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Does motor noise contaminate estimates of the precision of visual working memory?

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ABSTRACT

The continuous-report task, in which subjects report the colour of a visual working memory representation by clicking on a colour wheel, has become the gold standard for measuring the precision of representations stored in visual working memory. This task requires fine motor control, typically with a mouse, but the precision of responses have been interpreted as being entirely due to the precision of the memory representations. Here we tested the possibility that motor noise contaminates our estimates in the continuous-report task by simply asking subjects to complete the task using either their dominant or non-dominant hand on different blocks of trials. We found that subjects took longer with their non-dominant hand, but this did not affect the precision of their responses. Our findings suggest that this commonly used task to study visual memory may be relatively immune from contamination by motor noise at the output stage.

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Visual working memory; memory precision; motor noise; handedness

Essentially all models of cognitive processing propose that the extreme capacity limits of working memory constrain human cognition (e.g., Anderson, 1983; Burnett Heyes et al., 2012; Fukuda et al., 2010; Kieras et al., 1999). Because of this, an enormous volume of research has focused on understanding the capacity limits of visual working memory, defined as our ability to maintain visual representations over short periods of time in service of a variety of tasks (Luck & Vogel, 2013). Over the last decade, the modal task that is used to study these capacity limits has become the continuous-report task, in which subjects click on a wheel containing the full range of possible feature values, allowing subjects to communicate the remembered feature value without needing to verbally label the feature, or requiring researchers to interpret errors in the relatively coarse, two-alternative-forced-choice change-detection paradigm (Luck & Vogel, 1997; Phillips, 1983; Vogel et al., 2001).

The findings from colour continuous-report tasks have shaped our models of visual working memory storage (Luck & Vogel, 2013). These findings have been so impactful due to the distribution of subjects' responses providing a measure of the precision of their memory representations. That is, researchers interpret the standard deviation (SD) of the distribution of mouse clicks around the actual colour that was shown in the memory sample as due entirely to the precision of the memory representation itself (Bays et al., 2011; Zhang & Luck, 2008). If true, then this task provides process purity in terms of allowing us to readout the precision of our subjects' memory representation, without contamination from other potential sources of noise or variance.

However, cognitive scientists have long proposed that subjects' behavioural responses are due to processing across a series of stages, with each adding some amount of noise to the ultimate behaviour response that is produced (Donders, 1868/1969). Indeed, this is a typical motivation for the use of neuroscience to understand the subcomponents of cognition (e.g., Luck et al., 2000). Under this framework, the use of noisier channels will require more time to extract the same quality of signal or perform the same operation as a less noisy channel (Omrani

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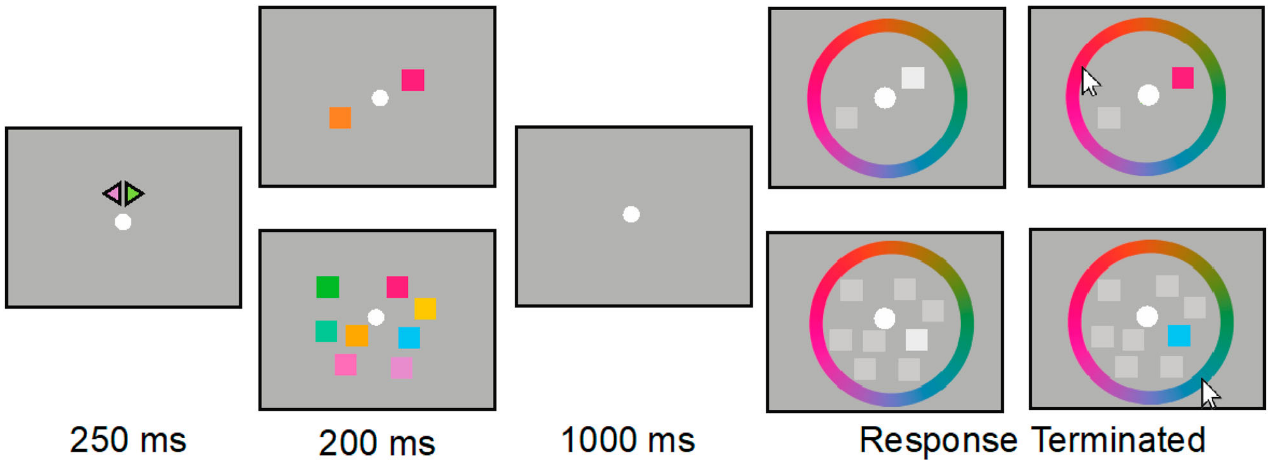

