < .01$, $\eta_p^2 = .40$], and a marginal session x condition interaction [$F(2, 36) = 2.80$, $p = .074$, $\eta_p^2 = .14$].

Gratton effect

The mean response times for correct trials and the accuracy for the Gratton effect are shown in table 2 and figure 3.

Table 2. Mean correct response times (in ms) and accuracy (in brackets) for the four trial transitions used to calculate the Gratton effect.

Group	Session	Stroop trial sequence			
		cC	cI	iC	iI
2D	Pre-NFT	383 (.96)	413 (.94)	401 (.97)	394 (.92)
	Post-NFT	381 (.97)	374 (.92)	367 (.98)	363 (.97)
3D	Pre-NFT	391 (.95)	425 (.93)	410 (.98)	418 (.96)
	Post-NFT	387 (.97)	388 (.98)	379 (.93)	382 (.95)

Note: cC = previous congruent, current congruent; cI = previous congruent, current incongruent, iC = previous incongruent, current congruent; iI = previous incongruent, current incongruent.

Accuracy

A 2 x 2 x 2 x 2 mixed ANOVA revealed a main effect of current condition [$F(1,18) = 2.30$, $p < .05$, $\eta_p^2 = .21$], with better accuracy for congruent compared to incongruent trials. There was also a significant session x previous condition x group interaction [$F(1, 18) = 5.17$, $p < .05$, $\eta_p^2 = .22$], which was due to a session x previous condition interaction [$F(1, 9) = 5.43$, $p < .05$, $\eta_p^2 = .38$] for the 3D group. Ultimately, these interactions were due to a slightly better accuracy for trials succeeding a congruent compared to an incongruent trial [$F(1, 9) = 3.85$, $p = .08$, $\eta_p^2 = .30$] in the post-NFT session for the 3D group. No other main or interaction effects reached significance.

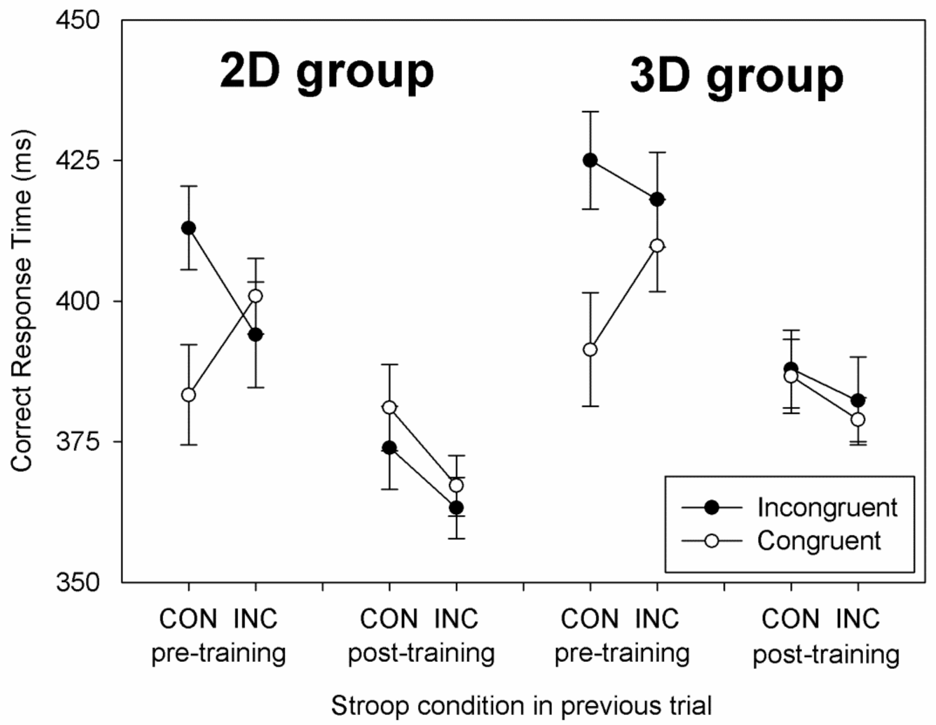

Figure 4. Mean correct response times (in ms) in the Stroop task in the pre- and post-training assessment session for both training groups broken down by the congruency of the previous condition. The two-way interactions seen in the pre-training session is the prototypical Gratton effect, which is theorised to be due to the deployment of top-down control when incongruency is detected.

