Probabilistic optimization in the human perceptuo-motor system

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Abstract Despite the variability of internal and external environments, the human central nervous system (CNS) can generate precise and stable perception and motor behaviors. What mechanism enables this ability? Answering this question is one of the significant goals in the human sciences, including neuroscience, cognitive science, physical education and sports science. The Bayesian integration theory proposes that the CNS learns the prior distribution of a task and integrates it with sensory information to minimize the effect of sensory noise. In this article, we introduce psychophysical reports using motor timing and temporal order judgment (TOJ) tasks that support the Bayesian integration theory. Subsequently, we demonstrate the event-related potentials (ERPs) behind Bayesian integration that operates in somatosensory TOJ.

Keywords : Bayesian, perception, motor behavior, timing, temporal order judgment, electroencephalogram, event-related potential

The problem of variability in the human perceptuo-motor system

We are exposed to variability in both our internal and external environments. Unlike electronic signals in artificial systems, the signals in our nervous system are noisy. This neural noise inevitably affects our sensory input. For example, if a baseball batter's sensory system detects a pitched ball at a certain location, the true (physical) ball location may be further upward, outward, or in other positions (Fig. 1A) due to the effect of neural noise. Our sensory information innately contains uncertainty. In addition, external events that we encounter in our daily life are also highly variable. For example, the behavior of the pitched ball is not constant, but instead fluctuates with every trial (Fig. 1B). Thus, uncertainty exists in our external as well as internal environments. To enable precise and stable perception and behavior, our central nervous system (CNS) must compensate for this internal and external variability.

Bayesian integration: An optimal solution for the problem of variability

The Bayesian integration theory¹⁻³⁾ provides us with the optimal solution to this problem. Let us return to the variability of the pitched ball (Fig. 1B). Due to trial-by-

trial variations, we cannot identify the ball's next course based on a single previous trial. However, if we observe the statistics of a behavior of interest over a longer period, a certain structure should appear in the probabilistic distribution, such as a Gaussian distribution (Fig. 1C). If we utilize this distribution as prior information (*i.e.*, a prior distribution), we can predict the most probable course of the ball.

Bayesian integration is the optimal strategy for utilizing the prior distribution. As its name indicates, the Bayesian integration theory is based on the Bayesian theorem⁴⁾. Defining the true state of an external target (*e.g.*, the course of a ball) as X_{true} and the sensory representation of the target state as X_{sensed} , we can calculate the posterior probability of X_{true} when the CNS detects X_{sensed} , as follows:

$$p(X_{\text{true}} | X_{\text{sensed}}) = \frac{1}{a} p(X_{\text{true}}) p(X_{\text{sensed}} | X_{\text{true}}) \quad (1),$$

where a is a normalization constant; $p(X_{\text{true}})$ is the prior probability of X_{true} ; $p(X_{\text{sensed}}|X_{\text{true}})$ is the likelihood of detecting X_{sensed} when the target state really is X_{true} .

Here, we assume that $p(X_{\text{true}})$ and $p(X_{\text{sensed}}|X_{\text{true}})$ have Gaussian distributions. Then, finding the X_{true} that maximizes the posterior $p(X_{\text{true}}|X_{\text{sensed}})$, we can obtain the optimal estimate for the external target (for details, see Körding and Wolpert. 2004¹⁾):

$$X_{\text{estimated}} = kX_{\text{sensed}} + (1 - k)\mu_{\text{prior}} \quad (2),$$

where

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Fig. 1 Variability in internal and external environments. **(A)** Variability in sensory information. The orange circle signifies the ball location represented in the batter's early sensory system. Neural signals include noise. The neural noise inevitably varies our sensory information; therefore, the true ball location (black circle) may be further upward, outward, or toward locations other than the sensed ball location. **(B)** Variability of external targets. Blue circles signify the trial-by-trial plots of the location of the pitched ball (the numbers on the balls signify the pitch order). The course of the ball thus varies with every trial. **(C)** However, by accumulating the plots, a certain structure should appear in the probabilistic distribution of the ball's course. Modified from Sakamoto and Miyazaki (2011)²⁰.

$$k = \frac{\sigma_{\text{prior}}^2}{\sigma_{\text{prior}}^2 + \sigma_{\text{sensed}}^2} \quad (3).$$

