Neural correlates of the deployment of spatial attention, and their modulation by repetitive movements

Cameron Smith & Daniel H. Baker

Abstract

Introduction

The ability to orient and control the deployment of our attention to spatial locations or features of our environment is essential to our ability to perform tasks, focusing on relevant stimuli and disregarding those that are unnecessary for the task at hand (Hopfinger et al., 2000; Knudsen, 2007; Rueda et al., 2011). A classic technique for studying the deployment of attention in space is the Posner cueing paradigm, which demonstrates that it is possible for attention to be deployed to spatial locations independently of eye movements (Posner, 1980).

Individuals with neurodevelopmental disorders such as attention deficit hyperactivity disorder (ADHD) and autism present with deficits in attention (American Psychiatric Association, 2013; (Allen and Courchesne, 2001). It has been suggested that repetitive stereotypies, or 'stimming' behaviours, are linked to these deficits in attention – in the few studies where they have been asked, individuals who stim report that it benefits their ability to focus, and that the behaviours aid in emotional regulation (Kapp et al., 2019; Steward, 2015). It has been proposed that an improved ability to focus through stimming may have a neural basis (McCarty and Brumback, 2021). Building on these theories and research, we tested the effect of stimming on performance in a Posner cueing task.

The Posner cueing paradigm (Posner, 1980) involves the participant attending to a central fixation point, then receiving a cue (which may be exogenous, where attention is captured through bottom-up processes; or endogenous, where attention is controlled by top-down processes, such as attending selectively to cues of the correct colour (Leblanc et al., 2008)) indicating that a stimulus is about to appear either to the left or the right of the fixation point (Thiery et al., 2016). The assumption underlying the task is that if participants successfully orient their attention to the cued location, then their reaction times will be shorter and responses more

accurate for congruent trials (where the stimulus appears at the cued location) than for incongruent trials (where the stimulus appears at the uncued location); this has been demonstrated extensively (Thiery et al., 2016). The reaction time difference was found by Posner (1978) to be 25ms faster for congruent trials and 40ms slower for incongruent trials, compared to a neutral cue condition.

This paradigm has been combined with EEG to investigate the neural basis of spatial attention. For example, Landau et al. (2007) investigated gamma-band activity during a Posner cueing task, comparing congruent and incongruent trials. Gamma range responses were associated with voluntary shifts in attention, e.g., attending to the left of the fixation point following a left-pointing arrow cue, but were absent when attention was involuntarily captured by the appearance of a stimulus in the uncued location on incongruent trials; this suggests that voluntary and involuntary processes of attention deployment are controlled by separate mechanisms. Thiery et al. (2016) investigated two specific ERPs, the N2pc component (a negative response typically seen at around 200ms post stimulus, in the posterior-contralateral region) and the SPCN component (sustained posterior contralateral negativity). They used multivariate pattern analysis and used the decoder accuracy to determine that these two components were able to predict the focus of participants' spatial attention. This was modulated by the varied distance of the stimulus from the central fixation (further being better decoded).

A combined EEG and TMS study by Capotosto et al. (2012) demonstrated that the application of TMS to the right intraparietal sulcus (IPS) impairs target detection, particularly on incongruent trials. They additionally noted that the P3 response amplitude was affected by this; on incongruent trials its amplitude was significantly lower, and on congruent trials it was significantly higher. The IPS has been previously identified as an important region in attentional deployment by Vossel et al. (2009) in an fMRI study identifying regions that are selectively active on congruent and incongruent trials. The right IPS and, additionally, the right inferior frontal gyrus were implicated in attentional processes related to both types of trial. Peelen et al. (2004) concluded that both endogenous and exogenous orienting cues involve the same network in their fMRI study, implicating frontal and parietal regions (the premotor cortex, posterior parietal cortex, medial frontal cortex, and right inferior frontal cortex). Fitzgerald et al. (2015) conducted an MRI study using the Posner cueing task and found that activation in the ventral attention network differed between individuals with autism and controls; individuals with autism also showed weaker functional connectivity in the dorsal attentional network compared to their neurotypical counterparts.

A number of developmental disorders involve deficits in attention, notably ADHD and autism. In the case of ADHD, attention deficits are a defining feature of the condition (American Psychological Association, 2013). For autism, attention deficits are not an explicit part of the diagnostic criteria (although restricted interests, which are included, are somewhat related), but both attentional deficits and strengths are widely reported in autistic individuals. They are typically more distractible, demonstrating 'underselective' attention, but also demonstrate 'overselective' attention where they attend intensely to a more limited subset of stimuli. This 'overselective' attention has been suggested to be linked to restricted interests, which is also

sometimes referred to as 'hyperfocus', where a task is the subject of intense focus for the individual (e.g., Dupuis et al., 2022). These differences appear to have a neural basis – they have been linked to unusually wide sulci in the parietal lobe (Allen and Courchesne, 2001). Hyperfocus is also widely self-reported in ADHD, despite a lack of clinical research into the phenomenon (Hupfeld et al., 2019).

