

The importance of causal-inference for audiovisual spatial recalibration

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Ventriloquism and its aftereffect



Models of multisensory recalibration

- Reliability-based: supported by Burge, Girshick & Banks (2010) for visual/haptic integration
- Fixed-ratio: supported by Zaidel, Turner & Angelaki (2011) for visual-vestibular integration
- Causal-inference: Introduced below

Reliability-based model

- Updates based on measurement discrepancy
- Updates proportional to the other modality's reliability
- Thus,

$$\Delta_A(t+1) = \Delta_A(t) + \alpha w_A (m'_V - m'_A)$$

and

$$\Delta_V(t+1) = \Delta_V(t) + \alpha w_V (m'_A - m'_V),$$

where

$$w_A = \frac{\sigma'_{AV,V}{}^{-2}}{\sigma'_{AV,V}{}^{-2} + \sigma'_{AV,A}{}^{-2}} = \frac{r_{AV,V}}{r_{AV,V} + r_{AV,A}}$$

$$w_V = 1 - w_A \quad (\text{Ghahramani et al., 2007})$$

Fixed-ratio model

- Updates in fixed proportion based on modality-specific learning rate
- Thus,

$$\Delta_A(t+1) = \Delta_A(t) + \alpha_A (m'_V - m'_A)$$

and

$$\Delta_V(t+1) = \Delta_V(t) + \alpha_V (m'_A - m'_V)$$

(Zaidel et al., 2011)

Causal-inference model

- Updates based on difference between measurement and estimate
- Thus,

$$\Delta_A(t+1) = \Delta_A(t) + \alpha_A (\hat{s}'_A - m'_A)$$

and

$$\Delta_V(t+1) = \Delta_V(t) + \alpha_V (\hat{s}'_V - m'_V),$$

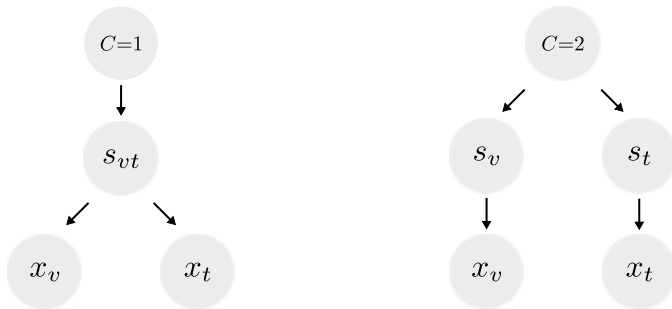
where the location estimates, the \hat{s}' values, are

determined using causal inference and model averaging.

- We also tested a single-rate model, where $\alpha_A = \alpha_V$

(Sato et al., 2007)

