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HOW DOES EXPECTATION CHANGE PERCEPTION?: A SIMULATION MODEL OF EXPECTATION EFFECT

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Abstract

Prior expectation affects posterior perception of physical variables, such as weight of a product. This psychological effect is called expectation effect. Two different patterns of expectation effect, contrast and assimilation, were observed. In this paper, we propose a simulation model of the expectation effect that explains the conditions of contrast and assimilation. We assume that perceived variable is estimated using a Bayes' inference of prior prediction and likelihood based on sensory stimuli. We formalize the expectation effect as a function of three factors: expectation error, prediction uncertainty, and external noise. We conducted computer simulations with the model and obtained a hypothesis of the conditions of assimilation and contrast. To validate the hypothesis, we conducted an experiment with participants using the size-weight illusion as a case of the expectation effect. Both the results of the simulation and the experiment revealed that 1) the pattern of expectation effect shifted from assimilation to contrast as the prediction error increased, 2) uncertainty decreased the extent of the expectation effect, 3) and external noise increased the assimilation.

Keywords: Numerical methods, Simulation, Emotional design, Perception, Expectation

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1 INTRODUCTION

According to the expectation confirmation theory (ECT), disconfirmation between prior expectation and posterior experience affects customer satisfaction of products and services as well as perception of their performance and quality (Oliver 1980, Oliver 1977). Expectation confirmation works as an appraisal component that evokes emotions such as contentment, satisfaction, disappointment, and dissatisfaction (Demir et al. 2009). Expectation disconfirmation evokes surprise and induces emotions that affect the consumer's overall opinion of a product (Ludden et al. 2012). Furthermore, prior expectations may affect and change posterior perception and experience. Researchers from a broad range of fields have observed this psychological bias, the so-called *expectation effect*, with regard to different cognitive processes such as desire for rewards (Schultz et al. 1997), emotions (Wilson et al. 1989, Geers and Lassiter 1999), and sensory perceptions (Deliza and MacFie 1996, Schifferstein 2001, Yanagisawa and Takatsuji in press). The expectation effect changes the disconfirmation between expectation and experience. Thus, the expectation effect is an essential factor to ensure the satisfactory design of products and services.

In a time sequence of user experience (UX) of a product, users shift from one sensory state to another in cyclic interactions involving action, sensation, and meaning (Krippendorff 2005). We expect that users would predict subsequent states between such transitions of state (e.g., we expect a meal to taste a certain way based on how it looks, the weight of a product before lifting it, the usability of a mouse by looking at it, etc.) This prior prediction affects posterior perception, that is, the expectation effect. The authors of this study previously found that visual expectation changes tactile perceptions of surface texture (Yanagisawa and Takatsuji in press). We can explain a kind of perceptual illusion using the expectation effect. For example, people perceive a smaller object as heavier than a larger one although the weight of both objects is identical. This well-known size–weight illusion (SWI) can be explained as a visual expectation effect. People expect a larger object to be heavier than a smaller one. Prior visual expectation of the objects' weights magnifies the perception of difference between the expected and actual weights. Although there exist many experimental findings on the expectation effect in different disciplines, the general mechanism on why and how the effect occurs is less well understood. A mathematical model of the expectation effect based on a fundamental mechanism enables us to estimate user perception of product and service. The authors of this study previously proposed a mathematical model of the expectation effect using the information theory (Yanagisawa et al. 2013). They modeled prior expectation as a subjective probability distribution and hypothesized that Shannon's entropy of the distributions representing uncertainty of prior expectation determines the occurrence of the expectation effect. An experimental result of the visual expectation effect of tactile texture supported the hypothesis.

On the other hand, two different patterns of expectation effect, *contrast* and *assimilation*, were observed. Contrast is a bias that magnifies the difference between prior expectation and posterior experience. Assimilation is a bias that diminishes expectation incongruence. It is important to understand whether the expectation effect is contrasting or assimilating, because they exaggerate or diminish the perception of expectation disconfirmation as a factor of satisfaction respectively. However, the mechanisms and conditions governing the contrasting and assimilating patterns have not been explained. In this paper, we propose a mathematical model of the expectation effect that explains the conditions of contrast and assimilation by applying knowledge found in the field of neuroscience. Based on the proposed model, we conduct computer simulations of the expectation effect and obtain an accurate hypothesis of the conditions of assimilation and contrast. Finally, we demonstrate the appropriateness of the hypothesis through a sensory experiment using the SWI as an expectation effect.