Figure 1. The continuous-report task. Observers were cued to remember stimuli (1 or 4) on either the left or right side of the display. After a brief delay, observers were cued to report the precise colour of one of the memory targets.

et al., 2017). It seems unlikely that the complex, visually guided mouse movements required in our continuous report tasks are a pure measure of memory precision uncontaminated by motor noise. To provide an initial test of this idea, we leveraged the subjects' inherent handedness to compare memory precision when reported with the dominant versus non-dominant hand. That is, motor responses are noisier when performed by the non-dominant hand than the dominant hand, with subjects requiring a longer time to click with the same accuracy as they do with their dominant hand (MacKenzie et al., 1991; Peters & Ivanoff, 1999). We asked whether this additional motor noise would obscure the typical set size effects observed with continuous report tasks.

Here we pitted two completing hypotheses against each other. Under the *process-purity hypothesis*, the continuous-report task where subjects click on a colour wheel to indicate their remembered colour provides a measure of the memory precision, uncontaminated by noise from other stages of processing. Under this hypothesis, if subjects were to make responses with a noisier effector that is harder to control, such as their non-dominant hand, this would have little effect on the precision of their responses relative to a condition in which they used their dominant hand to make these responses. The competing hypothesis is the *additive-noise hypothesis*, in which the precision of subjects' responses is a composite of noise from their memory representations and other cognitive mechanisms. Under this hypothesis, the precision of subjects' complex, visually guided mouse clicks is due to the precision of the memory representations, plus noise in induced during other stages of processing, such that when the non-dominant hand is used to control the mouse, we should see more noise (i.e., less precise responses). We tested this hypothesis using the continuous-report task shown in Figure 1. Subjects remembered 1 or 4 coloured squares and reported the colour of one square at the end of a brief retention interval. Across blocks of trials they switched between using their dominant and non-dominant hand.

Method

Participants

A total of 32 Vanderbilt University undergraduate students (18–21 years old) participated in the experiment for course credit. Participants reported normal colour vision and normal or corrected-to normal visual acuity, and provided informed consent to procedures approved by the Vanderbilt University IRB. Out of these 32 subjects, the data of 28 were included in the final sample. Two subjects were excluded because of data recording errors, one subject was excluded because they reported using one hand for computer activities and the other for everyday activities (all other participants confidently reported a clear response-hand preference), and one subject was excluded because their working memory performance on four item trials was at chance.

Apparatus and stimuli

Stimuli were generated in MATLAB using the Psychophysics Toolbox extension (Brainard, 1997; Pelli, 1997) and were presented on a 24-inch flat screen gaming monitor (120-Hz refresh rate). Viewing distance was approximately 80 cm and stimulus sizes calculated assuming this distance. A grey background (41.3 cd/m^2) and a white fixation dot (0.13° diameter, 255 cd/m^2) appeared in all displays. The colours of the square memory stimuli (0.79° × 0.79°) were chosen randomly from a set of 360 colours taken from a CIE L*a*b* colour space. To discourage subjects from grouping similar colours in memory, colours of stimuli on each trial were chosen randomly with the constraint that each stimulus in each hemifield (i.e., left and right) was a minimum of 29 degrees in colour space from the other stimuli in that hemifield.

Procedure

Participants were tested individually in a dimly lit testing room. On each block of trials, the block began with three lines of instructions. The first line consisted of which colour arrow to pay attention to (green or pink). The second line indicated which hand to use for the first block of trials (dominant or non-dominant), and the third line of instructions told the participant to click the mouse to start the experiment.

Each trial began with a grey screen for 500 ms, containing a central fixation point that was visible throughout each trial. Then, two arrow heads pointing left and right (~0.64° × 0.64 of visual angle), one green ($x = 0.283$, $y = 0.620$; 166 cd/m^2) and one pink ($x = 0.346$, $y = 0.147$; 43.4 cd/m^2), colour randomized, were presented for 250 ms 0.64° above the central fixation point. Each sample array of coloured squares was presented for 200 ms. The sample array consisted of either 1 or 4 squares in each hemifield. After a 1000 ms retention interval, the test array was presented, which consisted of dark grey squares (75.3 cd/m^2) at all previous square positions on the sample array, with a colour wheel surrounding them (Figure 1). One of the dark grey squares, on the half of the screen the subject was asked to pay attention to, was randomly selected each trial and filled in with a light grey square (155 cd/m^2). The subject was asked to be as accurate as possible when indicating the colour from the sample array of the probed square. Subjects completed this task using a one-button mouse to click the corresponding colour on the full colour wheel (Figure 1). As subject moved the mouse cursor around the colour wheel, the colour of the probe square was filled in with the colour that the cursor was on, to encourage accuracy. Finally, subjects were asked to click the mouse again to begin the next trial. The location of the squares in the sample arrays, the location of colours on the colour wheel, and condition were randomly assigned every trial.

