Divergent correlations between autism traits and multiplicative noise in fine and coarse motion discrimination tasks.

Edwina Orchard [1] and Jeroen J.A. van Boxtel [1,2]

[1] School of Psychology, Faculty of Health, University of Canberra, Canberra, Australia

[2] School of Psychological Sciences, Monash University, Clayton, Victoria 3800, Australia

Abstract

People with autism spectrum disorder (ASD) display abnormalities in motion processing. Motion perception abnormalities in ASD have been linked to high levels of internal noise (unreliable neuronal fluctuations), and deficits in motion pooling (integrating local motion into a global percept). However, the literature overall is equivocal. Traditionally, internal noise in ASD has been investigated through additive internal noise, comparing ASD and control groups. To date, multiplicative internal noise has not been investigated in ASD, and neither type of internal noise has been investigated in relation to traits of autism in the typically-developing population. Here, we investigate how additive and multiplicative internal noise and motion pooling vary across number of autistic traits in typically developed adults. We employed a visual motion integration task with a typically developed population, measuring autistic traits with the Autism Spectrum Questionnaire (AQ). Additive and

multiplicative internal noise and motion pooling were calculated from task accuracy and consistency across a range of external noise levels, using a double-pass paradigm. We found that multiplicative noise (but not additive noise, or motion pooling) correlated with AQ. Specifically, multiplicative noise increased with AQ in a coarse motion discrimination task, while it decreased with AQ in a fine motion discrimination task. We suggest that the differences in multiplicative noise may be indicative of decision-variable fluctuations, which are smaller in individuals with a higher number of autistic traits, i.e., they are more focused. Our findings indicate that looking beyond additive noise and incorporating multiplicative noise estimation paradigms can help establish whether there are differences in internal noise levels between individuals with ASD and those without.

Introduction

Although deficits in social, behavioural and cognitive functioning are considered core symptoms, sensory and perceptual abnormalities have long been shown in Autism Spectrum Disorder (ASD) in both empirical and anecdotal accounts (Grandin, 1992; Kern et al., 2006; O'Neill & Jones, 1997). Descriptions of these symptoms date back to original accounts of ASD (Asperger, 1944; Kanner, 1943). Sensory and perceptual abnormalities likely contribute to the complex behavioural, social, and cognitive deficits that define ASD, as they are evident in social (facial perception, gestural interpretation, unusual eye contact, difficulties with joint attention) and non-social (sensitivity to lights, repetitive/stereotyped behaviours) functional deficits (Simmons et al., 2009). Differences in sensory processing may even play a causative role in core features of autism (Marco, Hinkley, Hill, & Nagarajan, 2011), such as language delay (auditory processing) and difficulty with

reading emotion from faces (visual processing). Therefore, investigations into their mechanisms might uncover understanding of the neural underpinnings of ASD (Zwaigenbaum et al., 2005).

The origin of sensory and perceptual abnormalities in ASD is currently unknown, but the recent literature has suggested that the brain's internal noise (i.e., response variability) is larger in ASD than in typical development, which may be an underlying neural basis of these symptoms. Brain imaging studies have shown that individuals with ASD have increased internal noise levels (Dinstein et al., 2012; Domínguez, Velázquez, & Galán, 2013; E. Milne, 2011; Weinger, Zemon, Soorya, & Gordon, 2014). For example, the variability of evoked fMRI response was larger in ASD individuals (and consequent signal to noise ratios were lower), even though average evoked responses to sensory stimuli were typical (Dinstein et al., 2012). This pattern of results was found across modalities, in visual, auditory, and somatosensory cortices(Dinstein et al., 2012). Similar differences in neural variability were found using resting state measurements in magnetoencephalography (MEG; Domínguez et al., 2013), suggesting that high internal noise is a widespread cortical characteristic of ASD and may represent a fundamental physiological alteration of neural processing (but see, Butler, Molholm, Andrade, & Foxe, 2017; Coskun et al., 2009).

At a behavioural level, the impact of internal noise on visual perception in ASD has mostly been investigated in the motion and orientation domain (Manning, Tibber, Charman, Dakin, & Pellicano, 2015; Manning, Tibber, & Dakin, 2017; Park, Schauder, Zhang, Bennetto, & Tadin, 2017; Zaidel, Goin-Kochel, & Angelaki, 2015). Early evidence for motion processing deficits were reported when comparing performance in first-order (luminance-based) motion to second-order (contrast-based) motion, where individuals with ASD display similar motion discrimination for first-

order tasks, but were significantly impaired on second-order tasks (A. Bertone, Mottron, Jelenic, & Faubert, 2003). In later research, motion perception in ASD has often been investigated using motion coherence tasks (Simmons et al., 2009). This work has shown higher motion coherence thresholds (i.e., more dots need to move coherently before the shared movement is detected) in ASD compared to controls (E. Milne et al., 2002; J. V. Spencer & O'Brien, 2006), although not consistently (Brieber et al., 2010; Jones et al., 2011; Manning et al., 2015). Compared to control groups, ASD groups also appear to have an increased *range* of thresholds, speaking to the variability within ASD in general (Elizabeth Milne et al., 2006; Pellicano, Gibson, Maybery, Durkin, & Badcock, 2005). Although the behavioural data is equivocal about the potential impairment in motion processing, there is evidence that even when behavioural impairments are absent, neural differences exists between individuals with and without ASD (Brieber et al., 2010; Freitag et al., 2008; Herrington et al., 2007; Kaiser et al., 2010; McKay et al., 2012; Peiker et al., 2015). These neural differences suggest motion may be *processed* differently in ASD, even in the absence of behavioural differences. Could internal noise be a contributing factor to these processing differences?

There are two broad explanations for abnormal motion coherence thresholds in ASD. First, coherence thresholds could be increased due to poor estimation of local direction signals. The poor estimation could be due to high levels of internal noise, precluding accurate estimation of local motion signals (Barlow & Tripathy, 1997; Zaidel et al., 2015). Second, coherence thresholds could be increased due to impaired motion pooling (i.e., integration) of local direction signals (Dakin, Mareschal, & Bex, 2005). Pooling multiple local motion signals would typically ameliorate direction estimates, and thus combat external (and internal) noise on local motion signals. A

deficit in this process would thus worsen direction estimates (Dakin et al., 2005; Manning et al., 2015).

A recent study aimed to investigate both these processes in an ASD population (Manning et al., 2015). The authors found no evidence for a difference in internal noise between the two groups. However, they did find a difference in motion pooling. Contrary to expectation, individuals with ASD showed more motion pooling when external noise was high, causing ASD children to *outperform* controls. This finding was, however, not confirmed in a subsequent study, although combining both studies still showed a significantly more motion pooling (Manning et al., 2017). These results are consistent with earlier findings (Foss-Feig, Tadin, Schauder, & Cascio, 2013), that showed enhanced motion perception in ASD groups compared to controls in a different experimental design.

Although these findings are equivocal about whether ASD is linked to enhanced or worsened motion perception, previous research suggests that internal noise is unlikely to explain any difference in motion processing in ASD. However, the ASD literature to date has largely ignored the potential interaction between external noise on internal noise (but see a recent exception, Park et al., 2017, looking at orientation perception). Internal noise can be divided into at least two components: additive and multiplicative (Burgess & Colborne, 1988; Lu & Dosher, 2008). Additive noise is the internal noise 'baseline', which is *constant* across different amounts of input. It is this type of noise that is measured by previous paradigms (i.e., equivalent noise paradigms; Dakin et al., 2005; Lu & Dosher, 2008). Whereas, multiplicative noise is *proportional* to the input strength, thus interacting with the amount of noise present in

the external stimulus (Burgess & Colborne, 1988)[1]. A person's additive and multiplicative noise are distinct components, and combine to make up someone's total internal noise (Lu & Dosher, 2008). Importantly, when external noise is low (and thus multiplicative noise is low), the main source of internal noise is additive noise. As external noise increases, multiplicative noise increases too, and becomes the main source of internal noise. It is thus possible that in previous investigations, additive noise did not influence motion processing, but multiplicative noise, which was not measured, does.

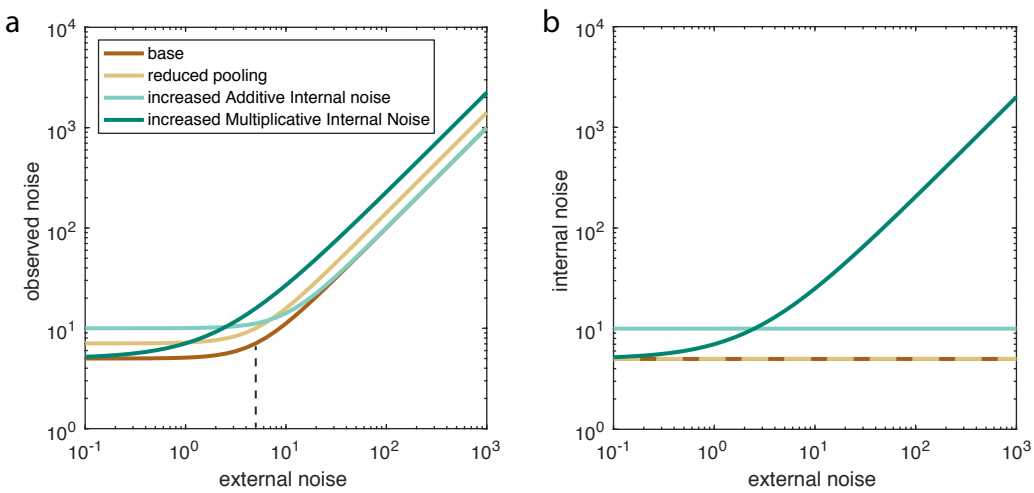

Figure 1. Effects of additive noise, multiplicative noise, and pooling. (a) As external (stimulus) noise is increased, performance thresholds (i.e., observed noise) increases too. When compared to a baseline (with a certain level of additive, but no multiplicative noise), the following effects are observed: reducing motion pooling leads to a upwards shift in the curve in log space; increasing additive noise increases thresholds mostly at low external

[1] Multiplicative noise was called induced noise by Burgess and Colborne (1988) and it may also be interpreted in terms of "noise exclusion" abilities (i.e., the ability to have external noise not influence internal noise). In this article, we will not distinguish between these different processes. We use the term multiplicative noise as it is the most general of the three terms.

noise values, but is large ineffective at large external noise values; including multiplicative noise increases thresholds especially at high levels of external noise. (b) When expressed in terms of the total amount of internal noise, there are clear differences between the different manipulations. Motion pooling has no effect on the internal noise; increasing additive noise elevates the internal noise by the same amount independent of the external noise, while internal noise shows a clear dependence on external noise, when multiplicative noise is included.