Causal inference

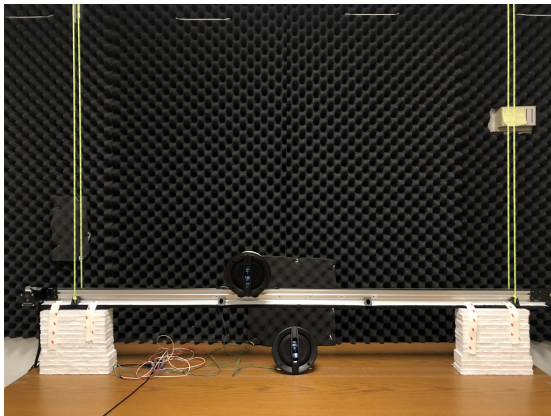


Körding et al., 2007

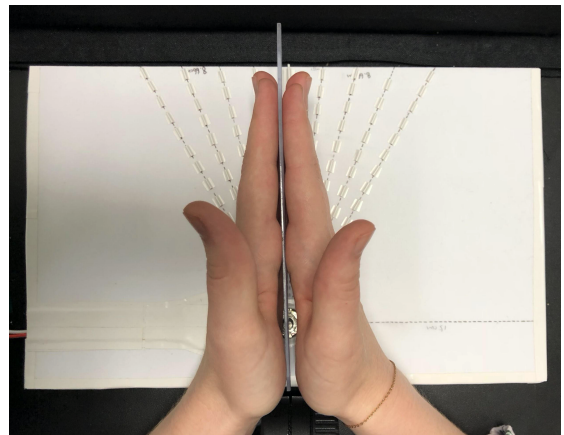
Apparatus: Projection screen



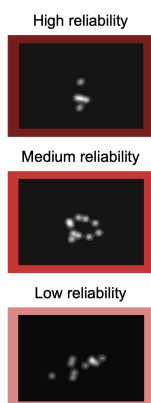
Apparatus: Movable speaker



Apparatus: Pointing device



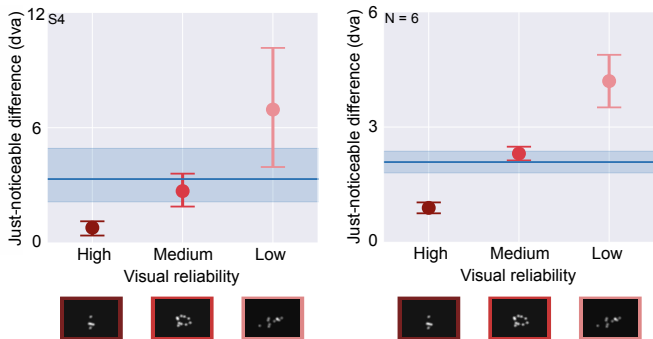
Visual stimuli with varied reliability



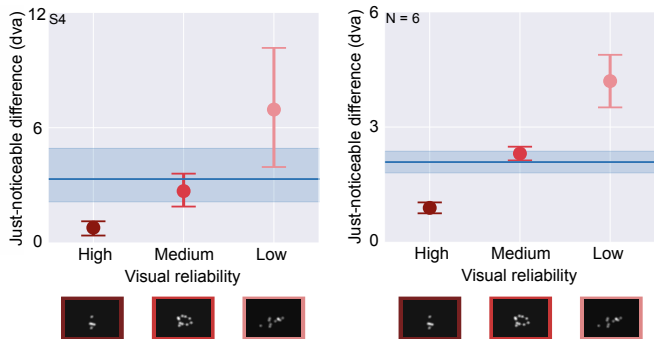
Experimental tasks/sessions

1. Unimodal spatial discrimination: To measure JNDs
2. Bimodal spatial discrimination: To measure bias
3. Pointing practice: For practice and to measure motor noise
4. Recalibration. Sessions: 2 directions of a fixed audiovisual perceived-location discrepancy x 3 visual reliabilities

Phase 1: Unimodal spatial discrimination

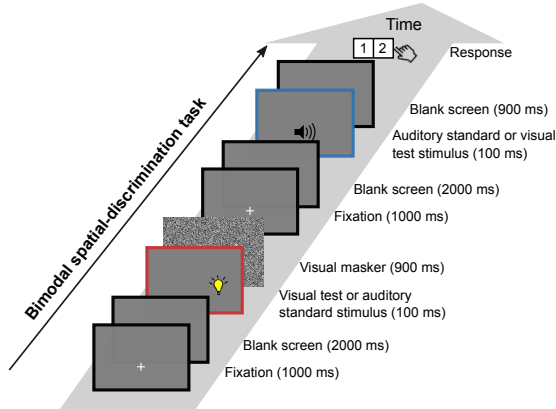


Phase 1: Unimodal spatial discrimination

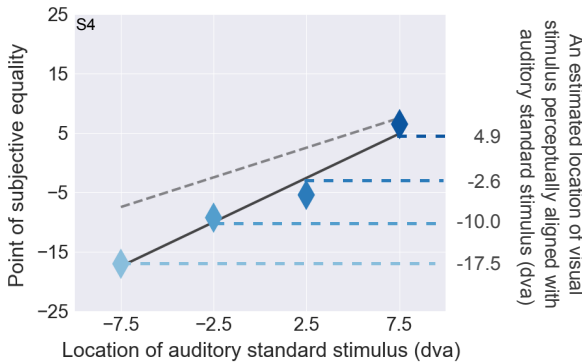


Thus, we successfully produced visual stimuli with reliability lower than, comparable to, and greater than auditory localization reliability