μ_{prior} and σ_{prior} denote the mean and standard deviation (SD) of the prior distribution, respectively. σ_{sensed} denotes the SD of the likelihood, that is, the magnitude of the sensory noise. As shown in Equations 2 and 3, the optimal estimate $X_{\text{estimated}}$ is obtained as a weighted sum of X_{sensed} and μ_{prior} (Fig. 2A). According to these equations, $X_{\text{estimated}}$ exhibits a greater dependence on X_{sensed} when σ_{prior} is greater (*i.e.*, the prior distribution is more variable/uncertain; Fig. 2B). Conversely, $X_{\text{estimated}}$ exhibits a greater dependence on μ_{prior} when σ_{prior} is smaller (*i.e.*, the prior distribution is more constant/certain; Fig. 2C). Thus, the CNS can maximize its accuracy by adequately shifting its final estimate towards the previous most frequent event. For simplicity, $X_{\text{estimated}}$ is represented only by a mean point in Fig. 2, but variability also exists in $X_{\text{estimated}}$. In theory, however, Bayesian integration minimizes the variable error of $X_{\text{estimated}}$. The mean square error (MSE) of $X_{\text{estimated}}$ can be expressed as:

$$MSE = k\sigma_{\text{sensed}}^2 \quad (4).$$

Note that the coefficient k (see Equation 3) is always

smaller than 1. This implies that Bayesian integration always reduces the effect of sensory noise that is inherent to our nervous system.

Bayesian integration in motor timing control

In recent years, psychophysical studies have revealed that our brain implements Bayesian integration in a variety of sensory-motor tasks, including spatial reaching^{1,5}), reproducing forces⁶), timing^{7,8}), and somatosensory temporal order judgment (TOJ)^{9,10}) (also see Yamamoto et al. 2012¹¹). In this article, we first introduce a report that studied the coincidence timing task⁸). In this task, the timing component of ball hitting or catching behaviors by humans was extracted. In this study, subjects performed the timing task by responding to the display shown in Fig. 3A. LEDs on the display illuminated in the order of S1→S2→S3. The time intervals from S1 to S2 and from S2 to S3 were identical for each trial. The subjects anticipated the illumination onset of S3 based on the time interval from S1 to S2, and pressed a button in such way that the button pressing and the onset of S3 were synchronized. The time interval between S1 and S2 (= S2 and S3) was the target state X_{true} in this task. The target time

Fig. 2 Optimal estimation by Bayesian integration. (A) X_{sensed} signifies the ball location obtained from sensory information. μ_{prior} signifies the mean of the prior distribution of the ball location. The optimal estimate of the ball location, $X_{\text{estimated}}$, was obtained by a weighted sum (*i.e.*, an intermediate dividing point) of X_{sensed} and μ_{prior} . The weighting behaves as follows: (B) When the variability of the prior distribution (*i.e.*, σ_{prior}) is greater, $X_{\text{estimated}}$ exhibits greater dependence on X_{sensed} . (C) When the variability of the prior distribution is smaller, $X_{\text{estimated}}$ exhibits greater dependence on μ_{prior} . For simplicity, $X_{\text{estimated}}$ is represented only by a mean point, but variability also exists in $X_{\text{estimated}}$. However, Bayesian integration minimizes the variable error of $X_{\text{estimated}}$ (see Equation 4). Modified from Sakamoto and Miyazaki (2011)²⁰.

Fig. 3 Bayesian integration in coincidence timing⁸⁾. (A) Display presenting task stimuli. (B) Prior distributions of the target time intervals: narrow prior distribution ($\mu_{\text{prior}} = 400$ ms, $\sigma_{\text{prior}} = 20$ ms) and wide prior distribution ($\mu_{\text{prior}} = 400$ ms, $\sigma_{\text{prior}} = 40$ ms). (C) Theoretical predictions of the constant timing errors as a function of target time intervals by the Bayesian integration model (see Equation 5). (D) Experimental results of the constant timing errors as a function of the target time intervals. The constant timing errors were in accordance with the Bayesian integration theory. Modified from Miyazaki et al. (2005)⁸⁾ and Sakamoto and Miyazaki (2011)²⁰.

interval X_{true} for each trial was randomly sampled from Gaussian prior distributions with a mean (μ_{prior}) of 400 ms. The trial-by-trial SD (σ_{prior}) of the target time interval X_{true} was 20 ms (narrow prior distribution) or 40 ms (wide prior distribution) (Fig. 3B). Half of the subjects

($N = 6/12$) first performed 480 trials of the task under the narrow-prior condition and subsequently performed 480 trials under the wide-prior condition; the other half of the subjects performed the task in the opposite order.