In this study, we examine the influence of additive noise, multiplicative noise, and pooling on motion processing in people with varying amounts of autistic traits. To obtain the measures of additive noise, multiplicative noise, and pooling we used the double-pass paradigm (Burgess & Colborne, 1988), which is considered to be a direct way of estimating internal noise (Burgess & Colborne, 1988; Lu & Dosher, 2008). In this paradigm, stimuli with additional noise are presented twice to individuals (with exactly the same noise and same signal). A person with high internal noise might perceive such identical stimuli as different in a test-retest (i.e. double-pass) scenario, due to high neural variation (Green, 1964; Haigh, Heeger, Dinstein, Minshew, & Behrmann, 2015). As the stimuli are exactly the same on both presentations, any perceptual difference is due to internal processes (Green, 1964). We can calculate internal noise by examining the accuracy (over individual trials) and consistency (between the two passes) of a person's response (Burgess & Colborne, 1988). For this task, a person is accurate if the dots are moving left (or right) and the participant responds "left" (or "right"). A person is consistent if they choose the same direction on both test and retest presentations of a trial, regardless of whether or not they were correct (and regardless of their reported confidence). The advantage of the double-pass paradigm over the commonly-used equivalent noise paradigm is that it does not assume that all noise is additive. Instead it allows one to estimate multiplicative noise as well (Burgess & Colborne, 1988; Lu & Dosher, 2008). The

method has previously been successfully employed to measure internal noise correlations with autism traits in the typically developing population on three non-motion tasks (Vilidaite, Yu, & Baker, 2017), although no estimates of multiplicative noise were derived.

We further tested the influence of additive and multiplicative noise in both a coarse and a fine motion direction discrimination task, because these tasks may depend on different sensory 'decoding rules' (Jazayeri & Movshon, 2007), and thus may be differently affected by noise. The difference between fine and coarse motion judgments has not been previously investigated in the context of ASD. However, as ASD is often linked to a more detail-oriented processing, comparing fine and coarse discrimination tasks is potentially very revealing about the underlying mechanisms that are affected in motion processing in ASD.

Coarse motion direction discrimination

Method

Participants

Ethics approval was obtained from the Monash University Human Research Ethics Committee (MUHREC), and written informed consent was obtained from all participants prior to participation. This study was completed in accordance with the approved guidelines. Participants, 45 healthy adults (31 female, 14 male), ranging from 18 – 40 years old (M_{age}= 22.07, SD_{age}= 4.96), were recruited from Monash University Clayton campus. All participants were proficient in English and had normal or corrected-to-normal vision, fulfilling our inclusion criteria. Participants received monetary compensation for their participation. Participants would be

excluded if their additive noise estimate was higher than the highest used external noise values, as multiplicative noise could then not be estimated. No participants were excluded on this basis.

Materials

The Autism Spectrum Questionnaire (AQ) was used to measure self-reported autistic traits (Baron-Cohen, Wheelwright, Skinner, Martin, & Clubley, 2001). The AQ comprises 50 items on a four-point Likert scale (*definitely agree, slightly agree, slightly disagree, definitely disagree*) and was administered and scored on a computer.

We also collected data from the *Kaufman Brief Intelligence Test second edition* (KBIT-2; Kaufman & Kaufman, 2004). Due to a large cohort of non-native English speakers, this test did not provide accurate estimates of the intelligence quotient, but all individuals scores > 70. We have not analysed these data beyond checking data quality, which we deemed insufficient for further analysis.

Apparatus

This study was completed in an experimental room without external lights, with artificial lights turned on. Participants sat comfortably in front of the computer, with their head stabilised by a chin rest. The experiment was displayed on a VIEWPixx/3D monitor, with a refresh rate of 120Hz and a resolution of 1920 x 1200 pixels, and viewed from a distance of 114 cm. All experimental displays (including stimuli and AQ administration and scoring) were created using Matlab and OpenGL, with PsychToolbox extensions (Brainard, 1997; Pelli, 1997).

Stimuli

Stimuli consisted of random-dot motion (See Figure 2), made up of 200 circular dots (100 black, 100 white, diameter 0.07°) moving within a circular aperture,

outlined in black, on a grey background. A red fixation mark was provided (diameter 0.13°), which was surrounded by a 0.53° exclusion zone, in which no dots were drawn in order to decrease potential pursuit eye-movements. Each individual dot moved (speed = 2.38°/sec, lifetime = 8 frames) in a direction randomly chosen from a wrapped normal Gaussian distribution (mean 22° left/right from vertical). The variability (noise) of the individual dot directions was determined by the standard deviation of the Gaussian distribution, which varied over trials, across eight noise levels: 0, 35, 45, 60, 70, 80, 90 or 100 degrees. A noise level of zero means that all dots move in the same direction (22° to the left or right of vertically upwards).

Participants indicated the perceived direction of the motion stimuli (left or right from vertical). The response screen consisted of a confidence 'wheel', with eight wedge-shaped quadrants, the same size as the stimulus aperture. The four quadrants on the left (or right) were used to indicate that the dots were, on average, perceived to move to the left (or right). The four quadrants were numbered (1= *Not at all sure*, 4=*Very Sure*) and shaded (1=lightest, 4=darkest) on each side to increase clarity. The confidence screen was circular to avoid presenting a clear reference for vertical.

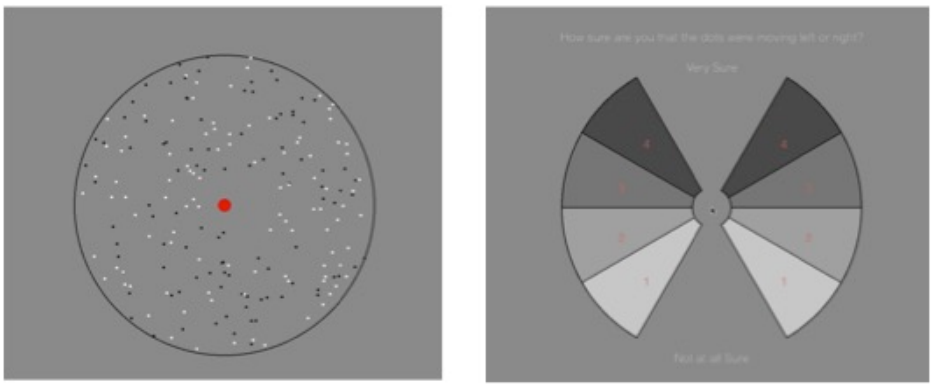

Figure 2. Screenshot of visual motion task stimuli (left) and response screen (right), created using Matlab. Participants viewed the stimuli and then gave a response, using a mouse click, according to a 2AFC paradigm as to whether the dots are moving to the left or right of vertical, and how confident they were in their response.

Procedure

Participants started with the KBIT-2, taking approximately 40 minutes, followed by the visual motion task, and then the AQ questionnaire.

The motion stimuli were presented for 0.75 seconds followed by a response screen. Participants were instructed to focus their attention on the fixation point (red dot) at the centre of the screen for the duration of the trials. Participants were required to determine the average direction of the moving dots, according to a two-alternative fixed choice paradigm (2AFC). Participants responded to the stimuli with a mouse click indicating in a single click, the perceived direction, and how confident they were in their decision (see Figure 2).

This study employed a double pass paradigm, similar to that used by (Burgess & Colborne, 1988), a method whereby the trials consist of two completely identical presentations (passes) of each stimulus. There were 100 unique trials, and therefore 200 trials in total, for each noise level. The first passes were run first in random order, followed by the second pass in the same order. Participants were given self-timed breaks after every 100 trials. A total of 1600 trials were run.

Data Analysis

We employed a double-pass paradigm to estimate internal noise values (Burgess & Colborne, 1988). Values for internal additive and multiplicative noise and motion pooling were calculated based on participants' performance on the visual motion task. Bayesian statistics were performed using JASP Version 0.9.0.1 (JASP Team, 2018).

Internal noise

According to Burgess and Colborne (1988), when noise levels are expressed as a ratio of internal over external noise ($\sigma_{int}/\sigma_{ext}$), there exists a fixed (non-linear) relationship between accuracy and consistency at different levels of $\sigma_{int}/\sigma_{ext}$ (Burgess & Colborne, 1988). These relationships are shown in Figure 3 for different ratios of $\sigma_{int}/\sigma_{ext}$ (grey dashed lines). Internal noise values can be calculated from experimental data by fitting such a curve to the data, and finding the ratio $\sigma_{int}/\sigma_{ext}$ that best captures the data. Then, because σ_{ext}, is known, σ_{int} can be calculated.

