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Cue combination in human spatial navigation

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ABSTRACT

This project investigated the ways in which visual cues and bodily cues from self-motion are combined in spatial navigation. Participants completed a homing task in an immersive virtual environment. In Experiments 1A and 1B, the reliability of visual cues and self-motion cues was manipulated independently and within-participants. Results showed that participants weighted visual cues and self-motion cues based on their relative reliability and integrated these two cue types optimally or near-optimally according to Bayesian principles under most conditions. In Experiment 2, the stability of visual cues was manipulated across trials. Results indicated that cue instability affected cue weights indirectly by influencing cue reliability. Experiment 3 was designed to mislead participants about cue reliability by providing distorted feedback on the accuracy of their performance. Participants received feedback that their performance with visual cues was better and that their performance with self-motion cues was worse than it actually was or received the inverse feedback. Positive feedback on the accuracy of performance with a given cue improved the relative precision of performance with that cue. Bayesian principles still held for the most part. Experiment 4 examined the relations among the variability of performance, rated confidence in performance, cue weights, and spatial abilities. Participants took part in the homing task over two days and rated confidence in their performance after every trial. Cue relative confidence and cue relative reliability had unique contributions to observed cue weights. The variability of performance was less stable than rated confidence over time. Participants with higher mental rotation scores performed relatively better with self-motion cues than visual cues. Across all four experiments, consistent correlations were found between observed weights assigned to cues and relative reliability of cues, demonstrating that the cue-weighting process followed Bayesian principles. Results also pointed to the important role of subjective evaluation of performance in the cue-weighting process and led to a new conceptualization of cue reliability in human spatial navigation.

1. Introduction

The ability to navigate through the environment is a skill that our prehistoric progenitors depended upon for survival, and one that even modern humans rely upon for many daily activities. Effective navigation depends on the ability to estimate one's position from information in the environment and from information internal to the organism. The accuracy and pre-

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cision of position estimates depend on a host of factors, including the reliability of these sources of information and the manner in which they are combined.

Spatial cues to position can be divided into two categories. Internal self-motion cues (idiothetic cues) refer to bodily information generated by self-movement, such as vestibular cues and proprioceptive cues. External environmental cues (allothetic cues) refer to inputs from the outside world, such as visual and auditory cues. Environmental cues can be further subdivided into those that are not directly informative about position but can be used to estimate position (e.g., optic flow) and those that are directly informative about position in the environment (e.g., landmark beacons). Navigation using self-motion cues (e.g., vestibular cues, proprioceptive cues) and environmental cues that themselves are not directly informative about position (e.g., optic flow) is referred to as path integration (Loomis, Klatzky, Golledge, & Philbeck, 1999). Many animals demonstrate remarkable abilities to navigate using path integration (Etienne & Jeffery, 2004; Wehner & Menzel, 1969). Humans, however, are relatively poorer at path integration than are ants and rodents, in particular (Loomis et al., 1993, 1999).

1.1. Bayesian approach to cue combination[1]

One heuristic to achieve better performance when multiple spatial cues are available is to combine spatial information from those cues instead of relying on one source, as every information source can be contaminated by noise and errors can be decreased by collecting multiple inputs. A second heuristic is to attend more to spatial cues considered as more reliable, so that limited cognitive resources are distributed efficiently. Bayesian principles of cue integration capture both of these heuristics.

Bayesian theory provides a systematic and quantitative method to investigate the manner in which different cues are integrated (Cheng, Shettleworth, Huttenlocher, & Rieser, 2007). Bayesian theory posits that the cue integration process involves linearly combining single-cue estimates, weighted by relative cue reliabilities,

$$C = w_A \times Q_A + w_B \times Q_B \tag{1}$$

In this formula, C is the combined estimate, Q_A and Q_B are the estimates from single cues, and w_A and w_B are weights assigned to individual cues. Cue reliability is usually inferred from subjects' performance and is inversely related to response variance,

$$r = 1/\sigma^2 \tag{2}$$

Thus, cue reliability is measured objectively and assesses the precision of the location representation associated with the cue.[2] Cue reliability reflects the level of performance when a cue is used exclusively in a given task. In the example shown in Fig. 1, cue A is more reliable than cue B. Based on Bayesian principles, the weights for cues A and B are,

$$w_A = r_A/(r_A + r_B) \tag{3}$$

$$w_B = r_B/(r_A + r_B) \tag{4}$$

Equivalently,

$$w_A = \sigma_B^2/(\sigma_A^2 + \sigma_B^2) \tag{5}$$

$$w_B = \sigma_A^2/(\sigma_A^2 + \sigma_B^2) \tag{6}$$

The cue weights are therefore complementary and must sum to 1.0.

The variance of the combined estimate is,

$$\sigma_c^2 = \sigma_A^2 \times \sigma_B^2/(\sigma_A^2 + \sigma_B^2) \tag{7}$$

Equivalently,

$$1/\sigma_c^2 = 1/\sigma_A^2 + 1/\sigma_B^2 \tag{8}$$

It is clear from Eq. (8) that the variance of the combined estimate must be less than the variance of the single-cue estimates. Bayesian cue combination is optimal in the sense that the combined parameter estimate will have maximum precision mathematically (Fig. 1, red curve). This is a key prediction of optimal cue combination.

When estimates derived from single cues are in disparity, the combined mean is a compromise between the two single-cue estimates and its proximities to the two single-cue estimates are determined by the relative cue reliabilities. The combined estimate will be closer to the single-cue estimate of the more reliable cue. Thus, the manner in which weights are distributed between cue A and cue B can be measured in terms of the relative proximities between single-cue response

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[1] Consistent with prior research on this topic, we refer to the approach as Bayesian, even though studies of human navigation (including ours) have assumed uniform priors for information sources. In fact, the approach used in our work is more accurately referred to as maximum-likelihood estimation.

[2] We discuss the concept of cue reliability, as an intrinsic property of cues and as it is measured, in depth in the General Discussion.