The Bayesian integration model predicts the subjects'

performance as follows (for details see Körding et al. 2004⁶⁾ and Miyazaki et al. 2005⁸⁾):

$$\langle \Delta x \rangle = \frac{\sigma_{\text{sensed}}^2}{\sigma_{\text{prior}}^2 + \sigma_{\text{sensed}}^2} (X_{\text{true}} - \mu_{\text{prior}}) \quad (5),$$

where $\langle \Delta x \rangle$ denotes the constant (mean) timing error. This equation indicates that $\langle \Delta x \rangle$ is linearly dependent on X_{true} and that the slope decreases (increases) as σ_{prior} increases (decreases). Thus, the Bayesian integration model predicts that the constant timing error as a function of the target time interval exhibits a greater slope under the narrow-prior condition and a smaller slope under the wide-prior condition (Fig. 3C). The experimental results revealed that the subjects exhibited the behavior predicted by the Bayesian integration model (Fig. 3D).

Bayesian integration in somatosensory temporal order judgment

A psychophysical phenomenon consistent with the Bayesian integration theory was also observed in somatosensory TOJ⁹⁾. In this study, subjects received a pair of tactile stimuli, one delivered to each hand (Fig. 4A), and judged which hand was stimulated first. Stimulus onset asynchronies (SOAs) between the two tactile stimuli were sampled from one of two biased prior distributions (Fig. 4B). One prior distribution had a mean (μ_{prior}) of 80 ms and an SD (σ_{prior}) of 80 ms (blue line in Fig. 4B; positive SOA values signify that the right hand was stimulated earlier than the left). Under this prior distribution, subjects were exposed to stimulus pairs with the right hand being stimulated earlier in approximately 84% of the trials. Conversely, under another prior distribution (red line; $\mu_{\text{prior}} = -80$ ms, $\sigma_{\text{prior}} = 80$ ms), subjects were exposed to stimulus pairs with the left hand earlier in approximately 84% of the trials. Half of the subjects ($N = 6/12$) first performed 1000 trials of TOJ in which the SOAs were sampled from the prior distribution biased toward the right hand first. They then performed 1000 trials in which the SOAs were sampled from the prior distribution biased toward the left hand first. The other half of the subjects performed the task in the opposite order.

The judgment proportion of TOJ as a function of SOAs ordinarily appears as a sigmoidal curve and can be fitted to a cumulative Gaussian function. The SOA at which the judgment proportion equals 0.5 (*i.e.*, the mean of the cumulative Gaussian function) represents the point of subjective simultaneity (PSS). The Bayesian integration theory predicts the PSS behavior under the biased prior distributions as follows (for details, see Miyazaki et al. 2006⁹⁾):

$$PSS = - \left(\frac{\sigma_{\text{sensed}}}{\sigma_{\text{prior}}} \right)^2 \mu_{\text{prior}} \quad (6).$$

This equation indicates that PSS shifts towards the opposite side of μ_{prior} (Fig. 4C). This PSS shift implies that

the subjects' TOJ was biased toward the order that they had previously experienced most frequently. For example, when subjects frequently experience stimulus pairs with the right hand stimulated earlier than the left (*i.e.*, prior bias to the right hand first; blue line Fig. 4B), their judg-

Fig. 4 Bayesian integration in TOJ of two tactile stimuli, one delivered to each hand⁹⁾. **(A)** Stimulus setting. **(B)** Prior distributions of the SOA between the two stimuli. On the x-axis, positive values of the SOA signify that the right hand was stimulated earlier than the left; and negative values signify that the left hand was stimulated earlier. The y-axis is the frequency of the SOA. The blue Gaussian has a mean (μ_{prior}) of 80 ms and a SD (σ_{prior}) of 80 ms (*i.e.*, biased to the right hand first). The red Gaussian has a mean (μ_{prior}) of -80 ms and a SD (σ_{prior}) of 80 ms (*i.e.*, biased to the left hand first). **(C)** Theoretical predictions of the TOJ responses by the Bayesian integration model (see Equation 6). The psychometric functions shift away from the peak frequencies of the prior distributions. **(D)** Experimental observations for the tactile TOJ. The psychometric functions of the subjects' responses were in accordance with the Bayesian integration theory. Modified from Miyazaki et al. (2006)⁹⁾ and Kudo et al. (2011)²¹⁾.