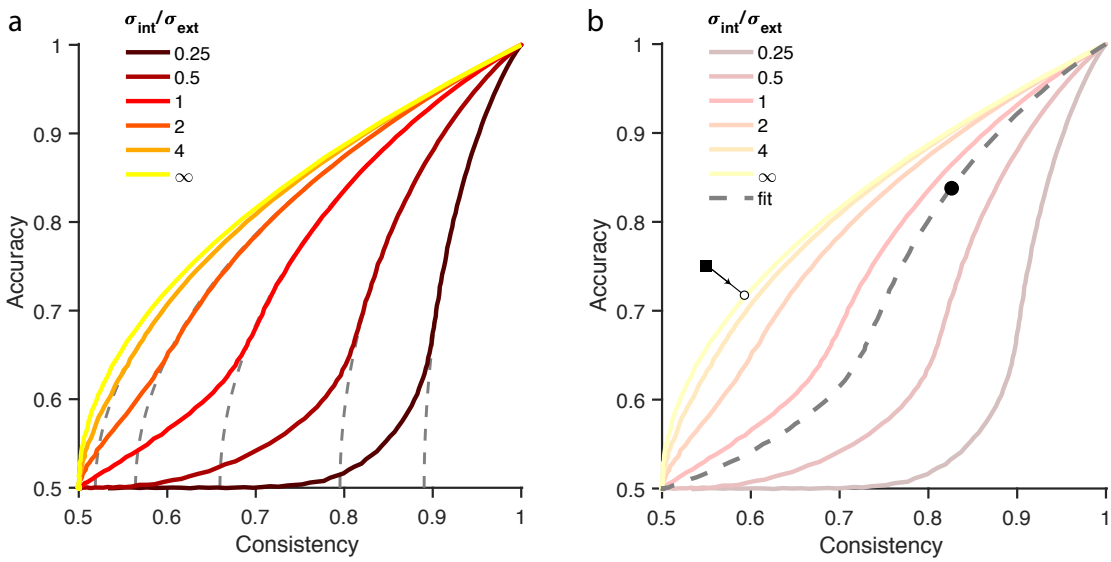

Figure 3. Relationship between accuracy and consistency, dependent on different ratios of $\sigma_{int}/\sigma_{ext}$. (a)Coloured lines are calculated using a wrapped Gaussian distribution, while the grey curves underneath are based on Gaussian distributions originally used by Burgess and Colborne (1988). The results based on a wrapped Gaussian distribution are specific to the used parameter (mean angle 22 degrees), in that the point where the curves start to deviate from the grey curves changes based on the parameters used. The line where $\sigma_{int}/\sigma_{ext} = \infty$ shows the case without external noise. (b) Schematic of how data is analysed for two example data points. Data that falls above the curve of $\sigma_{int}/\sigma_{ext} = \infty$, is mapped onto the nearest point on the $\sigma_{int}/\sigma_{ext} = \infty$ curve, and the internal noise associated with that point is taken as the measured internal noise. For all other data (circle) the best fitting line is found and $\sigma_{int}/\sigma_{ext}$ is determined.

However, the approach by Burgess and Colborne does not take into account that motion direction is a circular variable, leading to errors in the noise estimation if the underlying data is circular (see e.g., Dakin et al., 2005). Therefore, we extended the approach by Burgess and Colborne to circular data, using a wrapped-Gaussian distribution, instead of a Gausian distribution. Because there is no closed form for the wrapped-Gaussian, we calculated the curves numerically. Figure 3 shows a comparison of the non-circular and circular approach, using identical parameters. When the mean angle and standard deviation are small, the data is well approximated by an approach using Gaussian distributions, but when they are large, the curves deviated considerably from the standard approach by Burgess and Colborne.

Instead of fitting the data, we constructed a large lookup table for accuracy-vs-consistency curves ratios $\sigma_{int}/\sigma_{ext}$ of $(1.12^q-1)/25$, with q ranging from 1 to 59 in steps of 0.5. Individual data points were fitted to these curves, and the curve to which the data point showed the smallest squared error was taken as the best fit (see Figure 3b). The squared error was calculated taking into account deviations in terms of both accuracy and consistency. When the accuracy was <0.5 it was adjusted to (1-accuracy), so that fits could be made. This happened 6 times (out of $45 \times 8 = 360$ data points, i.e., 1.67% of all data points). This procedure then determined $\sigma_{int}/\sigma_{ext}$, as well as σ_{int} (because σ_{ext} is known). When a data point fell above the curve without external noise ($\sigma_{int}/\sigma_{ext} = \infty$), internal noise was estimated by finding the point on the internal-noise-only curve that was closest (in 2D) to the data point (see square in Figure 3b, which was mapped to the open circle). The internal noise value that was associated with that point on the curve was taken as the internal noise estimate for our data point. (For these data points, there was no observed external noise calculated, which meant that they were not used to estimate motion pooling, explained below.)

Determining Additive and Multiplicative internal noise

In equivalent noise paradigms, the amount of internal (additive) noise is determined by finding the elbow in the curve in Figure 1a, dashed line. This approach however, ignored the possible contributions of multiplicative noise. Therefore, if multiplicative noise influences the task at hand, estimates of additive noise can be incorrect. Unfortunately, it is difficult to determine from the plots in Figure 1a, whether multiplicative noise is present, because the curves are so similar (and can be made nearly overlapping by changing additive noise and pooling parameters). However, using the double-pass paradigm, one can plot the internal noise versus the external noise values (Figure 1b). In this plot, as external noise gets smaller and smaller, the internal noise asymptotes to the level of additive noise, which is not affected by pooling. Multiplicative noise can be derived from the increase in internal noise that depends on the level of external noise, with a slope of 0 indicating that there is no significant influence of multiplicative noise. This makes intuitive sense, as the internal noise only consists of a fixed level of constant additive noise, which is not changed by the level of external noise, thus tracing a flat line in the internal vs external noise plot.

According to Burgess and Colborne (1988), the multiplicative (induced) noise σ_{mult} is directly proportional to the external noise, and thus $\sigma_{mult} = m\ \sigma_{ext}$. The total internal noise is $\sigma_{int} = \mathrm{sqrt}(\sigma_{add}^2 + \sigma_{mult}^2) = \mathrm{sqrt}(\sigma_{add}^2 + (m\ \sigma_{ext})^2)$. To derive the multiplicative noise factor m, we use two approaches. First, as σ_{ext} becomes large, σ_{int} approaches $m\ \sigma_{ext}$, which means that $m = \sigma_{int}/\sigma_{ext}$, that is, the $\sigma_{int}/\sigma_{ext}$ ratio that we measure with the double-pass paradigm. Therefore, to derive $\sigma_{int}/\sigma_{ext}$, we found the best fitting $\sigma_{int}/\sigma_{ext}$ ratio curve (c.f., Figure 4) through the 5 data points from the

conditions with the largest 5 external noise values, this value was taken as the multiplicative noise factor *m*. We will refer to this method as the ratio-fitting method. Second, we fitted the curve $\sigma_{int} = \mathrm{sqrt}(\sigma_{add}^2 + (m\ \sigma_{ext})^2)$ through the whole internal-vs-external noise dataset of each participant, and derived *m* (as well as the additive noise) from the fit. We refer to this method as the internal noise fitting method. Both fitting methods minimised least squared errors.

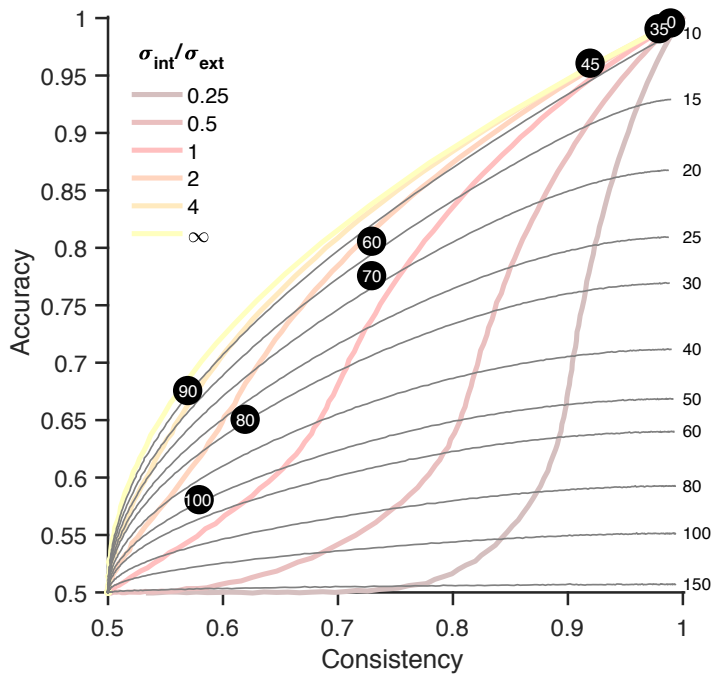

Figure 4. Observed external noise and motion pooling. This plot has the same layout as Figure 3, but also shown are iso-external noise lines. These lines show the accuracy and consistency expected when a certain external noise value (displayed on the far right of each curve) is used. The black dots are experimental data for one participant, with the external noise in the stimulus for each condition indicated within the dot. The external noise for each condition is higher than the iso-external noise line that it falls on, suggesting that the effective (i.e., observed) external noise is smaller than the external noise in the stimulus, than thus that motion pooling took place.

