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A Bayesian perspective

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Understanding spatial neglect: A Bayesian perspective

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Abstract

Spatial neglect has been a phenomenon of interest for perceptual and neuropsychological researchers for decades. However, the underlying cognitive processes remain unclear. We provide a Bayesian framework for the classic line bisection task in spatial neglect, regarding bisection responses as rational inferences in the face of uncertain information. A Bayesian observer perceives the left and right endpoints of a line with uncertainty, and leverages prior expectations about line lengths to compensate for this uncertainty. This Bayesian model provides a basis for characterizing different patterns of neglect behavior. Our model also captures the paradoxical cross-over effect observed in earlier studies. It provides measures that correlate well with measures from other neglect tests, and can accurately distinguish stroke patients from healthy controls.

Keywords: spatial neglect; visual neglect; line bisection; attention; perception; Bayes

Spatial neglect, a pronounced asymmetry of attention and behavior away from one side of space and towards the other, is a neuropsychological disorder that typically results from right hemispheric brain damage. The line bisection task is one of the most widespread tasks to measure spatial neglect (Schenkenberg, Bradford, & Ajax, 1980; Sperber & Karnath, 2016). Participants are required to mark the midpoint of a horizontal line (Figure 1a). Patients with spatial neglect typically mark to the right of the true midpoint, which is conventionally explained as a distortion or compression of the perceived left space (Bisiach, Bulgarelli, Sterzi, & Vallar, 1983; Milner, Harvey, Roberts, & Forster, 1993).

Some debates remain about how we should interpret the line bisection task. Firstly, the correlation between the directional bisection error measure (DBE, the average deviation of participants' responses from the true midpoints across trials) and other spatial neglect tasks, such as target cancellation or figure copying, is relatively low (Sperber & Karnath, 2016; McIntosh, Ietswaart, & Milner, 2017). Besides, it was found that neglect patients sometimes mark the midpoint as left rather than right of the true midpoint, a paradoxical finding known as the cross-over effect (Marshall & Halligan, 1988; McIntosh, Schindler, Birchall, & Milner, 2005).

One proposal to make sense of these data is that, rather than underestimating the leftward extent of the line, patients in the line bisection task may lack a clear idea of where the left endpoint is (McIntosh et al., 2005). Indeed, it was found that

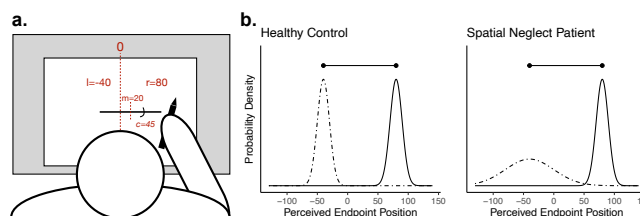


Figure 1: The line bisection task: a) Participants are asked to mark the midpoint of the line. Left endpoint (l), right endpoint (r), true midpoint (m), and response (c) are not marked on the stimulus sheet itself. b) Spatial neglect patients may have lower left-side perceptual precision.

when the left and right endpoint positions were manipulated independently across trials, patients' responses were much more affected by the right endpoint than the left endpoint, an asymmetry which was captured by a novel dependent measure called endpoint weightings bias (McIntosh et al., 2005, 2017; McIntosh, 2018, see below).

We show that a Bayesian framework provides a way to formalize and extend the above proposal, and can explain various patterns in human performance in the task. This Bayesian approach frames the bisection problem as one of rational inferences in the face of uncertain or unreliable information, so that observers must balance prior expectations and evidence when making decisions (De Lange, Heilbron, & Kok, 2018).

The Bayesian neglect model

Intuitively, as shown in Figure 1b, the Bayesian model assumes the observer's perceived left and right endpoints follow Gaussian distributions with a mean at the actual endpoint and some uncertainty. Three key assumptions guide the Bayesian perspective on the line bisection task:

1. The midpoint response c should have the same distance from the perceived left P_L and right P_R endpoints, i.e., $P_L = c - \frac{l}{2}$, and $P_R = c + \frac{r}{2}$, where l represents the expected line length.
2. There is uncertainty when one perceives the left endpoint (σ_L) and the right endpoint (σ_R), i.e., $l \sim N(P_L, \sigma_L)$, $r \sim N(P_R, \sigma_R)$, where l and r represent the left and right endpoints in the stimulus. Patients might exhibit especially high uncertainty on the left side (Figure 1b).
3. When endpoint uncertainty is high, one may have to estimate line lengths and midpoints from some prior expectations. We model line length expectations with a gamma distribution $l \sim \Gamma(\alpha, \beta)$, as well as midpoint expectations



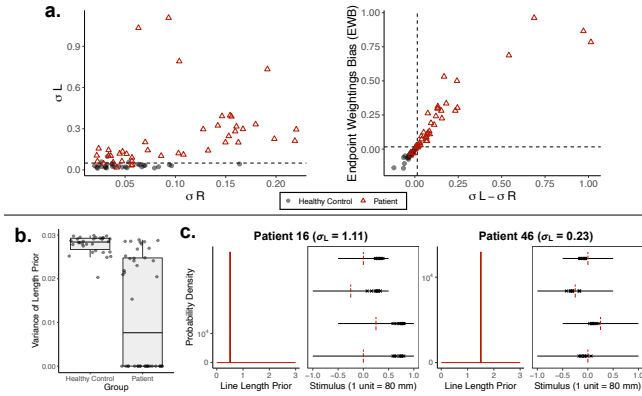


Figure 2: a) Scatter plots of parameters. The dashed lines show the best cut-off for the corresponding measure. b) The fitted line length prior variance in two groups. c) The line bisection responses and fitted line length priors of two patients.

that the midpoint tend to be at the center of the page, i.e., $c \sim N(0, \sigma_C)$.