Between blocks, subjects received a 30 s break, in which instructions were presented on which hand to use for responses in the next block. In total, subjects completed 10 blocks with 48 trials each (120 trials with hand for each set size). The starting assignment of which colour arrow and hand to start with was also equally randomly distributed.

Statistics and analysis

Response error on each trial was calculated as the number of degrees between the presented colour and the reported colour. Errors ranged from 0° (perfect response) to ±180° (a maximally imprecise response). The error distribution across trials can be modelled as a mixture of two distributions that reflect guesses and correct responses (Zhang & Luck, 2008). We used MemToolbox (Suchow et al., 2013) to calculate the probability of guessing (P_{guess}) and precision of responses (SD). A higher proportion of P_{guess} indicates subjects were guessing more, and a higher degree of SD indicated lower memory precision. We recognize that alternative approaches to modelling these responses are possible, so we also tested whether raw error varied across conditions.

Inferential statistical analyses were performed using JASP and MATLAB. To assess the reliability of differences in performance as a function of memory load and motor difficulty we performed a two-way repeated measures ANOVA on each of four variables: absolute value of raw error and reaction time as well as the two parameters derived from the mixture model: probability of guessing (P_{guess}) and memory precision (SD). Each ANOVA consisted of the within-subjects factors of memory load (one or four items) and response hand (dominant or non-dominant hand). To determine the likelihood that the null