Motion Pooling

Better performance in a task is not only achieved with lower noise level, but also when the direction information from multiple dots is combined. This is called (global) motion pooling (Dakin et al., 2005). To derive motion pooling in our task, we plotted iso-external noise lines in Figure 4. These lines trace, for one value of external noise, the expected values of consistency and accuracy (for the specific parameters of our stimulus). Each data point will fall on only one curve, and this curve will indicate the *observed* external noise. The data generally fall on a curve that has a lower level of *observed* external noise than the amount of external noise that was actually present in the stimulus, indicating that information from multiple dots is pooled (see e.g., the data points from $\sigma_{ext} = 80$, which falls on the line of observed external noise = 30; Figure 4).

The level of motion pooling is generally derived by a characteristic of the central limit theorem, namely that:

$$\sigma_{obs} = \sqrt{\frac{\sigma_{int}^2 + \sigma_{ext}^2}{n_{samp}}}$$

Where σ_{obs} is the observed standard deviation of the response, and n_{samp} is the number of samples that are combined to give a motion direction estimate (i.e., motion pooling). In our case

$$\sigma_{obs} = \sqrt{\frac{\sigma_{int}^2 + \sigma_{ext}^2}{n_{samp}}} = \sqrt{s_{int}^2 + s_{ext}^2}$$

Where σ_{int} and σ_{ext} are the real internal and external noise values, and s_{int} and s_{ext} are the observed values. The observed values have the motion sampling already

taken into account, which is why n_{samp} does not appear on the right-hand side of the equation. Since we know the ratio (α) between internal and external noise and thus $\sigma_{int} = \alpha * \sigma_{ext}$, this equation can be rewritten as

$$\sqrt{\alpha_1 s_{ext}^2 + s_{ext}^2} = \sqrt{\frac{\alpha_2 \sigma_{ext}^2 + \sigma_{ext}^2}{n_{samp}}}$$

and

$$\sqrt{(1+\alpha_1) s_{ext}^2} = \sqrt{\frac{(1+\alpha_2)\sigma_{ext}^2}{n_{samp}}},$$

which can be rewritten as:

$$n_{samp} = \frac{(1+\alpha_2)\sigma_{ext}^2}{(1+\alpha_1) s_{ext}^2}$$

Assuming that $\alpha_1 = \alpha_2$, namely that the motion pooling does not affect the ratio of internal over external noise, we can derive motion pooling as:

$$n_{samp} = \frac{\sigma_{ext}^2}{s_{ext}^2}$$

Since we know both σ_{ext} (the external noise, i.e., standard deviation of directional noise) and s_{ext} (the observed external noise), we can calculate the motion pooling n_{samp}.

Results

Influence of external noise on accuracy, consistency and confidence

Decreases in accuracy, consistency and confidence rating as external noise increased reflected increased task difficulty (see Figure 5). Of particular interest, both accuracy and consistency decreased from near-perfect to near-chance performance. This suggests that the spread of noise levels measured both the upper and lower limits of participant performance. The results pertaining to the confidence ratings do not form part of the analyses in this paper, and will not be discussed further.

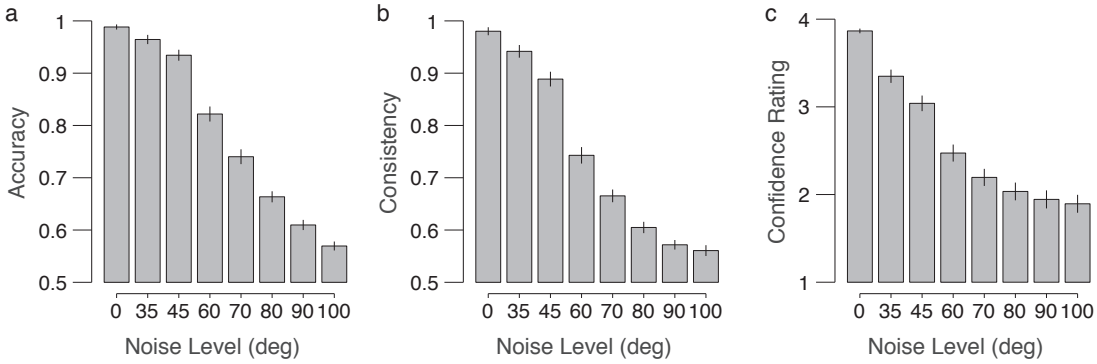

Figure 5. Mean behavioural performance. (a) Accuracy, (b) consistency, and (c) Confidence decrease as the external noise level increases, but remain significantly above chance level at all noise levels. Error bars are standard error of the mean over participants.

We first investigated whether AQ had a significant effect on the dependence of accuracy and consistency on noise. Numerically, the accuracy and consistency were lower in people with higher AQ scores. To test the statistical significance of this finding, we contructed an unrestricted linear model with AQ, noise level and their interaction as terms, and we compared them to models without the interaction, and models without both the interaction and the AQ term. Likelihood ratio tests revealed no significant differences between unrestricted models and those excluding the interaction (accuracy: $\chi^2(1) = 0.634$, $p = 0.426$; consisteny; $\chi^2(1) = 0.0104$, $p = 0.91$),

and unrestricted models and those exluding AQ and the interaction (accuracy: $\chi^2(2) = 4.75$, $p = 0.093$; consistency: $\chi^2(2) = 3.796$, $p = 0.1499$). Using *d'* instead of accuracy did not alter the pattern of results. A mixed-design repeated ANOVA with the factor external noise, and a group factor of AQ-level (using a median split to split the group of subjects in a low and high AQ score) did also not yield significant results. Overall, there appears to be no stiatiscally significant influence of AQ on the accuracy, consistency, or *d'* in our motion discrimination task.

Internal noise

Internal noise was derived from the accuracy-consistency plots (see methods). The level of internal noise, dependent on the external noise is plotted in Figure 6 over 45 participants (with the data from the participant in Figure 4 highlighted in grey). The plot clearly shows that internal noise values depend on external noise. A repeated-measures one-way ANOVA with the factor external noise was significant (internal noise transformed as $\log(\sigma_{int}+1)$, $F(2.48, 109.27) = 221.12$, $p < 0.0001$, $\eta_p^2 = 0.83$, Greenhouse-Geisser corrected). This suggests that motion discrimination is not only under the influence of additive noise, but also of multiplicative noise. When performing median split on the AQ scores (median = 18), we obtain a group of $n = 20$ that scored AQ < 18, and a group of $n = 20$ that scored AQ > 18 (we discard the subjects with a median score for this analysis). The mixed-design one-way repeated-measured ANOVA with the factor external noise, and group (Low vs High AQ) showed a significant effect of external noise ($F(2.11, 84.49) = 205.00$, $p < 0.001$, $\eta_p^2 = 0.84$, Greenhouse-Geisser corrected), and Group ($F(1,266) = 4.33$, $p = 0.044$, $\eta_p^2 = 0.10$), with internal noise increasing as external noise increased, and higher internal

noise for the high AQ group. The interaction was not significant ($F(7,266) = 0.21$, $p = 0.98$).

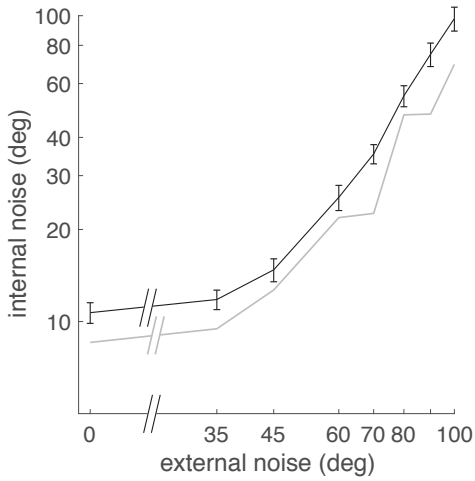

Figure 6. Dependence of mean (± s.e.m.) internal noise on external noise. The gray line is for the participant whose accuracy-consistency data was drawn in Figure 4. Datapoints which were estimated as 0 internal noise were ignored.

Additive noise

Additive noise is a person's baseline noise, and it was calculated by estimating internal noise levels when external noise was absent (left-most points in Figure 6). Unfortunately, our design did not allow very accurate estimation of additive noise, mainly because the task was too easy, resulting in near perfect performance. This reduced the power of our analyses. Many participants showed absent additive noise values, which resulted in positively skewed data and non-parametric tests were employed. Despite accounting for the assumption of normality, correlation analyses were still deemed inappropriate due to heteroscedasticity. Therefore, we performed a median split for AQ score, creating high ($n = 20$) and low ($n = 20$) AQ groups (excluding participants whose AQ equalled the median). There was no significant difference in additive noise between those with high and low AQ (Wilcoxon rank sum

test: $Z = 0.921$, $p = 0.36$). A Bayesian Mann-Whitney U test revealed that the data was inconclusive as to whether there was an effect or not (Cauchy scale 0.707, 1000 samples, $W = 170$, $BF_{10} = 0.51$).

Additive noise was also estimated by the internal noise fitting method (Figure 7a). Again, because there were a large number of subjects for which additive noise could not be estimated accurately, we performed a median split analysis, and found no significant difference ($Z = 1.20$, $p = 0.23$).