These marked differences in attentional deployment seen in both conditions are worth considering in the framework of the transdiagnostic approach, which seeks to identify core deficiencies that result in the presentation of traits from multiple disorders, instead of approaching different disorders as entirely separate even within the same individual (Newby et al., 2015). ADHD is the most common comorbidity of autism, and even without a dual diagnosis, 30-80% of individuals with autism present symptoms of ADHD, and 20-60% of children with ADHD exhibit autism-like traits (Zhang et al., 2022). Some shared deficiencies that have already been identified in the case of autism and ADHD include fine motor function and verbal fluency, alongside some structural differences in the brain (Zhang et al., 2022).

Stimming behaviours are commonly seen in individuals with diagnoses of autism and/or ADHD, and involve repetitive movements, typically featuring the arms, hands, or entire body (Chadehumbe, 2018), for example hand flapping (Kapp et al., 2019). They are also observed in neurotypical individuals, but at much lower rates than in neurodiverse individuals (Chadehumbe, 2018). The behaviours are typically defined as involuntary, but pleasant (Chadehumbe, 2018; Kapp et al., 2019; Steward, 2015), and are associated with emotional states such as stress, boredom, concentration, or excitement (Katherine, 2018). They are often defined as purposeless (e.g., Tan et al., 1997) but self-reports from individuals with autism claim that stimming aids the regulation of their emotions (Kapp et al., 2019; Steward, 2015).

A type of vocal stimming called echolalia has been consistently demonstrated to have benefits for autistic children in the acquisition of language (Charlop, 1983; Pruccoli et al., 2021). This is one of the few instances that stimming has been researched in terms of its potential function. Echolalic utterances, which typically involve repeating words spoken by another, have also been identified as having predominantly communicative functions (Prizant and Duchan, 1981). This opens up an avenue to research potential benefits that other types of stimming may provide.

Current research into stimming is largely focussed on designing interventions to eliminate the behaviours, for example the use of weighted vests (Fertel-Daly et al., 2001). Taking this approach without first attempting to understand if there are benefits to the behaviour seems ill-advised. McCarty and Brumback (2021), for example, proposed based on self-reports of the benefits of stimming (focus, coping with overwhelming sensory input, and relaxation) that regular motor movements may generate (or be a by-product of) rhythmic oscillations in the motor cortex, which entrain oscillations in the sensory cortex. This entrainment might improve information transfer in the sensory cortex, effectively normalising the atypical motor and sensory oscillations observed in the brains of autistic individuals both during tasks (Milne et al., 2009; Murphy and Benítez-Burraco, 2017; Snijders et al., 2013) and at rest (Berman et al., 2015; Wang et al., 2013).

There is heavy stigma around stimming behaviours, with many individuals reporting they have been explicitly instructed not to stim, despite attempts at repression causing them some discomfort (Steward, 2015). Individuals with autism state that they believe stimming should not be stigmatised in this way, and that they should be allowed to act in the way that feels natural to them (Kapp et al., 2019). Research into potential benefits of stimming is important as a step towards dispelling this stigma, and discouraging interventions that aim to eliminate the behaviour.

This study involved two experiments. In the first experiment, participants completed a Posner cueing task while EEG recordings were taken; a pattern classifier then attempted to differentiate, using the participants' brain activity, whether they attended to the left vs. to the right following the cue onset. This is similar to the methodology used by Thiery et al. (2016): by measuring the timecourse of classifier accuracy, we are provided with an index of the deployment of spatial attention.

The second study extended this paradigm by adding a stimming condition. The accuracy of the classifier was compared between conditions where the participants were permitted to stim during the trials, or instructed to keep still. In this case, we used decoding accuracy to assess whether stimming provided a benefit in terms of the deployment of spatial attention; if there was a benefit, the classifier accuracy would be higher, as the EEG signal would differ more between conditions due to the greater focus of attention in different spatial locations. For the purposes of our analyses, due to an insufficiently sized and heterogeneous clinical group, we grouped the participants based on whether or not they reported stimming in their everyday lives; as discussed previously, neurotypicals often engage in stimming (Chadehumbe, 2018), and 64% of our participants reported in the pre-experiment questionnaire that they typically engaged in stimming.

Methods

Participants

41 participants took part in Experiment 1, but four produced very noisy data so were excluded, leaving a sample of 37 participants (20 male, 17 female). A total of 22 participants took part in Experiment 2 (8 male, 14 female). Participants in Experiment 2 were asked to report diagnoses of neurodevelopmental disorders – 17 had no diagnosis, 2 had a diagnosis of autism, and 3 had a diagnosis of ADHD. 15/22 participants further reported they typically engaged in stimming behaviours, while 7 reported that they did not.

Apparatus and stimuli

Stimuli were displayed on a ViewPixx 3D display (VPixx Technologies Inc., Quebec, Canada) with a diagonal extent of 24 inches, a refresh rate of 120Hz, and a resolution of 1920x1080

pixels. The screen was viewed by the participant from a distance of 57cm, resulting in a spatial resolution of 36 pixels per degree of visual angle. The display was gamma corrected using a Minolta LS110 photometer to ensure a linear luminance response. Stimuli were generated and displayed using a Mac Pro computer running Matlab, with the experiment script making use of functions from Psychtoolbox 3 (Brainard, 1997; Kleiner et al., 2007; Pelli, 1997).