ment proportion of “right hand first” increases (blue line Fig. 4C), resulting in psychometric function, and the PSS accordingly shifts away from the peak frequency (*i.e.*, μ_{prior}) of the prior distribution. The experimental results demonstrate that the subjects exhibited shifts in psychometric functions as predicted by the Bayesian integration model (Fig. 4D).

Acquisition of multiple prior distributions

In the majority of studies that have reported psychophysical phenomena consistent with the Bayesian integration theory, the estimated target variables were sampled from a single prior distribution within a task period. Following a certain period of exposure to the prior distribution, subjects were tested on whether their estimation shifted based on the prior distribution, as predicted by the Bayesian integration theory. However, during the course of daily life, it is unreasonable to assume that people encounter only one prior distribution. Rather, prior distributions differ in a context-dependent manner. In fact, the Gaussian distribution with only one peak frequency,

described in the introduction of this article (Fig. 1C), should be met with skepticism, as baseball pitchers do not always aim to pitch a ball on only one course.

Nagai et al.¹⁰⁾ reported that human subjects can simultaneously acquire multiple prior distributions during somatosensory TOJ. In this study, subjects performed tactile TOJ in a procedure similar to that of Miyazaki et al. (2006)⁹⁾. However, the two prior distributions of opposite types were mixed; that is, SOAs were sampled from the two prior distributions in a random order. They first used color cues (green or red) to inform human subjects which prior distribution SOA was to be sampled for each trial (Fig. 5A), based on the reports that color cues enabled human and monkey subjects to adapt in parallel to two opposing force fields in reaching tasks¹²⁻¹⁴⁾. However, the experimental results of Nagai et al. revealed that the subjects were unable to differentially adapt to two prior distributions using color cues alone. In the second condition (Fig. 5B), the subjects shifted their gazes to upper or lower targets in response to the color cues, generating two different TOJ responses according to the two prior distributions, as predicted by the Bayesian integration theory.

Fig. 5 Acquisition of multiple prior distributions in tactile TOJ¹⁰⁾. The top panels display overviews of the experimental conditions. The mid-panels illustrate prior distributions biased to the right hand first (solid squares) and to the left hand first (open circles). The ordinate represents the sample number for each SOA summed across all subjects. The bottom panels display the average proportion of the trials in which the subjects judged their right hand as being stimulated first as a function of the SOAs. **(A)** Color cue only (condition 1). For each trial, one second before the delivery of the pair of tactile stimuli, the color (green/red) of the central LED informed subjects which prior distribution SOA was to be sampled. Subjects continued to fix their gaze to the center LED during the task. In this condition, the psychometric functions were not significantly split between the two prior distributions. **(B)** Color cues with eye movements (condition 2). Subjects moved their gaze to the top or bottom LED (non-illuminated) according to the color of the central LED. In this condition, the psychometric functions were shifted away from the peak frequencies of the prior distributions as predicted by the Bayesian integration theory. In addition, this study also tested the effect of mouth movements (condition 3) instead of eye movements. Subjects opened or closed their mouths according to the color cues; however, the psychometric functions were not significantly split between the two prior distributions. Modified from Nagai et al. (2012)¹⁰⁾.

Moreover, mouth movements were tested instead of eye movements. In the third condition, the subjects did not significantly distinguish between the two prior distributions, even though they opened or closed their mouths according to the color cues. These results indicate that body postures do not always serve as effective cues to acquire multiple prior distributions.