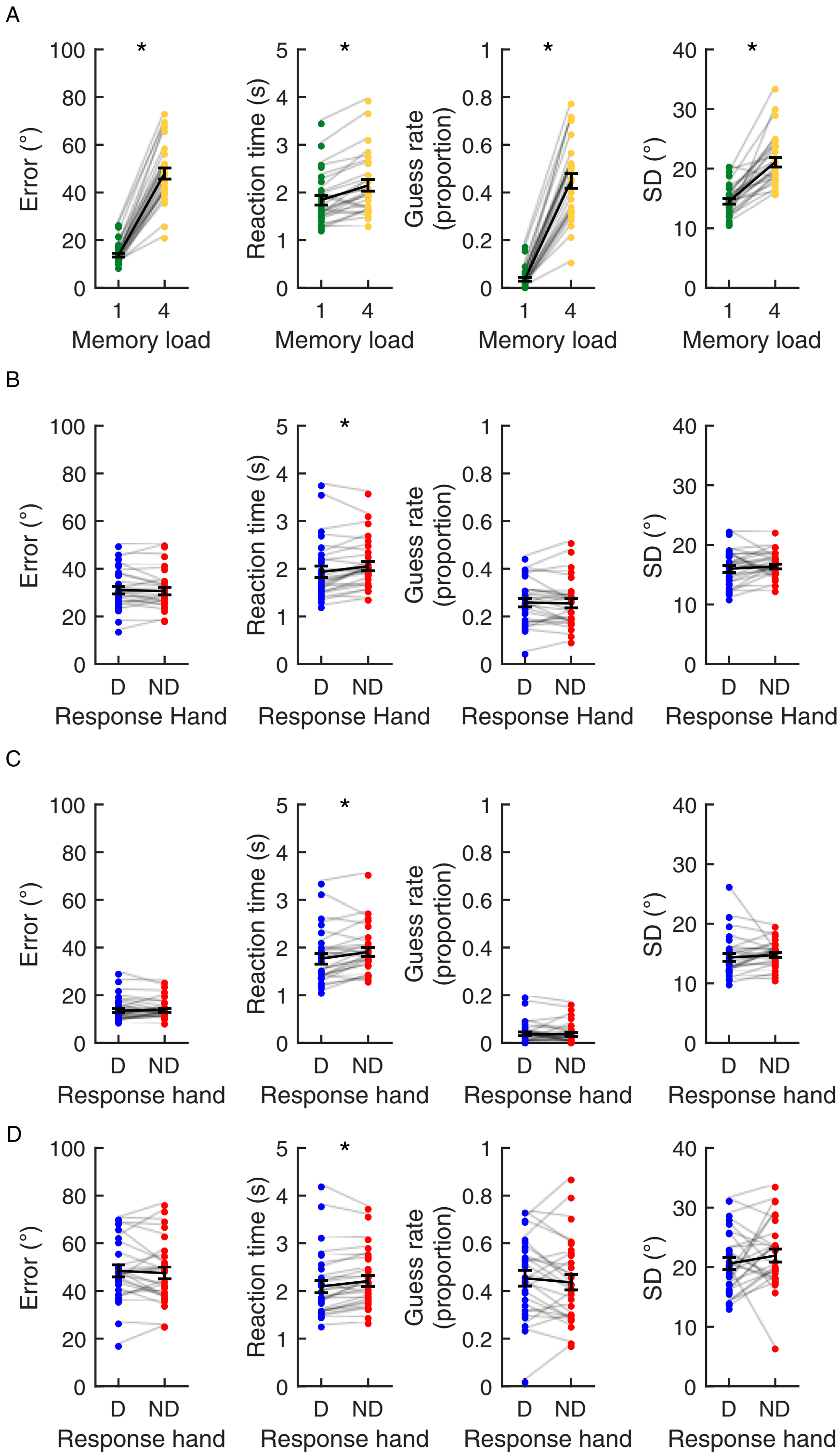

Figure 2. Memory performance across set size (A) and response hand (B) D stands for dominant hand and ND stands for non-dominant hand. Error bars reflect standard error of the mean. * indicates $p < .01$. Performance broken down by set size 1 (C) and 4 (D).

hypothesis was true, that is, that the response hand manipulation had no effect on accuracy of subjects' mouse clicks, we calculated the JZS Bays' factors for each accuracy measure (Rouder et al., 2009).

Results

The behavioural results are shown in Figures 2 and 3. Our data replicate the now canonical finding of

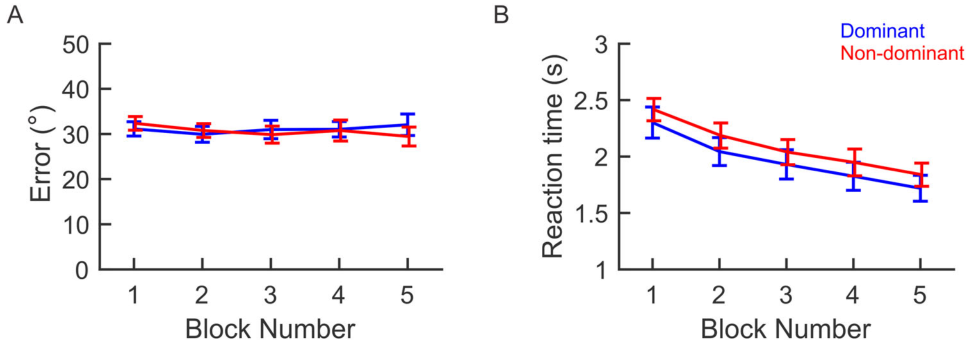

Figure 3. Raw error (A) and reaction time (B) across blocks. Error bars reflect standard error of the mean.

reduced precision and increased guessing as the memory set size increased from 1 to 4 coloured squares (Adam et al., 2017; Zhang & Luck, 2008). However, we found no evidence that the response hand manipulation changes these measures of accuracy. However, we did find an increase in median RT when subjects responded with their non-dominant hand relative to blocks in which they used their dominant hand (~100 ms).

Consistent with these observations, a repeated-measures ANOVA of raw error revealed a significant effect of memory load (Figure 2(a); $F(1,27) = 342.29$, $p < .001$), but neither a main effect of response hand (Figure 2(b); $F(1,27) = 4.24$, $p = 0.51$), nor an interaction of memory load and response hand ($F(1,27) = 0.481$, $p = 0.49$). Next, each mixture modelling parameter, P_{guess} and SD, was entered into a separate ANOVA with the factors of memory load (1 versus 4) and response hand (dominant versus non-dominant). Subjects guessed significantly more when probed about 4-item arrays than 1-item arrays ($F(1,27) = 243.36$, $p < .001$), and subjects' precision (SD) was significantly worse in 4-item arrays than 1-item arrays ($F(1,27) = 55.75$, $p < 0.001$). However, neither of these metrics showed a main effect of response hand (P_{guess}: $F(1,27) = 1.22$, $p = 0.279$; SD: $F(1,27) = 1.658$, $p = 0.209$) nor an interaction of response hand with memory load (P_{guess}: $F(1,27) = 0.433$, $p = 0.516$; SD: $F(1,27) = 0.524$, $p = 0.476$).