Response times

A 2 x 2 x 2 x 2 mixed ANOVA revealed a main effect of session [$F(1, 18) = 15.17$, $p < .01$, $\eta_p^2 = .46$], reflecting the speed up over the sessions. There were no significant interactions with the factor group, but there was a marginal session x previous condition x current condition [$F(1, 18) = 4.03$, $p = .060$, $\eta_p^2 = .18$]. As per our a priori focus on the Gratton effect (previous x current interaction), we analysed the source of the (marginal) 3-way interaction, which was a Gratton effect in the pre-NFT session [$F(1, 18) = 6.70$, $p < .05$, $\eta_p^2 = .27$], but not in post-NFT session. There was a significant congruency effect when the previous trial was congruent [$F(1, 18) = 9.72$, $p < .01$, $\eta_p^2 = .35$], but absent when the previous trial was incongruent, corroborating the visual comparisons in figure 3. Thus, NFT abolished the Gratton effect in both groups.

Association between learning rate and change in cognitive control

The final analysis concerned the association between learning rate and the change in the Gratton effect. The scatterplot is shown in figure 4 together with regression lines. To make interpretation intuitive, we plotted the data such that higher scores means better control (basically computing $\text{Gratton}_{\text{before}} - \text{Gratton}_{\text{after}}$).

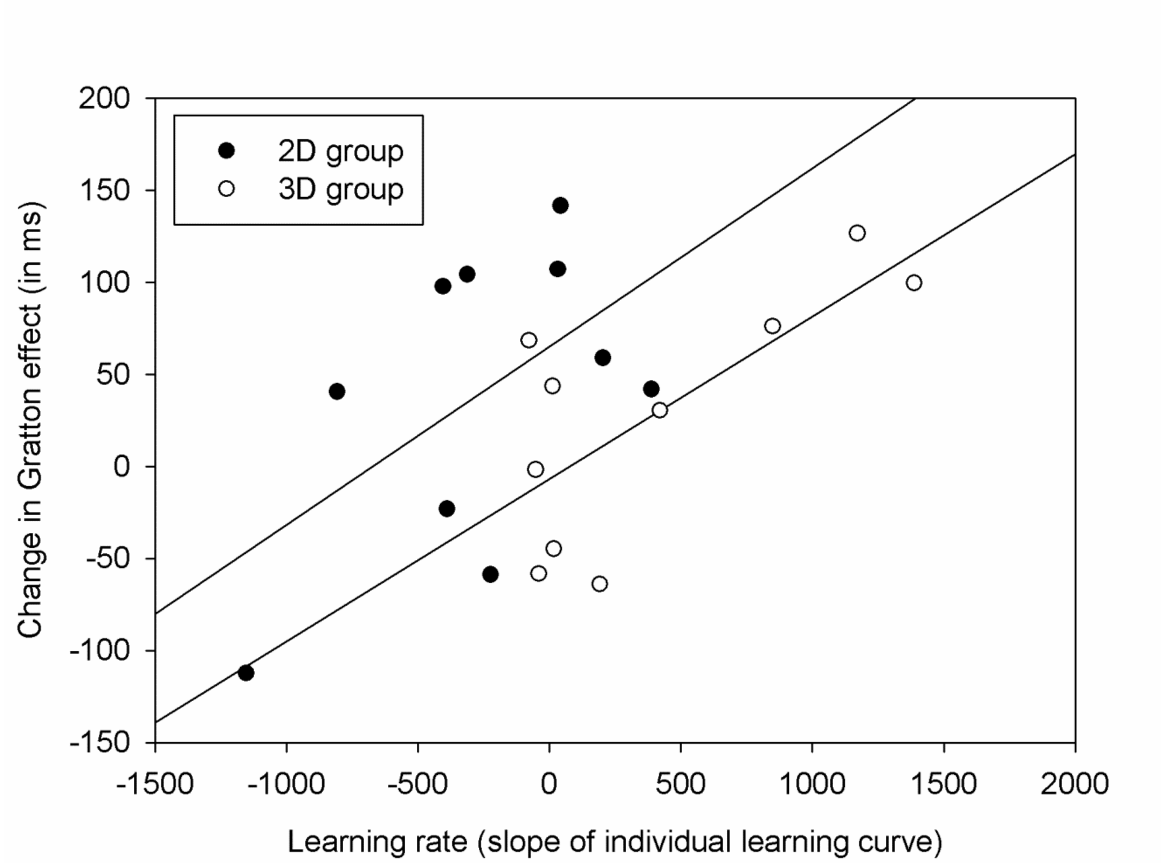

Figure 5. Scatterplot showing the association between the learning rate, i.e., the rate at which people learned to increase frontal alpha across sessions, and the change in the Gratton effect, which is 2-way interaction score, for both groups. To make the interpretation intuitive, we plotted better cognitive control as higher scores (indicating decrease in the Gratton effect). The regression lines are presented for both groups.