In both experiments, EEG recordings were acquired using an ANT Neuroscan 64-channel EEG system (ANT Neuro). Electrodes were mounted in a waveguard cap, arranged according to the 10/20 system, and were referenced to the whole head average with the ground electrode located at position AFz. EEG signals were recorded at 1kHz. In Experiment 2, participants' eye movements were also recorded using an EyeLink 1000 (SR Research Ltd., Ottawa, Canada) eye tracker, also sampling at 1kHz. Low-latency digital triggers were sent from the stimulus computer to the EEG system using an 8-bit parallel cable.

Target stimuli in both experiments were horizontal sine-wave gratings with a diameter of 4 degrees, and a spatial frequency of 2c/deg. The target appeared offset by 8 degrees to either the left or the right of the central fixation point. The base contrast of the target was 50%, and either the upper or lower half of the grating contained a contrast increment of a further 10%. Participants were asked to indicate whether the upper or lower half of the grating contained the increment using arrow keys on the computer keyboard. The fixation cross was 0.25×0.25 degrees, and was displayed throughout.

Each trial was preceded by a cue. In Experiment 1 the cue was a face with eyes pointing left or right. In Experiment 2 the cue was an arrow pointing left or right. The face cues used in Experiment 1 were the average of 22 female faces taken from the NimStim database (Tottenham et al., 2009) and were digitally altered so that the eyes were directed to the left or the right. The face had a width of 3 degrees and a height of 4 degrees and was displayed in the centre of the screen. The arrow cue used in Experiment 2 was 1.4 degrees long and was displayed in the centre of the screen.

Procedure

Participants in both experiments completed four blocks of the Posner cueing task, with each block consisting of 200 trials. They were instructed to keep their eyes focused on the central fixation cross, and to attend to the gratings without shifting their gaze. During each trial, participants viewed a fixation cross, which remained on the screen throughout the trial (excluding times when the cue appeared on the screen). The cue stimulus appeared for 200ms, followed by a randomly determined gap of 400-600ms before the grating appeared on the screen. The target grating was then displayed for 200ms. Participants were required to report whether the upper or lower half of the grating appeared higher in contrast; following their response, a randomly determined interval drawn from a normal distribution (average 1000ms, with a standard deviation of ±200ms) preceded the next appearance of the cue. This procedure is

illustrated in Figure 1 for the face cue (panel a) and the arrow cue (panel b). Cue congruence was 75% in both experiments, meaning that each participant contributed a total of 600 congruent trials and 200 incongruent trials across the experiment.
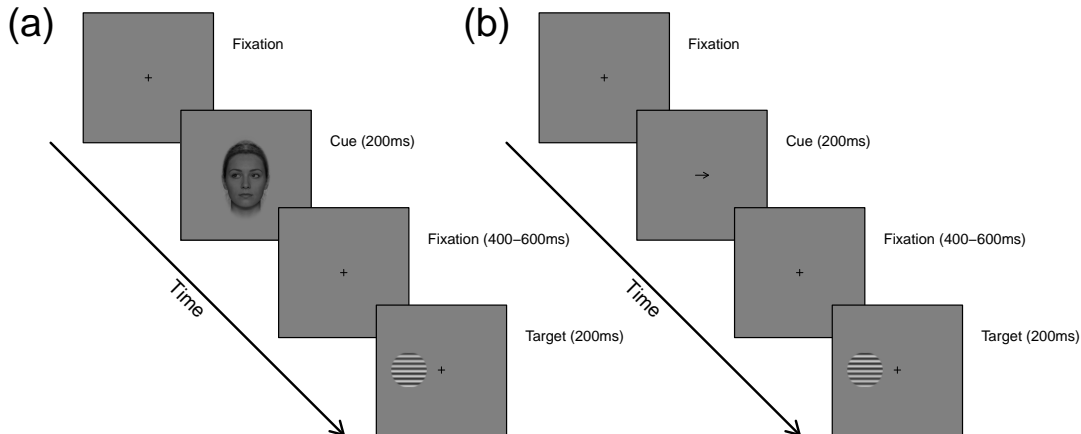

Figure 1: Illustration of trial procedure for both experiments. In panel (a), the cue was a face with eyes pointing to either the left (as pictured) or the right. In panel (b), the cue was an arrow. Target gratings had a contrast of 50%, plus a 10% increment in either the upper or lower half. Note that images are not drawn to scale in this schematic to aid visibility - see text for actual dimensions.

In Experiment 2, participants were additionally instructed to stim, using a movement restricted to one hand only, in half of the blocks. This was to ensure minimal distortion of the EEG signal resulting from movement. The order in which participants completed stimming or non-stimming blocks was counterbalanced; half the participants were instructed to stim on blocks 1 and 3, while the other half were instructed to stim on blocks 2 and 4.