Because the process-purity hypothesis predicts that our response-hand manipulation will have no influence on the accuracy of subjects' responses, we wanted to provide statistical support beyond asserting the null. To this end, we calculated JZS Bayes factors for handedness for each of the accuracy-derived measures analyzed in the preceding. These showed that the hypothesis that response hand had no effect was between 3.5 and 4.5 times more likely than the hypothesis that response hand influenced the accuracy of subjects' responses across all analyses or memory accuracy (Table 1).

Although all of our accuracy measures were uninfluenced by the response hand of report, we found that subjects' RTs were significantly influenced by both memory load and response hand (Figure 2). The RTs were slower when responding to the probe from a 4-item array than a 1-item array, resulting in a main effect of memory load (Figure 2(a); $F(1,27) = 39.57$, $p < .001$). Moreover, we observed a significant main effect of response hand ($F(1,27) = 12.37$; $p = 0.002$; Figure 2(b)), although the factors of memory load and response hand did not interact significantly ($F = 0.79$, $p = 0.383$).

Finally, we wanted to determine if there was initially an influence of response hand on performance that disappeared as people had more practice using their non-dominant hand to respond. A two-way repeated-measures ANOVA of raw error with

Table 1. Bayes factors and descriptive statistics for handedness comparisons.

	Error (°)	RT (ms)	Guess Rate (proportion)	Precision (°)
Mean dominant	31.0	1935	.258	16.0
Standard deviation dominant	8.4	630	.10	2.9
Mean non-dominant	30.6	2052	.254	16.4
Standard deviation non-dominant	8.1	531	.10	2.2
Bayes Factor$_{01}$	4.06	.14	4.55	3.55

within-subjects factors of response hand (dominant or non-dominant) and trial block (1–5) revealed no significant main effect of either block ($F(4,108) = .349$, $p = .844$) or response hand ($F(1,27) = .450$, $p = .508$). Critically, no significant interaction was observed between the response hand and response block (Figure 3(a); $F(4,108) = 1.015$, $p = .403$).

While response accuracy was not influenced by trial block or response hand, RTs were significantly influenced by both response hand and trial block (Figure 3(b)). RTs were slower when responding with the non-dominant hand, resulting in a significant main effect of response hand ($F(1,27) = 8.456$, $p = .007$). Furthermore, RTs became faster as observers completed more blocks of the task, resulting in a significant main effect of trial block ($F(4,108) = 29.62$, $p < .001$). However, no significant interaction was observed between response hand and trial block ($F(4,108) = .063$, $p = .993$).

General discussion

Here we tested two competing hypotheses regarding the relationship of response-stage processing and visual working memory storage, as measured with the continuous-report tasks that are common in visual cognition experiments. The process-purity hypothesis proposes that continuous-performance tasks are uninfluenced by motor-output noise, and provide a pure measure of the precision of subjects' memories.[1] In contrast, the additive-noise hypothesis proposes that noise from response selection and motor output are combined with noise from our memory representations to result in the measure of precision that we derive from continuous-report tasks. To manipulate the amount of motor noise that could contribute to subjects' responses, we had subjects perform the same colour report task with their dominant hand, and their non-dominant hand, on different blocks of trials. We found that subjects' responses were slowed when they used their non-dominant hand, but that responses were no less accurate compared to the same subjects using their dominant hand. Our findings support the view that the colour continuous-report task provides a process pure measure of the nature of subjects' memories.

Our findings have further theoretical implications. First, they suggest that motor functions and visual memory storage may depend on separate processing pathways. For example, Baddeley's multi-component model of working memory proposes that the brain has modality specific sub stores for different types of information (Baddeley, 1992). Under this view, the storage of visual working memory representations of object properties, such as colour, should be distinct from response selection and motor processes. An interesting exception to this could be when visual memory is storing spatial locations, as theoretical proposals have stated that we may store spatial locations in a representational format that interacts with motor control mechanisms (Baddeley & Logie, 1999; Logie, 1995). It is possible that this explains why theories of embodied cognition have proposed links between motor function to various memory functions (Casasanto & Dijkstra, 2010; Thomas, 2015). The embodied-cognition theories would otherwise appear to predict that we should have found that hand of response significantly influenced the accuracy of subjects' memory report.

Note

1. We note that a completely comprehensive assessment of the process-purity hypothesis in continuous-report tasks would involve determining whether this accepted measure of memory precision might be contaminated by noise injected in the frontend perceptual stage. We assume this does happen, and are testing such predictions in a separate long line of work (e.g., Kang et al., 2011).

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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