Nagai et al.¹⁰⁾ conducted further experiments to determine which of the eye or retinal cue positions were responsible for the acquisition of the two different prior distributions, because both the eye position and the retinal cue position changed with the direction of gaze in the above-mentioned experiments using color cues at a fixed position. In the additional experiments, instead of color cues, the LEDs placed above and below the initial fixation point were used to inform subjects which prior distribution SOA was to be sampled. In one condition, the subjects shifted their gaze to the illuminated LED, so that their eye position changed but the cue remained in the center of their retinas. In another condition, the subjects continued to gaze at the central fixation point regardless of the spatial cues, so that the cue positions on their retinas changed while their eye position remained constant. The experimental results revealed that the subjects in both conditions were able to respond differently according to the prior distributions, as predicted by the Bayesian integration model. These results indicate that in somatosensory TOJ, the human brain can acquire two prior distributions depending on the spatial cue positions on the retina as well as the eye positions. Although it is unclear whether these conditions are also effective in other perceptual/motor tasks at this stage, skilled sports players may utilize some supplementary motor or sensory cues to adapt their estimate to varieties of target statistics.

Neural activity behind Bayesian integration: ERPs during tactile TOJ

As described above, there is psychophysical evidence that supports the Bayesian integration theory. However, a question arises: What neural activities occur behind the behavioral effects of Bayesian integration? In one attempt to investigate this problem, we conducted electroencephalogram (EEG) recordings of subjects ($N = 14$) performing tactile TOJ, similar to the procedure used in Miyazaki et al. (2006)⁹⁾. EEGs were recorded from 31 scalp electrodes using a common average reference. Event-related potentials (ERPs) were constructed from the EEG signals of trials within the SOA range, from -20 to +20 ms (yellow band in Fig. 6A). ERPs were averaged time-locked to the first tactile stimuli separately for the prior distribution biased to the right hand first (blue lines in Fig. 6) and that biased to the left hand first (red lines in Fig. 6).

The ERP waveforms exhibited negative peaks approximately 140 - 160 ms (see Fig. 6B) from the onset of the tactile stimuli at the sites centered around CP3 and CP5

(left hemisphere on the scalp) and CP4 and CP6 (right hemisphere). The CP sites were placed approximately above the somatosensory areas. In previous studies^{15,16)}, somatosensory-evoked potentials in response to finger stimulations were recorded from scalp locations near CP3 and CP4. Tactile stimuli delivered to the hands were

Fig. 6 ERPs during tactile TOJ. **(A)** Average psychometric functions for tactile TOJ during EEG recordings. Half of the subjects ($N = 7/14$) performed 600 trials of TOJ in which the SOAs were sampled from the prior distribution biased to the right hand first (blue lines) followed by 600 trials in which the prior distribution was biased to the left hand first (red lines). The other half of the subjects performed the task in the opposite order. The prior distribution biased to the right hand first had a mean value of 80 ms and a SD of 80 ms, and that biased to the left hand first had a mean value of -80 ms and a SD of 80 ms. A pair of tactile stimuli was presented every 1.8 sec (*i.e.*, each trial lasted 1.8 sec). The PSS across the subjects was 34.28 ± 14.71 ms for the prior distribution biased to the left hand first and -40.60 ± 13.16 ms for the prior distribution biased to the right hand first; the difference was significant ($P = 0.00397$, paired *t*-test). **(B)** Average ERP waveforms at CP4. The waveforms were band-pass filtered at 0.05 - 10 Hz. ERP waveforms were constructed from the EEG signals of trials in which SOAs ranged within the yellow band in A (from -20 ms to +20 ms) separately for each prior distribution. Under this sampling, the mean SOAs did not become zero but exhibited small biases (-1.22 ± 0.39 ms for the prior distribution biased to the left hand first, 1.75 ± 0.41 ms for the prior distribution biased to the right hand first). Even when compensating for the SOA biases, the negative peak latencies at CP4 were significantly different between both priors. The adjusted peak latencies across the subjects were 141.80 ± 5.44 ms for the prior distribution biased to the left hand first and 159.68 ± 8.01 ms for the prior distribution biased to the right hand first ($P = 0.0198$).

projected to the contralateral somatosensory areas. The negative peaks at the right (left) hemisphere were considered to largely reflect neural activity in response to tactile stimulus to the left (right) hand. In this article, we focus on the negative ERP components at CP3 and CP4.

Vibell et al.¹⁷⁾ reported that PSS shifts in visual TOJ, due to tactile attention, corresponded to modulations in the latency of ERPs. Meanwhile, McDonald et al.¹⁸⁾ demonstrated that visual PSS shifts due to auditory attention were associated with modulations in ERP amplitudes. Based on the former report, we can assume the possibility that behind Bayesian PSS shifts (Fig. 6A), ERPs at CP4 (CP3) exhibit negative peaks earlier under the prior distribution biased to the left (right) hand first than under that biased to the right (left) hand first. Meanwhile, based on the latter report, we can assume the possibility that the ERPs at CP4 (CP3) exhibit negative peaks more intensely under the prior distribution biased to the left (right) hand first than under that biased to the right (left) hand first.