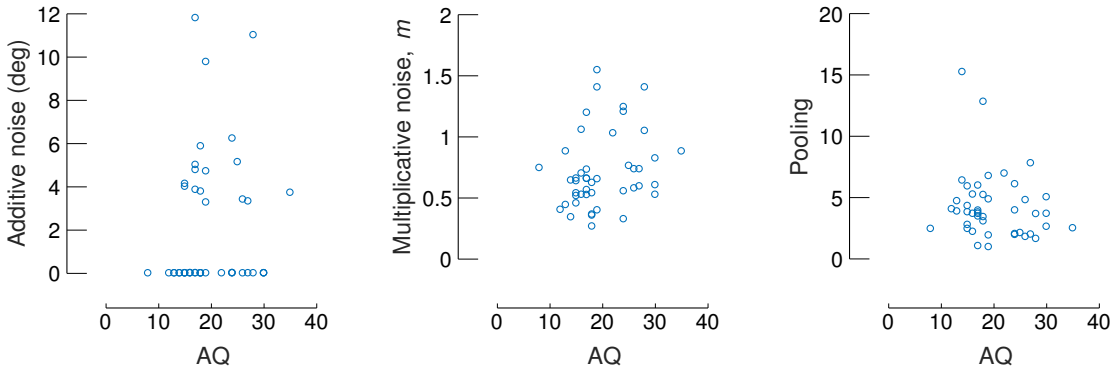

Figure 7. Experimental results for (a) additive internal noise, (b) the multiplicative noise factor m*, (c) motion pooling, dependent on AQ. One outlier was removed in (c).*

Multiplicative noise

Internal noise estimates increase with increasing external noise (Figure 6), which is a sign of the involvement of multiplicative noise. To obtain insight into whether this involvement differs between individuals with different levels of AQ, we estimated individual levels of multiplicative noise with two approaches. First, we used a ratio fitting method, by fitting one curve through the largest 5 external noise conditions per participant (see methods). The average multiplicative noise factor over participants was 4.3 (median 2.1), which is significantly larger than 0 (one sample t-test, $t(43) = 4.95$, $p < 0.0001$, Cohen's $d = 0.75$; one participant was excluded because the obtained multiplicative noise factor, when z-scored, was >3.29). These values did not correlate

with the AQ measure (Kendall's tau-b = 0.021, $p = 0.86$; Bayesian correlation Kendall's tau 0.021, $BF_{10} = 0.20$). Our second approach, the internal noise fitting method, fitted one curve through the individual data in Figure 6 (see methods). Multiplicative noise factors obtained this way were on average 0.71 (median 0.64), and were significantly different from 0 ($t(44) = 15.47$, $p < 0.0001$, Cohen's $d = 2.31$). A positive correlation between AQ and multiplicative noise was close to significance (Figure 7b; Kendall's tau-b = 0.20, p = 0.063). However, a Bayesian correlation suggested that the data is inconclusive (Kendall's tau 0.20, $BF_{10} = 1.16$).

The mean and median multiplicative noise factor derived from each of our methods are quite different. We consider the internal-noise fitting method superior, because it takes into account all data, and not just a subset of the data. The obtained mean and median value using this method are also more in line with published values of multiplicative noise (Burgess & Colborne, 1988; Lu & Dosher, 2008).

Motion pooling

We computed the motion pooling at each level of external noise for each participant. Then, we calculated the median pooling over all external noise conditions per participant, discarding conditions in which pooling could not be estimated (see methods). The mean value over participants (excluding one outlier, z-score > 3.29; Field, 2013) was 4.24 samples (median of 3.73 samples). This was significantly larger than 1 (one-sample t-test; $t(43) = 7.88$, $p < .001$). There was no correlation with AQ (Kendall's *tau* = -0.15, $p = 0.17$; Figure 7c); However, a Bayesian correlation suggested that the data is inconclusive (Kendall's *tau* = -0.15, $BF_{10} = 0.52$).

Fine discrimination task

Methods

Participants

37 healthy adults were recruited from Monash University Clayton campus. All participants were proficient in English and had normal or corrected-to-normal vision, fulfilling our inclusion criteria. Participants received a monetary compensation for their participation. Participants would be excluded if their additive noise estimate was higher than the highest used external noise value, as multiplicative noise could then not be estimated. Seven participants were excluded on this basis, leaving 30 participants in the final sample (20 females, 10 males, ranging from 18 – 33 years old, M_{age} = 24.46, SD_{age}= 5.14).

Stimuli

All stimuli and methods were identical to the coarse discrimination task except that the mean motion direction was +/- 5 degrees from vertical, and the standard deviations of the Gaussian noise were 0, 2.2, 3.7, 6.3, 10.6, 17.9, 30.3, and 51.2 degrees.

Lookup tables were recalculated for a signal value of 5 degrees from vertical.

Results

Influence of external noise on accuracy, consistency and confidence

As in the coarse discrimination task, the fine discrimination task showed decreases in accuracy, consistency and confidence rating as external noise increased, reflecting

increased task difficulty (see Figure 8). Internal noise estimates also increased as the external noise increased (Figure 9), reflecting an influence of multiplicative noise.

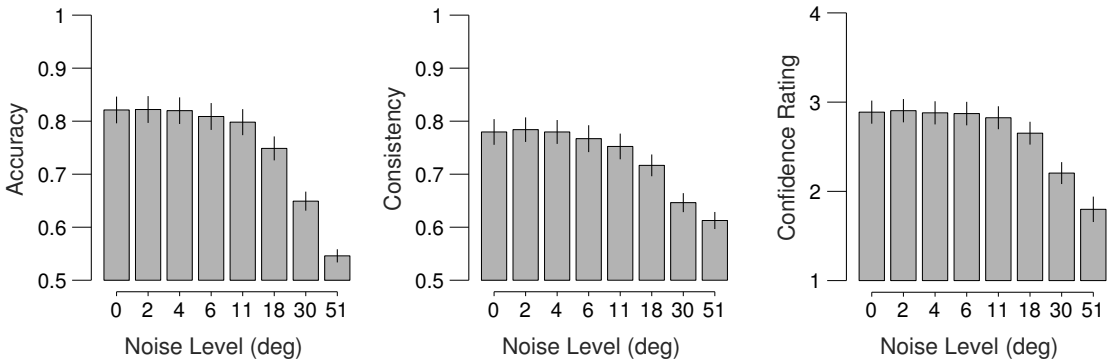

Figure 8. Mean behavioural performance in the fine discrimination task. (a) Accuracy, (b) consistency, and (c) Confidence decrease as the external noise level increases, but remain significantly above chance level at all noise levels. Errorbars are standard error of the mean over participants.

Likelihood ratio tests revealed no significant differences between unrestricted models (incuding AQ, noise level and their interaction as terms) and those excluding the interaction (accuracy: $\chi^2(1) = 0.132$, $p = 0.72$; consisteny; $\chi^2(1) = 0.115$, $p = 0.73$), and unrestricted models and those exluding AQ and the interaction (accuracy: $\chi^2(2) = 3.15$, $p = 0.21$; consistency: $\chi^2(2) = 5.63$, $p = 0.06$). Using *d'* instead of accuracy did not alter the pattern of results. Overall, accuracy tended to be lower in individuals with high AQ scores, while consistency was higher. However, a mixed-design repeated ANOVA with the factor external noise, and a group factor of AQ-level (using a median split to split the group of subjects in a low and high AQ score) also did not yield significant results for AQ group. Overall, there appears to be no influence of AQ on the accuracy, consistency, or *d'* in our fine motion discrimination task.

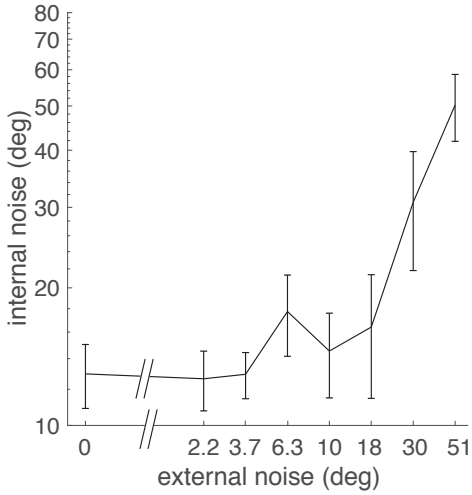

Figure 9. Dependence of mean (± s.e.m.) internal noise on external noise for the fine discrimination task. Datapoints which were estimated as 0 internal noise were ignored.

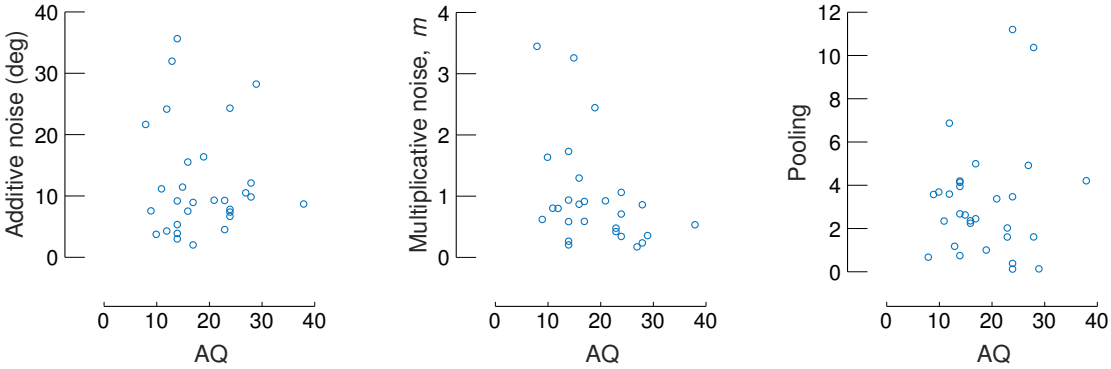

Figure 10. Experimental results for (a) additive internal noise, (b) the multiplicative noise factor m*, (c) motion pooling, dependent on AQ.*

Additive noise

As opposed to experiment 1, we were able to obtain individual additive noise estimates for all our participants in the fine discrimination task. Additive noise, taken as the observed internal noise when external noise was 0, was larger than 0 (Mean ± SEM of sample: 12.96 ± 2.07, $t(29) = 6.26$, $p = 7.77 \times 10^{-7}$, Cohen's $d = 1.14$). There was no significant correlation with AQ score (Kendall's *tau* = 0.15, $p = 0.27$).