Data analysis

Raw EEG data were converted into EEGlab .set format using Matlab and the EEGlab toolbox (Delorme and Makeig, 2004). We then used MNE python for the main analysis. Data were bandpass filtered between 0.2 and 30Hz, and then epoched using the event timestamps. We performed classification using a linear classifier with 10-fold cross-validation on the voltage data across all electrodes (excluding electrodes *M1* and *M2*), independently at each time point and for each participant. We then averaged classification accuracy across participants to generate the timecourses used in the main analysis. We calculate Bayes factors (Rouder et al., 2009) to compare classification accuracy to chance performance (50% correct) and to make between conditions and groups, but also report frequentist tests for comparison. We express Bayes factors in logarithmic units to account for extreme values ($log_{10}BF_{10}$), such

that a Bayes factor of 3 is a $log_{10}BF_{10} = 0.48$, and constitutes convincing evidence for the alternative hypothesis, a Bayes factor of 10 is a $log_{10}BF_{10} = 1$, and constitutes strong evidence for the alternative hypothesis, and a Bayes factor of 30 is a $log_{10}BF_{10} = 1.48$, and constitutes overwhelming evidence for the alternative hypothesis.

Open science practices

Raw and processed data are available for both experiments at the project repository on the Open Science Framework website: http://doi.org/10.17605/OSF.IO/YUHZ4. Experiment code and analysis code are provided in the linked Github repository (https://github.com/bakerdh/attentionstimming), which contains a fully computationally reproducible document written in Quarto, that generates this manuscript using the raw data.

Results

Experiment 1

We first analysed the behavioural responses during the experiment, comparing accuracy and reaction times between stimuli shown in the cued (i.e. a congruent target) and uncued (an incongruent target) location. There was a highly significant effect of cue congruency on both accuracy ($log_{10}BF_{10} = 1.77$, $t = 3.82$, $p <0.001$, $d = 0.61$) and reaction time ($log_{10}BF_{10} = 6.08$, $t = -7.26$, $p <0.001$, $d = 1.16$), as shown in Figure 2. Responses to targets in the cued location were both faster ($M_{diff} = 51$ ms) and more accurate ($M_{diff} = 3\%$) than for those in the uncued location, showing a classic Posner cueing effect.

