Bayesian modeling reveals distinct priors for tactile and proprioceptive localization

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Abstract

When a mosquito lands on your finger, swatting it requires your brain to calculate its location in the external space, which depends on the body's 3D posture. Two competing computational hypotheses explain how the brain solves this challenge: the integration hypothesis, where tactile signals are transformed into spatial coordinates by integrating touch and posture information; and the cueing hypothesis, where touch merely cues a location on the body whose position is specified via proprioception. If touch merely triggers proprioceptive localization (cueing hypothesis), both localizing touch and body parts in space should rely on the same Bayesian computations, with identical prior expectations about the mosquito's spatial location; if they involve different computational processes (integration hypothesis), the underlying priors might differ. Twenty-one participants localized their fingers via proprioception or touch in nine hand positions. We compared Bayesian model variants with different parameter sharing structures and quantified the overlap between these processes. Models allowing different prior distributions between modalities provided the best fit for most participants. The distances between fitted spatial priors showed 15 out of 19 participants had significantly different prior distributions across modalities. Our findings provide computational evidence that tactile localization involves different processes beyond those used in proprioceptive localization, providing evidence against the cueing hypothesis.

Keywords: tactile localization; proprioception; Bayesian modeling; spatial perception; sensory integration

Introduction

When a mosquito lands on your finger, your brain calculates its location in external space—a process that depends on your hand's position. How exactly does the brain transform a skin-based sensation into external spatial coordinates? Two competing frameworks explain this challenge. According to the *integration hypothesis*, touch (i.e., the mosquito) is initially coded in a somatotopic reference frame and transformed into external space by integrating tactile and 3D postural information (Longo, Mancini, & Haggard, 2015; Tamè, Azañón, & Longo, 2019; Canzoneri, Ferrè, & Haggard, 2014). In contrast, the *cueing hypothesis* suggests that tactile signals merely serve as a cue to a specific location on the body, which is localized via proprioception (Heed, Burbach, Rödenbeck, Habets, & Fuchs, 2024; Maij, Seegelke, Medendorp, Medendorp, & Heed, 2020). The key distinction is that in the cueing hypothesis, localizing touch is identical to localizing the body; touch functions merely as a proprioceptive cue, directing attention to a body part whose spatial position is computed through the same mechanisms used for proprioceptive localization.

We formalize spatial localization as Bayesian inference in a two-dimensional workspace (Figure 1). When a target appears at location $\mathbf{x}$, it generates sensory evidence $\mathbf{e}$. The brain estimates location $\mathbf{x}$ using Bayes' rule: $P(\mathbf{x}|\mathbf{e}) \propto L(\mathbf{e}|\mathbf{x}) \times \Pi(\mathbf{x})$, where $L(\mathbf{e}|\mathbf{x})$ is the likelihood function and $\Pi(\mathbf{x})$ is the prior distribution. The integration hypothesis predicts that the additional transformations required for tactile remapping could introduce distinct noise patterns in the likelihood function ($L_t(\mathbf{e}|\mathbf{x}) \neq L_p(\mathbf{e}|\mathbf{x})$) and unique biases in the prior distribution ($\Pi_t(\mathbf{x}) \neq \Pi_p(\mathbf{x})$). In contrast, the cue hypothesis proposes identical computational processes where touch merely indicates which body part to localize via proprioception, predicting identical priors ($\Pi_t(\mathbf{x}) = \Pi_p(\mathbf{x}) = \Pi_c(\mathbf{x})$) and likelihoods ($L_t(\mathbf{e}|\mathbf{x}) = L_p(\mathbf{e}|\mathbf{x}) = L_c(\mathbf{e}|\mathbf{x})$), resulting in: $P_t(\mathbf{x}|\mathbf{e}) = P_p(\mathbf{x}|\mathbf{e}) \propto L_c(\mathbf{e}|\mathbf{x}) \times \Pi_c(\mathbf{x})$.

Computational models have proven powerful for understanding perceptual biases in both domains (Goldreich, 2007; Peviani, Joosten, Miller, & Medendorp, 2024), yet formal comparisons remain lacking. Our study addresses this gap by implementing a Bayesian modeling framework that directly compares tactile and proprioceptive spatial localization.

Methods

We modeled prior and likelihood as 2D Normal distributions: $L(\mathbf{e}|\mathbf{x}) = \mathcal{N}(\mathbf{x}^*, \Sigma_{\text{lik}})$ and $\Pi(\mathbf{x}) = \mathcal{N}(\mu_{\text{pr}}, \Sigma_{\text{pr}})$, where $\mathbf{x}^*$ represents true touch location, therefore the likelihood is unbiased.

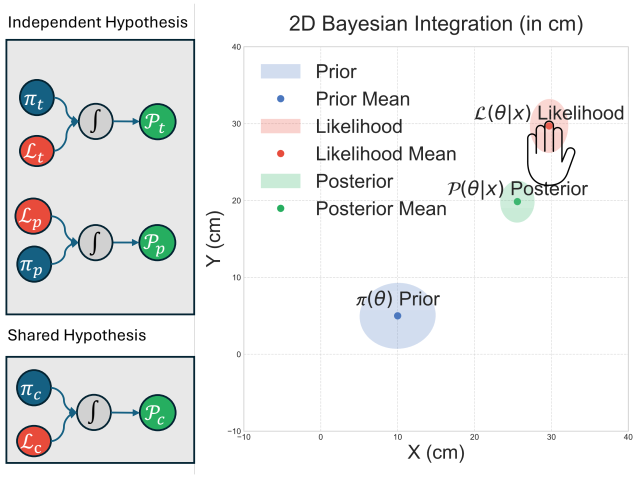

Figure 1: A. Independent and Shared Model. B 2D Bayesian Localization Framework (θ refers to model parameters)

We developed four model variants differing in how parameters are shared across modalities: (1) **Independent Model**, with distinct priors and likelihoods for each modality; (2) **Fully Shared Model**, with all parameters shared; (3) **Shared Prior Model**, with a common spatial prior but modality-specific sensory likelihoods; and (4) **Shared Likelihood Model**, with shared sensory likelihoods but distinct spatial priors. The two models represent intermediate points between the integration hypothesis and the cue hypothesis, offering weaker forms of each hypothesis respectively.