Additive noise was also estimated by the internal noise fitting method. Additive noise obtained this way was larger than 0 (Mean ± SEM of sample: 11.98 ± 1.62, $t(29) = 7.41$, $p = 3.67 \times 10^{-8}$, Cohen's $d = 1.35$). There was again no significant correlation with AQ score (Kendall's *tau* = 0.08, $p = 0.55$; Figure 10a).

Multiplicative noise

The influence of multiplicative noise was again shown by an increase in internal noise estimated with increasing external noise (Figure 9). As opposed to experiment 1, there was a *negative* dependence of internal multiplicative noise on AQ (Figure 10b). When multiplicative noise was estimated based on the $\sigma_{int}/\sigma_{ext}$ ratio from the largest 5 external noise values, it was 3.44 (median 1.55), which is significantly larger than 0 (one sample t-test, $t(29) = 3.60$, p = 0.001, Cohen's d = 0.66). The individual values correlated negatively with the AQ measure (Kendall's *tau-b* = -0.46, $p = 0.0006$; $BF_{10} = 95.15$). When estimating multiplicative noise through the internal noise fitting method, multiplicative noise factors were on average 0.97 (median 0.79), and were significantly different from 0 ($t(26) = 5.91$, $p = 3.12 \times 10^{-6}$, Cohen's $d = 1.14$). A negative correlation analysis between AQ and multiplicative noise was significant (Kendall's *tau-b* = -0.29, $p = 0.038$; Figure 10b).

Motion pooling

Mean pooling was 3.20 samples (median 2.63), which was significantly larger than 1 (one-sample t-test: $t(29) = 4.62$, $p = 7.26 \times 10^{-5}$, Cohen's $d = 0.84$). There was no correlation with AQ (Kendall's *tau* = -0.042, $p = 0.76$; Figure 10c). A Bayesian

correlation suggested moderate evidence for the absence of a correlation (BF_{10} = 0.248).

Comparing the fine and coarse discrimination tasks

From Figure 6 and Figure 9, it appears that the internal noise is larger in the fine discrimination task than in the coarse discrimination task. We compare internal noise between the two tasks at similar external noise conditions. We found that internal noise is significantly larger in two of the three comparisons (Wilcoxon rank sum test; at $\sigma_{ext} = 0$, $Z = 4.62$, $p < 0.0001$; at fine $\sigma_{ext} = 30.5$, coarse $\sigma_{ext} = 35$, $Z = 1.22$, $p = 0.22$; at fine $\sigma_{ext} = 51.2$, coarse $\sigma_{ext} = 45$, $Z = 5.70$, $p < 0.0001$).

Since the internal noise at $\sigma_{ext} = 0$, equals the additive noise, these results suggest that the additive noise is larger in the fine discrimination task. When comparing the additive noise values obtained from the internal noise fitting method, we find again that additive noise is larger in the fine discrimination task ($Z = 6.00$, $p < 0.0001$).

Mean multiplicative noise was not different between the two tasks, when comparing the data obtained from ratio-fitting method ($Z = 0.60$, p = 0.55, Wilcoxon rank sum test), or from the internal noise fitting method ($Z = 1.94$, $p = 0.053$, Wilcoxon rank sum test). However, the correlation coefficients with AQ were significantly different between the fine and coarse tasks, for both the ratio fitting method ($z = 2.09$, $p = 0.037$, using the Fisher r-to-z transformation), and the internal noise fitting method ($z = 1.96$, $p = 0.05$).

Comparing the motion pooling data between coarse and fine discrimination tasks showed that the coarse task resulted in more motion pooling ($Z = 2.13$, $p = 0.033$, Wilcoxon rank sum test).

Discussion

We investigated how fine and coarse motion discrimination is influenced by internal noise (both additive and multiplicative), and pooling. These influences were linked to Autism Spectrum Disorder (ASD) traits in a typically developed adult population. We found evidence for an influence of both additive and multiplicative noise on motion processing, and that the latter was influenced by autism traits. Motion pooling also took place in our task, but was not correlated with autism traits.

Additive noise influences on motion perception

Recent literature has reported high internal noise in ASD populations compared to control groups using brain-imaging techniques such as functional magnetic resonance imaging (fMRI; Dinstein et al., 2012; Haigh et al., 2015), electroencephalography (EEG; E. Milne, 2011; Weinger et al., 2014) and magnetoencephalography (MEG; Ishikawa, Shimegi, & Sato; Peiker et al., 2015). These results led us to anticipate a positive correlation between AQ score and additive noise. However, our findings did not support this hypothesis; we found no correlation between AQ and additive noise in either of our tasks. Additive noise has not been previously investigated across AQ in a typically developed population, and our results suggest that additive noise does not vary with traits of ASD in the general population.

These results are consistent with other research that, contrary to previously mentioned studies, did not find significant differences in additive noise between ASD and control groups, in both behavioural (Manning et al., 2015) and brain-imaging (Coskun et al., 2009) studies.

It should be noted that in our coarse discrimination task, additive noise values were likely underestimated, and could in fact not be established for a large number of our participants because the task was too easy when external noise was low. Therefore, our findings on additive noise in the coarse discrimination task, along with their implications for ASD populations, must be interpreted with caution.

Apart from the absent link to ASD, our results do speak to the involvement of additive noise in the perception of motion. We found considerable differences in the amount of additive internal noise, between individuals, and between tasks. These individual differences in noise were correlated with (and in fact, calculated from) differences in performance measures (accuracy and consistency) in a motion discrimination task. This suggest that internal additive noise can determine task performance differences between individuals, although at the moment it appears that it cannot stratify individuals along the broad ASD spectrum.

Multiplicative Noise

Non-zero multiplicative noise has been found in several tasks, including motion processing. However, so far, multiplicative noise in motion processing tasks was found to not be correlated with variables of interest, like migraine diagnosis (Webster, Edwin Dickinson, Battista, McKendrick, & Badcock, 2011)] or with aging (Bower &

Andersen, 2012). In motion tasks, multiplicative noise has not been previously investigated in relation to ASD, either between ASD and control groups, or across AQ score within the broader spectrum. Instead, studies have investigated *internal noise* without splitting the types of noise measured into additive and multiplicative noise. For example, Manning et al. (2015) varied the amount of external noise in a motion discrimination task but only looked at two levels of noise. Overall, they found better performance at high noise levels for individuals with ASD relative to the control group, but no difference at low noise levels. The authors tentatively attributed performance differences at high noise levels to differences in motion pooling (Manning et al., 2015), but because motion pooling should also affect performance at low noise levels, this explanation was speculative. Our results for the fine motion discrimination tasks show no difference in motion pooling dependent on AQ, but instead, suggest that multiplicative noise is smaller in individuals with many autism traits. Lower multiplicative noise would yield better performance at high external noise levels but not at low external noise levels (see e.g. Figure 1B), consistent with previous findings (Manning et al., 2015; Manning et al., 2017). Therefore, we suggest that the cause for the increased performance in ASD on the motion task is due to decreased multiplicative noise (or increased noise exclusion), and not due to increased motion pooling.

For our coarse discrimination task, we found evidence for increases in multiplicative noise with increased numbers of autism traits. This is consistent with the general findings that people with ASD are poorer in coherent motion tasks, which involve coarse left versus right discriminations. However, alternative accounts for this diminished performance in ASD have been given, such as a decreased ability to separate signal from noise (i.e., segregation; Manning et al., 2015).

What could be a potential origin of the multiplicative noise? Burgess and Colborne (1988) derived from a model introduced by Wilcox (1968) that multiplicative noise could be explained by fluctuations in a decision-variable; where higher decision-variable fluctuations lead to larger multiplicative noise. Applying the same interpretation to our results suggests that individuals with higher AQ scores—those who have lower multiplicative noise in the fine discrimination task—have smaller fluctuations in the decision variable. Because one orgin of these fluctuations could be attentional lapses, we hypothesise that people with higher number of autism traits are more focused and have fewer attentional lapses (i.e., a lower lapse rate), consistent with an earlier report (Bach & Dakin, 2009). We can estimate the lapse rate by looking at the accuracy in conditions without noise. Since this is a clear stimulus, any error is likely due to attentional lapses (especially in the coarse discrimination task). The lapse rate should correlate with the multiplicative noise measures that we observed. Indeed we found that in both the fine and coarse discrimination task these correlations were significant (one-sided; coarse discrimination, $r = -0.43$, $p = 0.0015$, or nearly so (one-sided; fine discrimination: $r = -0.34$, $p = 0.043$). (Correlations with additive noise were also significant.) This analyis supports our interpretation.

Performance levels

We show no evidence for a uniformly impoverished motion processing in individuals with increased levels of autism traits, which is consistent with the literature. We find that accuracy is generally lower in individuals with higher levels of autism traits, but this was not significant. In the literature, there is evidence for both increased (Foss-Feig et al., 2013; Manning et al., 2015) and decreased (e.g.,

Koldewyn, Whitney, & Rivera, 2010; E. Milne et al., 2002; J. V. Spencer & O'Brien, 2006) motion perception in ASD (see also Simmons et al., 2009).