We next explored the EEG data in response to both the cue presentation and the target presentation. There were typical evoked potentials in response to both types of stimulus, as summarised in Figure 3b,c,e,f. Patterns of voltage across the scalp showed similar lateralisation effects both for cues pointing to either the left or right, and for targets presented to either the left or right. Multivariate pattern analysis was able to decode the side of cue presentation from around 300ms after cue onset (see Figure 3a), with a maximum accuracy of 69%, and a plateau of high performance from around 500-1000ms. This relatively late onset of above-chance classification likely reflects the deployment of covert spatial attention to one side of the visual field, and is therefore a neural index of attentional focus. The pattern classifier could decode the side of target presentation with much greater accuracy (maximum of 89%), from around 100ms after target onset (black curve in Figure 3d). Finally, we were able to decode cue congruency (i.e. whether the target presented was on the side indicated by the cue) with a maximum accuracy of 62%, and a similar timecourse to the decoding of target side (green curve in Figure 3d). Overall, these results indicate that our EEG data are sufficiently sensitive to provide an index of the deployment of spatial attention.
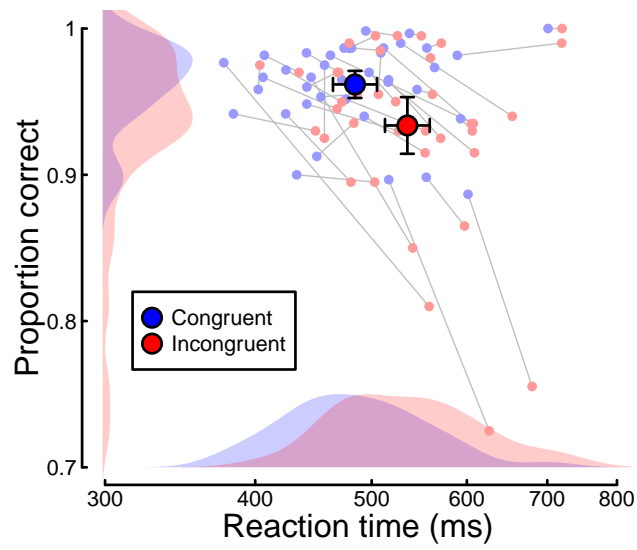
Figure 2: Summary of reaction time and accuracy data for the cueing task in Experiment 1. Small points show data for individual participants (N = 39), and larger points give the group means. Error bars indicate 95% confidence intervals.
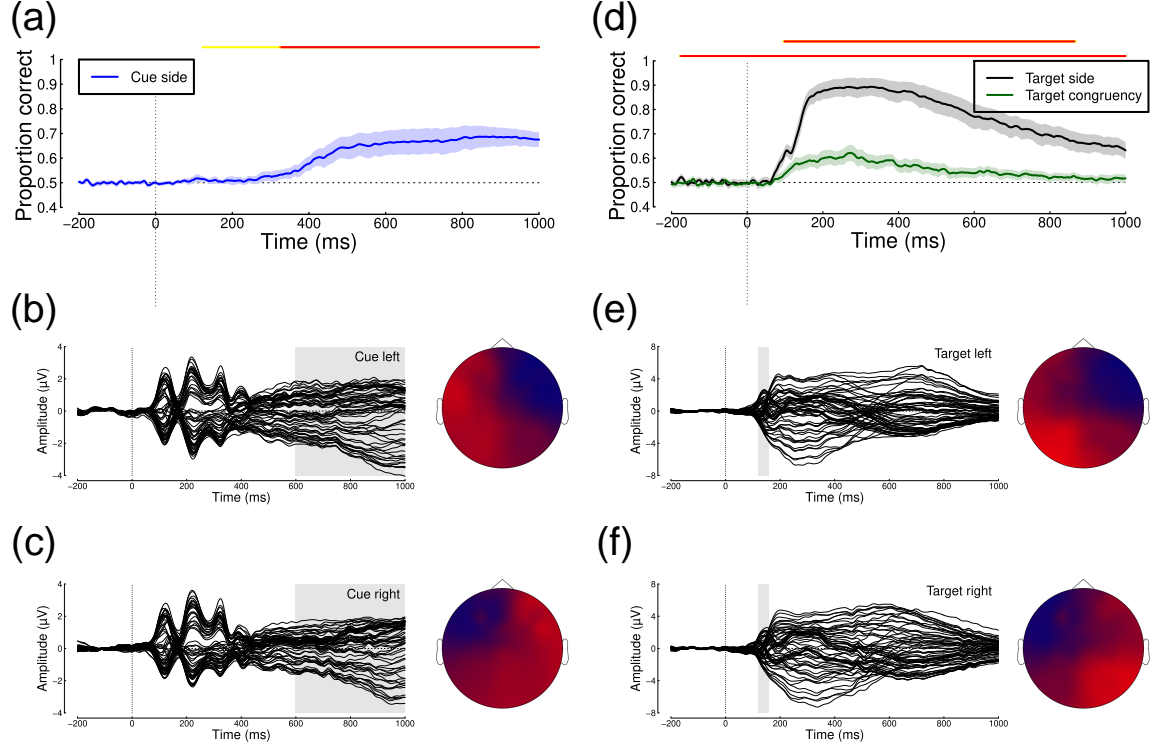
Figure 3: Summary of EEG data from Experiment 1. Panel (a) shows decoding accuracy of a pattern classification algorithm trained on responses to the cue stimulus (Time 0 is the cue onset). ERPs and scalp topographies are shown for cues pointing left (b) and right (c), with the shaded regions indicating the time period over which voltages were averaged to generate the scalp plots. Panel (d) shows decoding accuracy for classifying target location (black curve) or cue congruency (green curve) in response to the target (Time 0 is the target onset). ERPs and scalp topographies are shown for targets on the left (e) and right (f) side of fixation, with the shaded regions indicating the time period over which voltages were averaged to generate the scalp plots. Shaded regions in panels (a,d) indicate 95% confidence intervals, and lines above y=1 indicate Bayes factor scores above 3 (yellow >3; orange >10; red >30).