Twenty-one healthy adults participated. Participants sat upright in a chair, their gaze directed downward onto a monitor mounted horizontally (screen facing upward) on a rigid aluminium frame. A gap between the desk and the monitor allowed the left forearm to pass underneath the screen so that the left hand rested on a platform with three solenoid tactors. These solenoids were aligned with the pads of the index, middle, and ring fingers delivering tactile stimulation. Participants performed tactile localization (responding to solenoid taps) or proprioceptive localization (responding to targets given by text on the screen) by clicking perceived locations on the screen using the mouse with their right hand. An opaque cloth on their left forearm prevented visual feedback of the hand. (Figure 2).

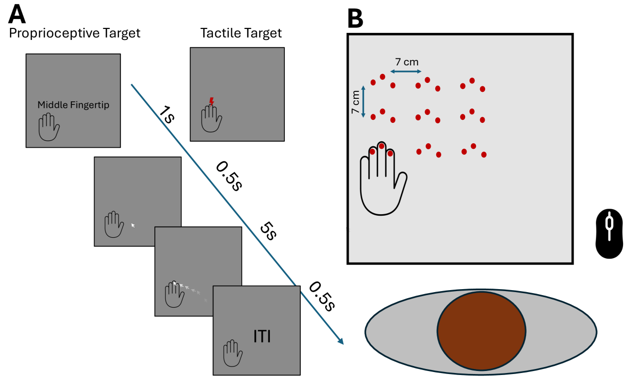

Figure 2: A. Trial structure, B. Experimental set up

Results

We first compared the models based on how well they explain the localization data. Our model comparison revealed that the Independent Model provided the best fit for the most participants (Figure 3. 16 out of 19 participants, Δ BIC difference relative to the fully shared model ranging from –425.21 to 4.65, with a mean of -210.28)

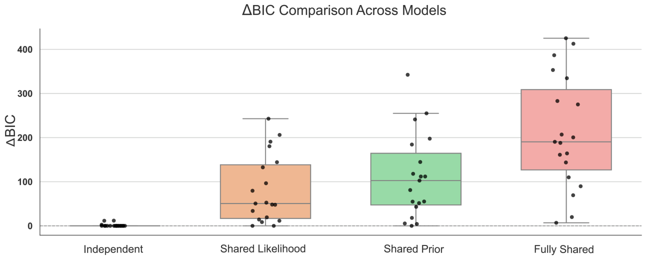

Figure 3: Model comparison across participants using Δ BIC relative to the best model. Each dot represents an individual participant's Δ BIC for a given model.

Figure 4 shows an example participant with fitted priors. To investigate if the fitted priors are different, which would be inconsistent with the cueing hypothesis's prediction of identical priors, we calculated the distances between the fitted priors for tactile and proprioceptive modalities using the Wasserstein-2 metric (Figure 5). We found that most of the participants exhibited significantly distinct spatial priors between modalities ($p < 0.05$, permutation test).

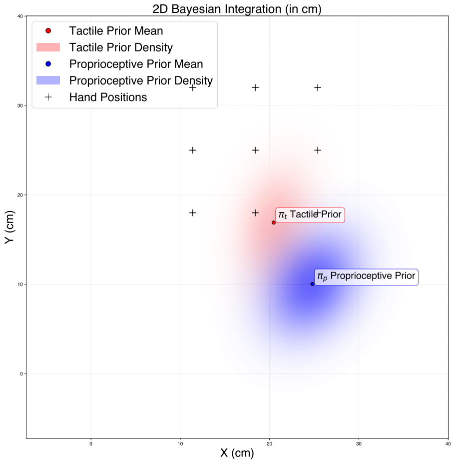

Figure 4: Fitted Tactile and Proprioceptive priors for a participant.

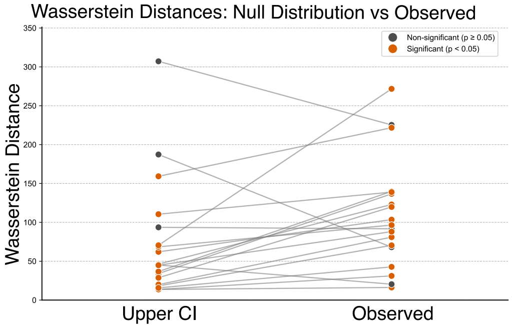

Figure 5: Observed Wasserstein-2 distances vs 95th percentile thresholds from null distributions (1000 shuffles per participant). Orange points indicate significantly different priors between modalities.

Conclusion

Our results suggest that tactile and proprioceptive spatial localization rely on distinct computational mechanisms, which is inconsistent with the cueing hypothesis but compatible with the integration hypothesis. The different prior distributions across the modalities indicate that tactile localization involves transformations beyond those used in proprioceptive localization, contributing to our understanding of how the brain constructs spatial representations from different sensory inputs.

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