Methods

We used the Bayesian neglect model to estimate individual differences in data from McIntosh et al. (2017). In this study, patients diagnosed with unilateral right hemisphere stroke ($N = 42$; 12 female, 30 male; $68.64 \text{ years} \pm 9.76$) and a healthy control group ($N = 30$; 18 female, 12 male; $71.27 \text{ years} \pm 9.12$) finished the line bisection task. Four types of lines were created by combining endpoint locations with two different distances from the midpoint of the page: $[-40, 40]$, $[-80, 40]$, $[-40, 80]$, and $[-80, 80]$ mm (we standardized the data by treating 80 mm as 1 unit in later analysis, McElreath, 2020). We model each individual's data and obtain five parameters (σ_L , σ_R , α , β , σ_C) for each person using RStan package in R (Stan Development Team, 2022).

Results

Stroke patients indeed exhibited higher σ_L than the healthy controls ($t(70) = 4.69$, $p < .001$, Figure 2a). Meanwhile, the difference between left-side and right-side uncertainty (i.e. $\sigma_L - \sigma_R$) was larger in the stroke patients than in the healthy controls ($t(70) = 3.80$, $p < .001$). It highly correlated ($r = 0.923$, Figure 2a) with the “endpoint weightings bias” measure built on linear regressions ($EWB = d_{PR} - d_{PL}$, where $c = (d_{PL} \cdot l) + (d_{PR} \cdot r) + k$, see McIntosh et al., 2005), which is consistent with the theoretical assumption that both of them measure the relative sensitivity on the left and right sides.

Classification We found that σ_L itself serves as an informative indicator to classify participants from healthy controls. We applied one linear algorithm (logistic regression) and one non-linear algorithm (decision tree), and used leave-one-participant-out cross-validation to assess accuracy. The single σ_L can achieve 0.90 accuracy under logistic regression and 0.92 under decision tree. These are higher than the result of directional bisection error (logistic regression: 0.76; decision tree: 0.64) and the endpoint weightings bias (logistic

Table 1: Correlations between line bisection and other tasks.

	LINES	STARS	COPY	DRAW	MULTI
DBE	0.47	0.28	0.27	0.21	0.61
EWB	0.61	0.52	0.49	0.40	0.77
σ_L	0.59	0.42	0.40	0.37	0.75
$\sigma_L - \sigma_R$	0.61	0.40	0.34	0.37	0.73

regression: 0.85; decision tree: 0.82). After adding σ_R , the accuracy remained the same under both algorithms.

Correlation with other tasks Table 1 showed the correlation between line bisection measures and other spatial neglect tasks (see McIntosh et al., 2017, for the full description of those tasks). The correlations of the Bayesian measure σ_L or $\sigma_L - \sigma_R$ were higher than the directional bisection error, and similar to the endpoint weighting bias.

Expectation parameters The Bayesian neglect model provided two parameters α and β that can help examine the line length expectations (mean and variance) participants had. In the healthy control group, participants' line expectations on average were 1.48 units, which was around the average line length across trials (1.5 units). The stroke patients' line expectation was 1.38 units on average, shorter than that of the healthy controls ($t(70) = 2.32$, $p = .02$). The expectation variance was smaller in the patient group than in the healthy control group ($t(70) = 6.45$, $p < .001$, Figure 2b). For example, the Bayesian model identified that Patient16 had a strong expectation that the line was short (Figure 2c). Accordingly, most of their responses were close to the right endpoint. Patient46 demonstrated a strong expectation of a medium line length. Accordingly, their responses showed a fixed distance from the right endpoint, and many responses turned out to be on the left side of the true middle points (Figure 2c).

Discussion

In this paper, we provide a new model to describe the perceptual process in the line bisection task. The advantages of the current Bayesian neglect model are multifaceted. Firstly, it captures a general and intuitive representation of the perceptual processes in the line bisection task, i.e., the uncertainty in perceiving the left and right endpoints. Spatial neglect could be naturally explained as greater uncertainty on the left side, and reduced to parameters, σ_L or $\sigma_L - \sigma_R$, in our model. We demonstrated that both measures performed well in distinguishing stroke patients from healthy controls. They also correlated better with other spatial neglect tasks than the conventional directional bisection error. In addition, the Bayesian neglect model naturally integrates the role of prior beliefs, which can explain the paradoxical cross-over effect: If the patient has a strong line length expectation and a poor ability to perceive the left side, they would frequently mark responses that have the same distance from the right endpoint. These responses could be leftward under particular stimulus lengths. In sum, the results showed the Bayesian neglect model has the potential to facilitate spatial neglect studies and inform clinical decisions.

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