There is a stronger case for impoverished motion perception in a particular type of global motion perception, namely biological motion processing. Here too, there is both evidence in favour of (e.g., Blake, Turner, Smoski, Pozdol, & Stone, 2003; Koldewyn et al., 2010; van Boxtel, Dapretto, & Lu, 2016; van Boxtel, Peng, Su, & Lu, 2017), and against (e.g., Cleary, Looney, Brady, & Fitzgerald, 2014; Cusack, Williams, & Neri, 2015; Saygin, Cook, & Blakemore, 2010) a deficit in processing, but a recent meta-analysis found that there was a small decrement in ASD versus typically developing individuals (Van der Hallen, Manning, Evers, & Wagemans, 2018). It may therefore be worthwhile to look at the influence of internal noise on biological motion (as done in van Boxtel & Lu, 2015), while focusing on the link to ASD.

Motion Pooling

Previous literature has provided both evidence for and against a difference in motion pooling in ASD versus typically developing individuals (Manning et al., 2015; Pellicano et al., 2005). We found no significant correlation between motion pooling across AQ score, and Bayesian statistics suggested that there was moderate evidence for the absence of a correlation in the fine motion discrimination task, while the data was inconclusive in the coarse discrimination task. As mentioned above, the increased motion pooling in ASD, reported in previous studies (Manning et al., 2015; Manning et al., 2017), is instead potentially attributable to decreased multiplicative noise (or increased noise exclusion).

Coarse versus fine discrimination tasks

The reduction of multiplicative noise in individuals with more autism traits, is consistent with recent reports of increased motion perception in ASD (Foss-Feig et al., 2013; Manning et al., 2015). However, several other reports show decreased performance in ASD (e.g., Koldewyn et al., 2010; E. Milne et al., 2002; J. V. Spencer & O'Brien, 2006), especially in motion coherence tasks (Simmons et al., 2009). These differences could be due to the large variability within the autism spectrum, but it could also be due to the different parameters used in the different studies. Indeed, our results support the suggestion that small parameter differences can impact the results, as we found that, while multiplicative noise decreased with autism traits in the fine discrimination task, this was not the case in the coarse motion discrimination. The coarse discrimination task showed signs of increased multiplicative noise with increased autism traits. These correlations were significant using null hypothesis significance tests, although Bayesian tests suggested that there was insufficient evidence. Because our stimuli were nearly identical, this shows that small parameter changes can have a large effect on the results.

What are the processing differences that could underlie the different findings in our fine and coarse discrimination tasks? Because the stimuli in our two experiments were nearly identical, the difference cannot be attributed to some general motion perception deficit, or other commonly suggested deficits in ASD, such as, a dorsal stream deficit (Grinter, Maybery, & Badcock, 2010; J. Spencer et al., 2000), a magnocellular dysfunction (Sutherland & Crewther, 2010), or difficulty with complex stimuli (A. Bertone et al., 2003; Armando Bertone, Mottron, Jelenic, & Faubert, 2005).

The results do align with the general ideas about autism that suggest that these individuals are more detail focused (Happé & Frith, 2006; Mottron, Dawson, Soulieres, Hubert, & Burack, 2006), as the lower levels of multiplicative noise in fine discrimination tasks could in fact drive this increased focus. An alternative, not mutually exclusive, account is that different 'decoding rules' are used for fine and coarse discrimination tasks (Jazayeri & Movshon, 2007), and that they are differentially affected by noise, and autism traits. This suggestion is supported by our comparison of internal noise values between the two tasks. We find that internal noise, specifically additive noise, is larger in the fine discrimination task, and that the correlations between AQ and multiplicative noise are significantly different between fine and coarse motion discrimination tasks. These data suggest that the type of task influences the amount of internal noise, even with near identical stimuli.

Conclusions

This research is believed to be the first to investigate additive and multiplicative noise across Autism Spectrum Questionnaire (AQ) score. We show influences of additive and multiplicative noise as well as motion pooling on motion perception. Additive noise, and motion pooling do not correlate with ASD traits, but multiplicative noise does. There is a strong negative correlation between multiplicative noise and ASD traits in the fine motion discrimination task, while there is a small positive correlation in the coarse discrimination task.

The impact of multiplicative noise on motion perception is very relevant to ASD research, because multiplicative noise affects the perception of supra-threshold

stimuli, as opposed to additive noise which mostly affects peri-threshold perception. This implicates internal noise as an explanation for (perceptual) atypicallities in ASD, including hyper- and hyposensitivity.

References

Asperger, H. (1944). Die „Autistischen Psychopathen" im Kindesalter. *Archiv für psychiatrie und nervenkrankheiten, 117*(1), 76-136.

Bach, M., & Dakin, S. C. (2009). Regarding "Eagle-eyed visual acuity: An experimental investigation of enhanced perception in autism". *Biological Psychiatry, 66*(10), e19-e20.

Barlow, H., & Tripathy, S. P. (1997). Correspondence noise and signal pooling in the detection of coherent visual motion. *Journal of Neuroscience, 17*(20), 7954-7966.

Baron-Cohen, S., Wheelwright, S., Skinner, R., Martin, J., & Clubley, E. (2001). The autism-spectrum quotient (AQ): evidence from Asperger syndrome/high-functioning autism, males and females, scientists and mathematicians. *Journal of autism and developmental disorders, 31*(1), 5-17.

Bertone, A., Mottron, L., Jelenic, P., & Faubert, J. (2003). Motion perception in autism: a "complex" issue. *Journal of Cognitive Neuroscience, 15*(2), 218-225. doi:10.1162/089892903321208150

Bertone, A., Mottron, L., Jelenic, P., & Faubert, J. (2005). Enhanced and diminished visuo-spatial information processing in autism depends on stimulus complexity. *Brain, 128*(10), 2430-2441.

Blake, R., Turner, L. M., Smoski, M. J., Pozdol, S. L., & Stone, W. L. (2003). Visual recognition of biological motion is impaired in children with autism. *Psychological Science, 14*(2), 151-157.

Bower, J. D., & Andersen, G. J. (2012). Aging, perceptual learning, and changes in efficiency of motion processing. *Vision Research, 61*, 144-156.

Brainard, D. H. (1997). The Psychophysics Toolbox. *Spatial vision, 10*(4), 433-436.

Brieber, S., Herpertz-Dahlmann, B., Fink, G. R., Kamp-Becker, I., Remschmidt, H., & Konrad, K. (2010). Coherent motion processing in autism spectrum disorder (ASD): an fMRI study. *Neuropsychologia, 48*(6), 1644-1651. doi:10.1016/j.neuropsychologia.2010.02.007

Burgess, A. E., & Colborne, B. (1988). Visual signal detection. IV. Observer inconsistency. *Journal of the Optical Society of America. A, Optics and image science, 5*(4), 617-627.

Butler, J. S., Molholm, S., Andrade, G. N., & Foxe, J. J. (2017). An Examination of the Neural Unreliability Thesis of Autism. *Cereb Cortex, 27*(1), 185-200. doi:10.1093/cercor/bhw375

Cleary, L., Looney, K., Brady, N., & Fitzgerald, M. (2014). Inversion effects in the perception of the moving human form: a comparison of adolescents with autism spectrum disorder and typically developing adolescents. *Autism, 18*(8), 943-952. doi:10.1177/1362361313499455

Coskun, M. A., Varghese, L., Reddoch, S., Castillo, E. M., Pearson, D. A., Loveland, K. A., . . . Sheth, B. R. (2009). Increased response variability in autistic brains? *Neuroreport, 20*(17), 1543-1548. doi:10.1097/WNR.0b013e32833246b5

Cusack, J. P., Williams, J. H., & Neri, P. (2015). Action perception is intact in autism spectrum disorder. *The Journal of neuroscience : the official journal of the Society for Neuroscience, 35*(5), 1849-1857. doi:10.1523/JNEUROSCI.4133-13.2015

Dakin, S. C., Mareschal, I., & Bex, P. J. (2005). Local and global limitations on direction integration assessed using equivalent noise analysis. *Vision Res, 45*(24), 3027-3049. doi:10.1016/j.visres.2005.07.037

Dinstein, I., Heeger, D. J., Lorenzi, L., Minshew, N. J., Malach, R., & Behrmann, M. (2012). Unreliable evoked responses in autism. *Neuron, 75*(6), 981-991. doi:10.1016/j.neuron.2012.07.026

Domínguez, L. G., Velázquez, J. L. P., & Galán, R. F. (2013). A model of functional brain connectivity and background noise as a biomarker for cognitive phenotypes: application to autism. *PLoS ONE, 8*(4), e61493.

Field, A. (2013). *Discovering statistics using IBM SPSS statistics*: sage.

Foss-Feig, J. H., Tadin, D., Schauder, K. B., & Cascio, C. J. (2013). A substantial and unexpected enhancement of motion perception in autism. *Journal of Neuroscience, 33*(19), 8243-8249.