9

Experiment 2

In Experiment 2, we replicated the basic design of Experiment 1, but this time with an added 'stimming' condition, and with participants divided into groups based on their self-reported stimming behaviour. Pooling across all participants, for accuracy there was no effect of cue congruency ($log_{10}BF_{10}$ = -0.64, $F = 0.06$, $p = 0.803$, $\eta^2_G = 0$), stimming condition ($log_{10}BF_{10}$ = -0.65, $F = 0$, $p = 0.977$, $\eta^2_G = 0$), nor an interaction between the two ($log_{10}BF_{10}$ = -0.48, $F = 0.8$, $p = 0.383$, $\eta^2_G = 0$). For reaction time, there were significant effects of cue congruency ($log_{10}BF_{10} = 3.1$, $F = 29.28$, $p < 0.001$, $\eta^2_G = 0.07$) and stimming condition ($log_{10}BF_{10} = 1.09$, $F = 7.1$, $p = 0.01$, $\eta^2_G = 0.04$), as well as an interaction between the two ($log_{10}BF_{10}$ = -0.33, $F = 12.03$, $p = 0.002$, $\eta^2_G = 0.01$). Note that reactions were faster in the non-stimming condition (591 ms) than in the stimming condition (632 ms). These effects remained significant in the group who reported stimming (N=14) for the effects of cue congruency ($log_{10}BF_{10} = 1.47$, $F = 11.42$, $p < 0.005$, $\eta^2_G = 0.06$), stimming condition ($log_{10}BF_{10} = 0.41$, $F = 4.89$, $p = 0.045$, $\eta^2_G = 0.03$), and their interaction ($log_{10}BF_{10}$ = -0.33, $F = 8.71$, $p = 0.011$, $\eta^2_G = 0.01$). For the group who did not report stimming (N=8), only the effect of cue congruency was significant ($log_{10}BF_{10} = 1.03$, $F = 40.15$, $p < 0.001$, $\eta^2_G = 0.11$).
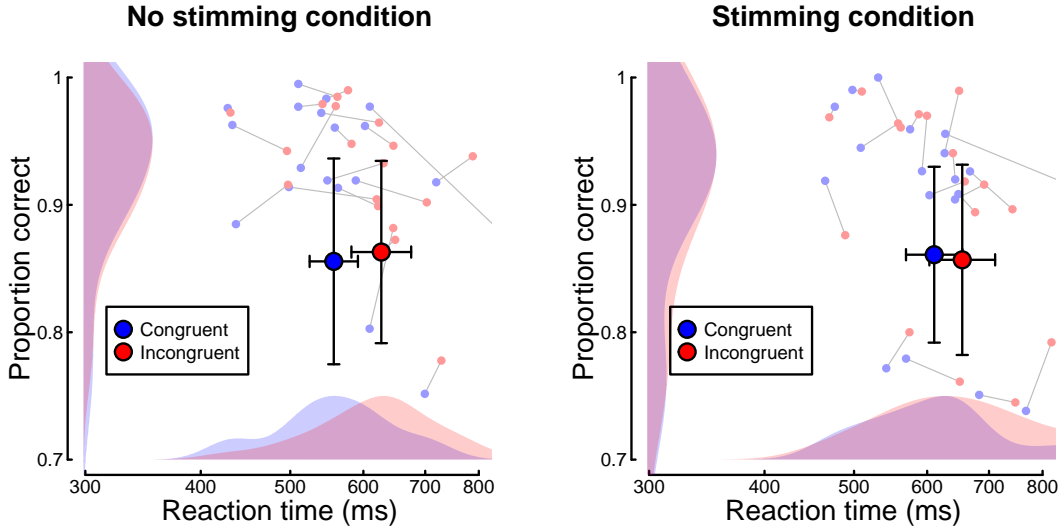

Figure 4: Summary of reaction time and accuracy data for the cueing task in Experiment 2. Small points show data for individual participants (N = 22), and larger points give the group means. Error bars indicate 95% confidence intervals.

The EEG results from Experiment 2 are summarised in Figure 5. Panels (a,b) demonstrate that multivariate pattern analysis is able to decode cue direction, target side, and target congruency with similar timecourses to Experiment 1 (see Figure 3), though with somewhat

lower accuracy overall. We then compared decoding accuracy for cue side and cue congruency between the stimming group (N=14), and the non-stimming group (N=8). Although decoding accuracy appeared to be slightly higher for the no stimming group for cue side (Figure 5c), this difference was not convincing. Accuracy for cue congruency was very similar for the two groups (Figure 5d). Finally, we compared the deployment of spatial attention between stimming and non-stimming conditions for each of the two groups. There appeared to be a slight decrease in decoding accuracy in the non-stimming group when they were asked to stim (Figure 5f), but no differences in the stimming group (Figure 5e).

Discussion

References

Allen G, Courchesne E. 2001. Attention function and dysfunction in autism. *Front Biosci* **6**:D105–19. doi:10.2741/allen

Berman JI, Liu S, Bloy L, Blaskey L, Roberts TPL, Edgar JC. 2015. Alpha-to-gamma phase-amplitude coupling methods and application to autism spectrum disorder. *Brain Connect* **5**:80–90. doi:10.1089/brain.2014.0242

Brainard DH. 1997. The psychophysics toolbox. *Spat Vis* **10**:433–6.

Capotosto P, Corbetta M, Romani GL, Babiloni C. 2012. Electrophysiological correlates of stimulus-driven reorienting deficits after interference with right parietal cortex during a spatial attention task: A TMS-EEG study. *J Cogn Neurosci* **24**:2363–71. doi:10.1162/jocn_a_00287

Chadehumbe M. 2018. A comprehensive review of motor stereotypies in children. *Current Pediatrics Reports* **6**:30–33. doi:10.1007/s40124-018-0153-z

Charlop MH. 1983. The effects of echolalia on acquisition and generalization of receptive labeling in autistic children. *J Appl Behav Anal* **16**:111–26. doi:10.1901/jaba.1983.16-111

Delorme A, Makeig S. 2004. EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *J Neurosci Methods* **134**:9–21. doi:10.1016/j.jneumeth.2003.10.009

Dupuis A, Mudiyanselage P, Burton CL, Arnold PD, Crosbie J, Schachar RJ. 2022. Hyperfocus or flow? Attentional strengths in autism spectrum disorder. *Front Psychiatry* **13**:886692. doi:10.3389/fpsyt.2022.886692

Fertel-Daly D, Bedell G, Hinojosa J. 2001. Effects of a weighted vest on attention to task and self-stimulatory behaviors in preschoolers with pervasive developmental disorders. *The American Journal of Occupational Therapy* **55**:629â 640. doi:10.5014/ajot.55.6.629