The regression analysis was significant [$F(3,16) = 3.51$, $p < .05$, $R^2 = 0.40$] and revealed that there was significant slope [$b_{\text{session}} = 0.10$, $SE = 0.04$, $p < .05$] and an effect of group [$b_{\text{group}} = 71.87$, $SE = 33.32$, $p < .05$], but no slope x group interaction ($p > .88$).

Discussion

We examined the effect of alpha oscillations over the prefrontal cortex (Fp2) on behavioural measures of top-down cognitive control. We used neurofeedback training to manipulate the magnitude of alpha power within the same participants. In order to enhance the variability in learning rates, we provided feedback either in a 2D or a 3D virtual reality environment. Our main finding is that larger learning rates, and thus larger frontal alpha power at the end of the training, are associated with enhanced attentional control.

Evidence of neural learning across sessions was found in the 3D but not in the 2D group. Our expectation was that learning would occur in both groups, with an advantage for the 3D condition. One explanation may be that the 2D group consisted of many non-learners: previous research found that 30-50% of participants do not show any neural learning (e.g. Hanslmayr et al., 2005; Zoefel et al., 2011). However, it is unlikely that all participants in the 2D group would randomly fall in the non-learner category. Furthermore, a 50% rate would mean that learning is merely at chance level, undermining the idea of neurofeedback.

An alternative explanation is that learning was hindered by the 2D environment itself. This would explain the negative learning slopes observed with some participants in the 2D group. Compared to the 3D experience, the 2D environment was rather monotonous and dark. This could increase boredom and reduce alpha. Dekker and colleagues counteracted such possibility by interspersing NFT sessions with cognitive tasks, thus ensuring that effects of boredom and routine are controlled (Dekker et al., 2014). This would certainly be a useful modification to the current study. Overall, however, the possibility of influences of boredom strengthens our call for a more immersive feedback protocol.

Furthermore, one could argue that the simplicity of the 2D environment should have facilitated an increase in alpha power. If alpha amplitudes decrease in response to a visual stimulus (see Berger, 1929), then habituation to that stimulus should reverse this effect. In fact, critics of NFT argue that this is what accounts for all effects observed in neurofeedback research (e.g., Beyerstein, 1990). In the present study, however, habituation is likely to have occurred in both conditions. If at all, the simple 2D environment should have been more susceptible to habituation, thus leading to faster increases in alpha amplitude.

Perhaps the overall effect was not very strong and slight immersion benefits pushed it over the significance level for the 3D group. Possible reasons for that could relate to the short schedule. Even though Zoefel et al. (2011) and Escolano et al. (2011) reported success with the same schedule, both studies did so after excluding one third of their sample. Our analysis was carried out on the full sample, but it is worth exploring whether a longer schedule could have strengthened the outcomes. In addition, it is possible that more sessions are needed to observe neural learning when training over anterior compared to over posterior electrode sites.

An interesting suggestion for the potentially modest learning effects comes from a study conducted by Witte et al. (2013). Using a sensorimotor rhythm protocol (SMR), they found that SMR was negatively correlated with the locus of control, and more specifically, with the confidence in one's ability to control technical devices. With the exception of three participants, our entire sample came from a technology company, so subjects were above-average in terms of technological literacy. Despite being instructed to relax into the paradigm, it is possible that their attitudes towards technology negatively affected the overall learning scores. Informal interviews post experiment indeed revealed that many participants experienced success only once they "stopped trying".

Learning did not appear to persist over sessions. There are several possible explanations. First, because our electrodes were attached to the VR device, baseline measures were taken while in the 2D/3D environment (albeit without any feedback-related movement). While this could have added a level of consistency and experimental control, it is also possible that such an environment was too stimulating to reflect a resting state. To avoid stimulation, some argue that baseline measures should be taken with eyes closed. However, such measures are likely to inflate the threshold, as naturally occurring alpha levels tend to be highest in the absence of any visual input. This would make the task of exceeding the threshold a near impossible endeavour. Thus, more recent recommendations are for an eyes-open baseline, as used in the present design. To control for the effects of visual stimulation, a baseline measure could be taken outside of the feedback medium, e.g., while facing a blank wall.