At CP4, modulations of the negative peaks consistent with the Bayesian PSS shifts were observed. The grand average ERP waveforms (Fig. 6B) exhibited the negative peak earlier and more intensely under the prior distribution biased to the left hand first (red arrow in Fig. 6B) than under that biased to the right hand first (blue arrow in Fig. 6B). The negative peak latencies across the subjects were significantly earlier under the prior distribution biased to the left hand first (mean $\pm$ SEM = 140.57 $\pm$ 5.62 ms) than under that biased to the right hand first (161.43 $\pm$ 8.08 ms) ($P = 0.0095 < 0.05/2$, one-tailed paired t -test with Bonferroni correction) just as the former assumption in the last paragraph. However, there was no difference in the negative peak amplitudes across the subjects ($P = 0.48$). Thus, the negative ERP components at CP4 (right hemisphere on the scalp) exhibited negative peaks earlier when the subjects' TOJs were biased to the left hand first compared to when they were biased to the right hand first.

However, ERP modulations were not observed in the negative peak latencies nor in the negative peak amplitudes at CP3, located at the left hemisphere on the scalp. The negative peak latencies across the subjects were 146.29 $\pm$ 7.95 ms under the prior distribution biased to the right hand first and 151.43 $\pm$ 7.21 ms under that biased to the left hand first; however, the difference was not significant ($P = 0.22$).

In the experimental results at this stage, the ERPs revealed modulations in negative peak latency that were consistent with the Bayesian PSS shifts of tactile TOJ at CP4 but not at CP3. The contrast between CP4 and CP3 suggests the possibility that the modulations of the negative peak latencies are dominant in the right hemisphere of the brain. TOJs are made based on the difference between the subjective timing of two stimuli; therefore, a Bayesian PSS shift can occur *via* the modulation of the timing of only one side.

It is also noteworthy that the difference in the negative

peak latency (approximately 20 ms) was smaller than the PSS difference (approximately 80 ms) between the prior distributions. In TOJ using the task procedure without a response or answer bias, the Bayesian PSS shifts decreased in magnitude⁹⁾, indicating that not only perceptual processes, but also cognitive and/or motor response biases contribute to Bayesian PSS shifts. The negative peak modulations of the ERPs that occurred approximately 140 - 160 ms from the onset of tactile stimuli would only reflect the effects of relatively early perceptual processes. However, it is important to use caution when drawing conclusions about the neural substrate(s) from which these negative peaks are derived. EEGs detect not only the activity of the brain regions just below the sites at which the electrodes are applied, but also reflect the activity of other brain areas. To clarify the remaining questions, we must expand and improve our measurements and analyses.

Summary and concluding remarks

To enable precise and stable perceptions and motor behavior, the human CNS must overcome internal and external variability. Signals in our nervous system are noisy; therefore, our sensory information does not always provide sufficient information. Moreover, external events in our daily lives are usually not static but fluctuate. However, upon observing the statistics of a target behavior for an extended time period, a certain structure generally appears in the probabilistic distribution. In theory, the effect of sensory noise can be minimized by Bayesian integration, in which the probabilistic distribution of the target is integrated with sensory information as prior information. We reviewed the psychophysical evidences that support the Bayesian integration theory by considering the reports studying coincidence timing and somatosensory TOJ as examples. Furthermore, we introduced a recent report that revealed that eye and retinal cue positions enable subjects to acquire multiple prior distributions in somatosensory TOJ. Finally, we described the observation that in ERPs at CP4, negative peaks approximately 140 - 160 ms from the onset of tactile stimuli exhibit modulations in latency that are consistent with Bayesian PSS shifts in somatosensory TOJ. The latency modulation of these negative peaks can reflect a perceptual contributor to the Bayesian PSS shifts. However, it is necessary to expand and improve measurements and analyses to elucidate the entirety of the neural processes involved in Bayesian integration. Current studies implementing other brain imaging techniques, such as fMRI (e.g., Vilares et al. 2012¹⁹⁾), are now in progress by researchers around the world, including our group.

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