Fitzgerald J, Johnson K, Kehoe E, Bokde ALW, Garavan H, Gallagher L, McGrath J. 2015. Disrupted functional connectivity in dorsal and ventral attention networks during attention orienting in autism spectrum disorders. *Autism Res* **8**:136–52. doi:10.1002/aur.1430

Hopfinger JB, Buonocore MH, Mangun GR. 2000. The neural mechanisms of top-down attentional control. *Nat Neurosci* **3**:284–91. doi:10.1038/72999
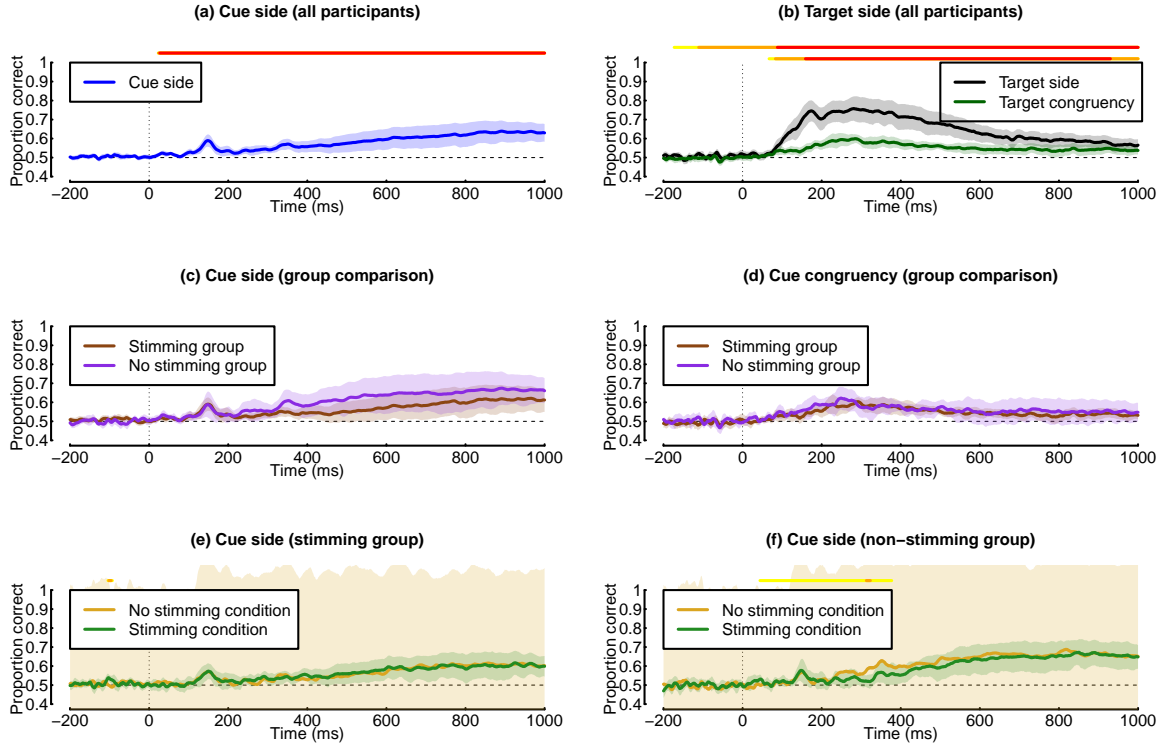
Figure 5: Summary of EEG data from Experiment 2. Panel (a) shows decoding accuracy of a pattern classification algorithm trained on responses to the cue stimulus (Time 0 is the cue onset) for the full sample of participants (N=22). Panel (b) shows decoding accuracy for classifying target location (black curve) or cue congruency (green curve) in response to the target (Time 0 is the target onset), again for all participants. Panels (c,d) compare decoding between the stimming (N=14) and non-stimming (N=8) participants for cue side and cue congruency. Panels (e,f) compare decoding accuracy for cue side within each group, and between the stimming and no stimming conditions. Shaded regions in all panels indicate 95% confidence intervals, and lines above y=1 indicate Bayes factor scores above 3 (yellow >3; orange >10; red >30).

Hupfeld KE, Abagis TR, Shah P. 2019. Living "in the zone": Hyperfocus in adult ADHD. *Atten Defic Hyperact Disord* **11**:191–208. doi:10.1007/s12402-018-0272-y

Kapp SK, Steward R, Crane L, Elliott D, Elphick C, Pellicano E, Russell G. 2019. 'People should be allowed to do what they like': Autistic adults' views and experiences of stimming. *Autism* **23**:1782–1792. doi:10.1177/1362361319829628

Katherine M. 2018. Stereotypic movement disorders. *Seminars in Pediatric Neurology* **25**:19–24. doi:https://doi.org/10.1016/j.spen.2017.12.004

Kleiner M, Brainard DH, Pelli DG. 2007. What's new in psychtoolbox-3? *Perception* **36S**:14.

Knudsen EI. 2007. Fundamental components of attention. *Annu Rev Neurosci* **30**:57–78. doi:10.1146/annurev.neuro.30.051606.094256

Landau AN, Esterman M, Robertson LC, Bentin S, Prinzmetal W. 2007. Different effects of voluntary and involuntary attention on EEG activity in the gamma band. *Journal of Neuroscience* **27**:11986–11990.