Freitag, C. M., Konrad, C., Haberlen, M., Kleser, C., von Gontard, A., Reith, W., . . . Krick, C. (2008). Perception of biological motion in autism spectrum disorders. *Neuropsychologia, 46*(5), 1480-1494. doi:10.1016/j.neuropsychologia.2007.12.025

Grandin, T. (1992). An inside view of autism *High-functioning individuals with autism* (pp. 105-126): Springer.
Green, D. M. (1964). Consistency of Auditory Detection Judgments. *Psychol Rev, 71*, 392-407.
Grinter, E. J., Maybery, M. T., & Badcock, D. R. (2010). Vision in developmental disorders: is there a dorsal stream deficit? *Brain research bulletin, 82*(3-4), 147-160.
Haigh, S. M., Heeger, D. J., Dinstein, I., Minshew, N., & Behrmann, M. (2015). Cortical variability in the sensory-evoked response in autism. *Journal of autism and developmental disorders, 45*(5), 1176-1190. doi:10.1007/s10803-014-2276-6
Happé, F., & Frith, U. (2006). The weak coherence account: detail-focused cognitive style in autism spectrum disorders. *Journal of autism and developmental disorders, 36*(1), 5-25. doi:10.1007/s10803-005-0039-0
Herrington, J. D., Baron-Cohen, S., Wheelwright, S. J., Singh, K. D., Bullmore, E. T., Brammer, M., & Williams, S. C. R. (2007). The role of MT+/V5 during biological motion perception in Asperger syndrome: An fMRI study. *Research in Autism Spectrum Disorders, 1*(1), 14-27.
Ishikawa, A., Shimegi, S., & Sato, H. (2006). Metacontrast masking suggests interaction between visual pathways with different spatial and temporal properties. *Vision Research, 46*(13), 2130-2138.
JASP Team. (2018). JASP (Version 0.9)[Computer software].
Jazayeri, M., & Movshon, J. A. (2007). A new perceptual illusion reveals mechanisms of sensory decoding. *Nature, 446*(7138), 912-915. doi:10.1038/nature05739
Jones, C. R., Swettenham, J., Charman, T., Marsden, A. J., Tregay, J., Baird, G., . . . Happe, F. (2011). No evidence for a fundamental visual motion processing deficit in adolescents with autism spectrum disorders. *Autism Res, 4*(5), 347-357. doi:10.1002/aur.209
Kaiser, M. D., Hudac, C. M., Shultz, S., Lee, S. M., Cheung, C., Berken, A. M., . . . Pelphrey, K. A. (2010). Neural signatures of autism. *Proceedings of the National Academy of Sciences of the United States of America, 107*(49), 21223-21228. doi:10.1073/pnas.1010412107
Kanner, L. (1943). Autistic disturbances of affective contact. *Nervous child, 2*(3), 217-250.
Kaufman, A., & Kaufman, N. (2004). KBIT-2: Kaufman Brief Intelligence Test–Second Edition.
Kern, J. K., Trivedi, M. H., Garver, C. R., Grannemann, B. D., Andrews, A. A., Savla, J. S., . . . Schroeder, J. L. (2006). The pattern of sensory processing abnormalities in autism. *Autism, 10*(5), 480-494. doi:10.1177/1362361306066564
Koldewyn, K., Whitney, D., & Rivera, S. M. (2010). The psychophysics of visual motion and global form processing in autism. *Brain, 133*(Pt 2), 599-610. doi:10.1093/brain/awp272
Lu, Z. L., & Dosher, B. A. (2008). Characterizing observers using external noise and observer models: assessing internal representations with external noise. *Psychol Rev, 115*(1), 44-82. doi:10.1037/0033-295X.115.1.44
Manning, C., Tibber, M. S., Charman, T., Dakin, S. C., & Pellicano, E. (2015). Enhanced integration of motion information in children with autism. *The*

Journal of neuroscience : the official journal of the Society for Neuroscience, 35(18), 6979-6986. doi:10.1523/JNEUROSCI.4645-14.2015
Manning, C., Tibber, M. S., & Dakin, S. C. (2017). Visual integration of direction and orientation information in autistic children. *Autism & Developmental Language Impairments, 2*, 2396941517694626.
Marco, E. J., Hinkley, L. B., Hill, S. S., & Nagarajan, S. S. (2011). Sensory processing in autism: a review of neurophysiologic findings. *Pediatr Res, 69*(5 Pt 2), 48R-54R.
McKay, L. S., Simmons, D. R., McAleer, P., Marjoram, D., Piggot, J., & Pollick, F. E. (2012). Do distinct atypical cortical networks process biological motion information in adults with Autism Spectrum Disorders? *Neuroimage, 59*(2), 1524-1533. doi:10.1016/j.neuroimage.2011.08.033
Milne, E. (2011). Increased intra-participant variability in children with autistic spectrum disorders: evidence from single-trial analysis of evoked EEG. *Front Psychol, 2*, 51. doi:10.3389/fpsyg.2011.00051
Milne, E., Swettenham, J., Hansen, P., Campbell, R., Jeffries, H., & Plaisted, K. (2002). High motion coherence thresholds in children with autism. *Journal of child psychology and psychiatry, and allied disciplines, 43*(2), 255-263.
Milne, E., White, S., Campbell, R., Swettenham, J., Hansen, P., & Ramus, F. (2006). Motion and form coherence detection in autistic spectrum disorder: Relationship to motor control and 2: 4 digit ratio. *Journal of autism and developmental disorders, 36*(2), 225-237.
Mottron, L., Dawson, M., Soulieres, I., Hubert, B., & Burack, J. (2006). Enhanced perceptual functioning in autism: an update, and eight principles of autistic perception. *Journal of autism and developmental disorders, 36*(1), 27-43. doi:10.1007/s10803-005-0040-7
O'Neill, M., & Jones, R. S. (1997). Sensory-perceptual abnormalities in autism: a case for more research? *Journal of autism and developmental disorders, 27*(3), 283-293.
Park, W. J., Schauder, K. B., Zhang, R., Bennetto, L., & Tadin, D. (2017). High internal noise and poor external noise filtering characterize perception in autism spectrum disorder. *Sci Rep, 7*(1), 17584. doi:10.1038/s41598-017-17676-5
Peiker, I., Schneider, T. R., Milne, E., Schöttle, D., Vogeley, K., Münchau, A., . . . David, N. (2015). Stronger neural modulation by visual motion intensity in autism spectrum disorders. *PLoS ONE, 10*(7), e0132531.
Pelli, D. G. (1997). The VideoToolbox software for visual psychophysics: Transforming numbers into movies. *Spatial vision, 10*, 437-442.
Pellicano, E., Gibson, L., Maybery, M., Durkin, K., & Badcock, D. R. (2005). Abnormal global processing along the dorsal visual pathway in autism: a possible mechanism for weak visuospatial coherence? *Neuropsychologia, 43*(7), 1044-1053. doi:10.1016/j.neuropsychologia.2004.10.003
Saygin, A. P., Cook, J., & Blakemore, S. J. (2010). Unaffected perceptual thresholds for biological and non-biological form-from-motion perception in autism spectrum conditions. *PLoS ONE, 5*(10), e13491. doi:10.1371/journal.pone.0013491

Simmons, D. R., Robertson, A. E., McKay, L. S., Toal, E., McAleer, P., & Pollick, F. E. (2009). Vision in autism spectrum disorders. *Vision Research, 49*(22), 2705-2739. doi:10.1016/j.visres.2009.08.005

Spencer, J., O'brien, J., Riggs, K., Braddick, O., Atkinson, J., & Wattam-Bell, J. (2000). Motion processing in autism: evidence for a dorsal stream deficiency. *Neuroreport, 11*(12), 2765-2767.

Spencer, J. V., & O'Brien, J. M. (2006). Visual form-processing deficits in autism. *Perception, 35*(8), 1047-1055. doi:10.1068/p5328

Sutherland, A., & Crewther, D. P. (2010). Magnocellular visual evoked potential delay with high autism spectrum quotient yields a neural mechanism for altered perception. *Brain, 133*(Pt 7), 2089-2097. doi:10.1093/brain/awq122

van Boxtel, J. J., Dapretto, M., & Lu, H. (2016). Intact recognition, but attenuated adaptation, for biological motion in youth with autism spectrum disorder. *Autism Res, 9* (10), 1103–1113. doi:10.1002/aur.1595

van Boxtel, J. J., & Lu, H. (2015). Joints and their relations as critical features in action discrimination: evidence from a classification image method. *J Vis, 15*(1), 20, 21-17. doi:10.1167/15.1.20

van Boxtel, J. J., Peng, Y., Su, J., & Lu, H. (2017). Individual Differences in High-level Biological Motion TasksCorrelate with Autistic Traits. *Vision Res, 141*, 136-144

Van der Hallen, R., Manning, C., Evers, K., & Wagemans, J. (2018). *Global Motion Perception in ASD: A Meta-Analysis.* Paper presented at the IMFAR, Rotterdam, Netherlands.

Vilidaite, G., Yu, M., & Baker, D. H. (2017). Internal noise estimates correlate with autistic traits. *Autism Res, 10*(8), 1384-1391. doi:10.1002/aur.1781

Webster, K. E., Edwin Dickinson, J., Battista, J., McKendrick, A. M., & Badcock, D. R. (2011). Increased internal noise cannot account for motion coherence processing deficits in migraine. *Cephalalgia : an international journal of headache, 31*(11), 1199-1210. doi:10.1177/0333102411414440

Weinger, P. M., Zemon, V., Soorya, L., & Gordon, J. (2014). Low-contrast response deficits and increased neural noise in children with autism spectrum disorder. *Neuropsychologia, 63*, 10-18.

Wilcox, G. (1968). *Inter-observer agreement and models of monaural auditory processing in detection tasks.* University of Michigan, Ann Arbor, Michigan.

Zaidel, A., Goin-Kochel, R. P., & Angelaki, D. E. (2015). Self-motion perception in autism is compromised by visual noise but integrated optimally across multiple senses. *Proceedings of the National Academy of Sciences, 112*(20), 6461-6466.

Zwaigenbaum, L., Bryson, S., Rogers, T., Roberts, W., Brian, J., & Szatmari, P. (2005). Behavioral manifestations of autism in the first year of life. *Int J Dev Neurosci, 23*(2-3), 143-152. doi:10.1016/j.ijdevneu.2004.05.001