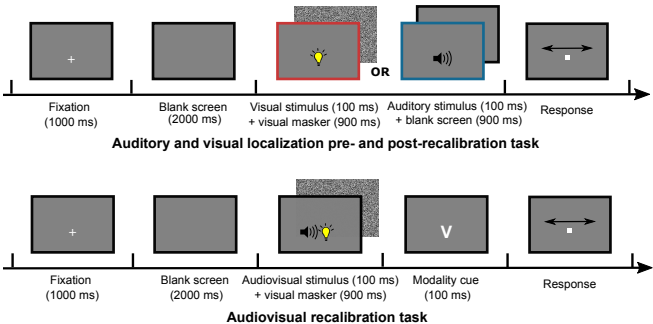
Phase 2: Bimodal spatial discrimination



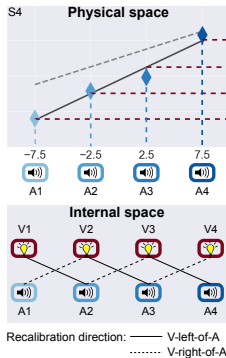
Phase 2: Bimodal spatial discrimination



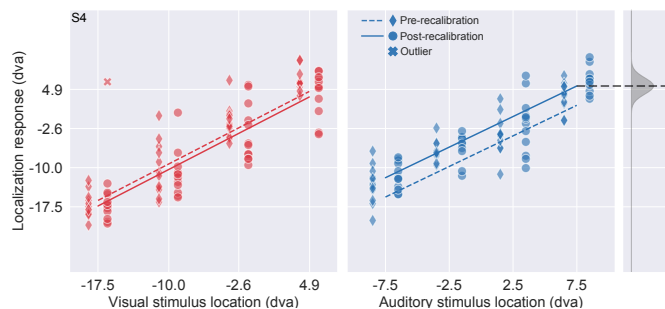
Main experiment: Recalibration



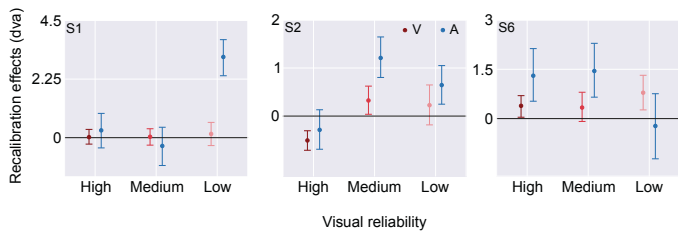
Main Experiment: Recalibration



Main Experiment: Recalibration



Main Experiment: Recalibration



We found that auditory recalibration can fall, rise, or rise and then fall, with decreasing visual reliability.

Modeling

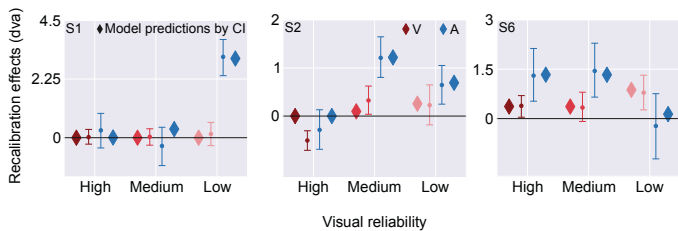
We compare three models

- Reliability-based
- Fixed-ratio
- Causal-inference

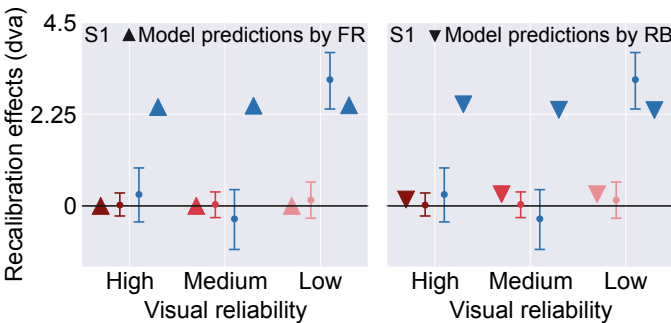
We jointly fit the models to the data from

- Unimodal discrimination
- Bimodal discrimination
- Pre- and post-recalibration unimodal localization

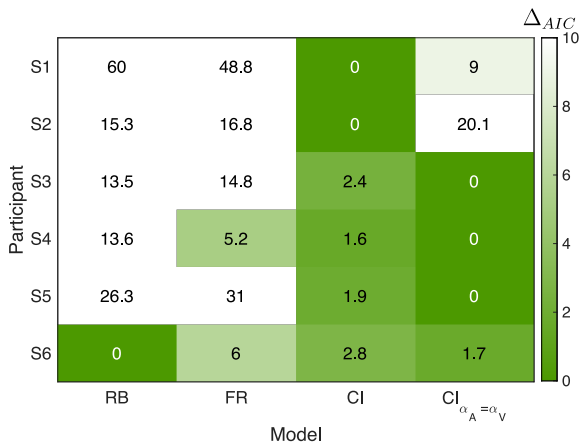
Model fit results: Causal-inference model



Failure to fit: Other models



Model comparison



Conclusions

- A causal-inference-based model of cue recalibration is required to explain the diverse patterns of recalibration with varying cue reliability across participants
- This is possible because of the non-monotonic effects of cue reliability and cross-cue discrepancy on both the ventriloquism effect and aftereffect

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Conclusions

- A causal-inference-based model of cue recalibration is required to explain the diverse patterns of recalibration with varying cue reliability across participants
- Given the presence of biases across cues, biases should be measured and taken into account in understanding multisensory integration
- Predictions are more clear-cut if stimuli across modalities are equated for these biases

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