Leblanc E, Prime DJ, Jolicoeur P. 2008. Tracking the location of visuospatial attention in a contingent capture paradigm. *J Cogn Neurosci* **20**:657–71. doi:10.1162/jocn.2008.20051

McCarty MJ, Brumback AC. 2021. Rethinking stereotypies in autism. *Seminars in Pediatric Neurology* **38**:100897. doi:https://doi.org/10.1016/j.spen.2021.100897

Milne E, Scope A, Pascalis O, Buckley D, Makeig S. 2009. Independent component analysis reveals atypical electroencephalographic activity during visual perception in individuals with autism. *Biol Psychiatry* **65**:22–30. doi:10.1016/j.biopsych.2008.07.017

Murphy E, Benítez-Burraco A. 2017. Language deficits in schizophrenia and autism as related oscillatory connectomopathies: An evolutionary account. *Neurosci Biobehav Rev* **83**:742–764. doi:10.1016/j.neubiorev.2016.07.029

Newby JM, McKinnon A, Kuyken W, Gilbody S, Dalgleish T. 2015. Systematic review and meta-analysis of transdiagnostic psychological treatments for anxiety and depressive disorders in adulthood. *Clin Psychol Rev* **40**:91–110. doi:10.1016/j.cpr.2015.06.002

Peelen MV, Heslenfeld DJ, Theeuwes J. 2004. Endogenous and exogenous attention shifts are mediated by the same large-scale neural network. *NeuroImage* **22**:822–830. doi:https://doi.org/10.1016/j.neuroimage.2004.01.044

Pelli DG. 1997. The VideoToolbox software for visual psychophysics: Transforming numbers into movies. *Spat Vis* **10**:437–42.

Posner MI. 1980. Orienting of attention. *Q J Exp Psychol* **32**:3–25. doi:10.1080/00335558008248231

Posner MI. 1978. Chronometric explorations of mind. Lawrence Erlbaum.

Prizant BM, Duchan JF. 1981. The functions of immediate echolalia in autistic children. *J Speech Hear Disord* **46**:241–9. doi:10.1044/jshd.4603.241

Pruccoli J, Spadoni C, Orsenigo A, Parmeggiani A. 2021. Should echolalia be considered a phonic stereotypy? A narrative review. *Brain Sci* **11**. doi:10.3390/brainsci11070862

Rouder JN, Speckman PL, Sun D, Morey RD, Iverson G. 2009. Bayesian t tests for accepting and rejecting the null hypothesis. *Psychon Bull Rev* **16**:225–37. doi:10.3758/PBR.16.2.225

Rueda MR, Posner MI, Rothbart MK. 2011. 15: Attentional control and self-regulation. In: Vohs KD, Baumeister RF, editors. Handbook of Self-Regulation. Guilford Press. pp. 284–299.

Snijders TM, Milivojevic B, Kemner C. 2013. Atypical excitation-inhibition balance in autism

captured by the gamma response to contextual modulation. *Neuroimage Clin* **3**:65–72. doi:10.1016/j.nicl.2013.06.015

Steward R. 2015. Repetitive stereotyped behaviour or "stimming": An online survey of 100 people on the autism spectrum.

Tan A, Salgado M, Fahn S. 1997. The characterization and outcome of stereotypical movements in nonautistic children. *Mov Disord* **12**:47–52. doi:10.1002/mds.870120109

Thiery T, Lajnef T, Jerbi K, Arguin M, Aubin M, Jolicoeur P. 2016. Decoding the locus of covert visuospatial attention from EEG signals. *PLoS One* **11**:e0160304. doi:10.1371/journal.pone.0160304

Tottenham N, Tanaka JW, Leon AC, McCarry T, Nurse M, Hare TA, Marcus DJ, Westerlund A, Casey BJ, Nelson C. 2009. The NimStim set of facial expressions: Judgments from untrained research participants. *Psychiatry Res* **168**:242–9. doi:10.1016/j.psychres.2008.05.006

Vossel S, Weidner R, Thiel CM, Fink GR. 2009. What is "odd" in posner's location-cueing paradigm? Neural responses to unexpected location and feature changes compared. *J Cogn Neurosci* **21**:30–41. doi:10.1162/jocn.2009.21003

Wang J, Barstein J, Ethridge LE, Mosconi MW, Takarae Y, Sweeney JA. 2013. Resting state EEG abnormalities in autism spectrum disorders. *J Neurodev Disord* **5**:24. doi:10.1186/1866-1955-5-24

Zhang M, Huang Y, Jiao J, Yuan D, Hu X, Yang P, Zhang R, Wen L, Situ M, Cai J, Sun X, Guo K, Huang X, Huang Y. 2022. Transdiagnostic symptom subtypes across autism spectrum disorders and attention deficit hyperactivity disorder: Validated by measures of neurocognition and structural connectivity. *BMC Psychiatry* **22**:102. doi:10.1186/s12888-022-03734-4