An alternative explanation for the lack of learning effects on baseline measurements relates to the environment in which training itself was conducted. Participants were tested in their workplace, often coming from or rushing to meetings. Taking the baseline measure at the start of the paradigm meant that many were stressed, only relaxing during the training session.

Despite the lack of persistent effects and the scope for methodological improvements, our study did corroborate the 3D advantages found by Gruzelier et al. (2010). Participants in the virtual reality group showed faster learning slopes than the 2D group. These benefits were achieved with commercial and portable EEG and VR devices, making our paradigm easier to replicate in research or adapt for clinical and commercial use. Since our groups differed only in the level of immersion, the effects cannot be attributed to differences in the learning environments (computer screen vs CAVE™ in Gruzelier et al., 2010), highlighting the importance of an engaging feedback interface.

The Stroop task is an established test of cognitive control and although a between-subjects ANOVA did not show any group-level effects, this was the result of the high variability in neural and behavioural measures. Such individual variability is widely reported in NFT research (see Gruzelier, 2014a) and a common approach to dealing with it is the exclusion of non-responders. A better way is to include all individuals in a regression analysis linking neural learning to behavioural outcome. Surprisingly, most NFT studies do not report whether measures of neural learning are correlated with behavioural changes. Gruzelier (2014a) notes that out of 23 studies showing successful NFT learning and improvements on behavioural measures, only 7 carried out these analyses.

Our regression analyses enabled us to harness the across-subject variability, thus revealing associations, which would not have been apparent otherwise. Our analyses showed that change in attentional control, as measured with the Gratton effect, was observed in both groups, decreasing in association to the learning rate of alpha upregulation. This provides the necessary prerequisite for assuming causality between frontal alpha and attentional control. This is in line with the predictions made using the conflict/control loop model by Botvinick and colleagues, which implicates the prefrontal cortex in directing the attention (Botvinick et al., 2001; 2004) and is in line with recent theoretical views on the functional role of alpha oscillations (e.g., Klimesch et al., 1999; Cooper et al., 2003; Doppelmayr et al., 2005; Klimesch et al., 2007). Although the latter theories were developed from data at non-frontal sites, the present study suggests that they can be extended to also capture prefrontal processing. This study therefore expands on the findings by Zoefel et al. (2011) and Escolano et al. (2011) who investigated alpha-related cognitive control in posterior locations only.

One may question whether the results are valid without the presence of a control group. However, our research question on the association between frontal alpha and control required a within-subjects design. Although a statistical discussion is beyond the scope of this paper, a group that did not do NFT or was trained on a different protocol will not affect the association obtained within the main group. Recently, Davelaar (2017) compared frontal alpha, Fz-theta, and SMR NFT protocols and demonstrated specific influences on first- and second-order measures of attention. This was obtained using both the standard between-groups analysis and a model-based analysis that address the underlying latent cognitive processes.

Although the current results confirm and extend previous research, further replications are needed with possible improvements of methodological nature, such as longer training schedules and a larger, more diverse participant sample. Beyond methodological improvements, our study suggests new directions for future development in NFT research. We used readily available and cost-effective commercial VR and EEG devices, showing how such feedback interfaces can be optimised to increase learning. This can be further extended by creating multi-modal feedback interfaces, providing better incentives and optimising reward structures. Building on research from human-computer interface design, different games could be created to cater for research with children and clinical samples. Linking back to Gruzelier et al. (2010) and Friedrich et al. (2014) such games could explore scenarios that optimise transferability of neural learning onto real life situations.

Conclusion

We created a new research paradigm using commercial VR and EEG devices to investigate the role of frontal alpha on attentional control. We showed using an individual differences approach that increase in frontal alpha is associated with enhanced attentional processing. We showed that learning slopes were higher in participants who received feedback in 3D virtual reality, highlighting the importance of immersion and engagement. Thus, the results favour 3D virtual learning environments and support the view that alpha oscillations are related to cortical processing efficiency.

Acknowledgements

We thank Roc Ramon and Pere Perez from Vysion360 for creating the bespoke software and providing all equipment used (free of charge) and Mervyn Etienne for his helpful comments and literature recommendations. This research did not receive any specific grant from funding agencies in the public, commercial, or non-for-profit sectors.

Disclosure Policy

The authors declare that there is no conflict of interest regarding the publication of this paper.

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