2 MATHEMATICAL MODEL OF EXPECTATION EFFECT

2.1 Model of perception with prior expectation

We define *perception* as an estimation of external physical property, such as the weight of an object. Sensory stimulus from the external physical world, such as pressure applied to a hand, are transformed to patterns of neural signals. We call the neural representation of an external physical variable *encoding*. Based on the pattern of neural signals, our brain estimates the physical variable. We call this estimation process *decoding*. We assume that sensory stimuli are encoded as certain firing rates of neural populations. This type of neural coding is called *rate coding*. Based on the firing rate distributions from a sensory stimulus, R, our brain forms the *likelihood function*, $\lambda(\theta \mid R)$, of a physical variable, θ. On the other hand, a physical property has certain frequency distributions in the world. Human beings learn such frequency distributions throughout their life. Based on such learned distributions, human beings predict a physical variable, θ, before experiencing sensory stimulus. For example, in the SWI, people predict the weight of an object by looking at it before actually lifting it up. Predicted physical variable should follow certain probability distributions. We define such distribution as *prior*, $P(\theta)$. Recent studies in neuroscience showed that estimation of a physical variable, that is, decoding, follows the Bayesian estimator (e.g., Ernst and Banks 2002, Brayanov and Smith 2010). Based on Bayes' theorem, our brain estimates the distributions of perceptions or *posterior*, $P(\theta|R)$, using prior and likelihood.

$$P(\theta|R) = \frac{\lambda(\theta \mid R) P(\theta)}{\sum_X \lambda(\theta \mid R) P(\theta)} \tag{1}$$

Since the denominator of the right-hand side of Equation (1) is a constant for normalization, the posterior is proportional to the product of prior and likelihood. A peak of posterior, θ_{post}, is an estimate of a physical variable. We can define the expectation effect, ε, as the difference between θ_{post} and the maximum likelihood value of the obtained firing rate, θ_{lik}.

$$\varepsilon = \theta_{post} - \theta_{lik} \tag{2}$$

We define *expectation disconfirmation*, d, as a difference between a peak of prior, θ_{pri}, and θ_{post}. We call the difference between θ_{pri} and θ_{lik} *prediction error*, Δ. Therefore, the expectation disconfirmation is a sum of the prediction error and expectation effect. We can define contrast and assimilation as follows.

Contrast: $\varepsilon > 0$ if $\Delta > 0$, $\varepsilon < 0$ if $\Delta < 0$ (3)

Assimilation: $\varepsilon < 0$ if $\Delta > 0$, $\varepsilon > 0$ if $\Delta < 0$ (4)

Equation (1) indicates that the Bayesian estimate, θ_{post}, always comes close to a peak of prior, θ_{pri}, form a peak of the likelihood estimate of sensory stimulus, θ_{lik}. We call the effect *attractive influence* of prior. The attractive influence alone involves assimilation as an expectation effect. The question then arises: How does contrast occur?

Wei and Stocker (2012) proposed a neural encoding framework based on the efficient coding principal to create a direct link between prior and likelihood. According to the encoding framework, the Bayesian estimate shifts away from the peaks of the prior distribution. This phenomenon corresponds to the contrast pattern of the expectation effect. Efficient coding hypnosis (Barlow 1961) proposes that the tuning characteristics of a neural population are adapted to the prior distribution of a sensory variable such that the neural population optimally represents the sensory variable. In Wei and Stocker's (2012), efficient coding defines the shapes of the tuning curves in physical space by transforming a set of homogeneous neurons using a mapping, F^{-1}, that is, the inverse of the cumulative of the prior, F. Therefore, the likelihood shape is constrained by the prior distribution, showing heavier tails on the side of lower prior density. In other words, efficient encoding typically leads to an asymmetric likelihood function whose mean value is away from the peak of prior. The Bayesian estimate is determined by a combination of prior and shifted likelihood means, and it shifts away from the prior peak. We apply this efficient encoding to explain contrast in our model. Figure 1 shows how the Bayesian estimate (perceived value), θ_{post}, shifts from a peak of the asymmetric likelihood function away from a peak of prior. We call the perceptual shift *repulsion influence*. The repulsion influence increases as the distance between prior distribution and peak of likelihood, that is, prediction error, Δ, increases, because the extent of asymmetry of likelihood increases away from peak of prior.

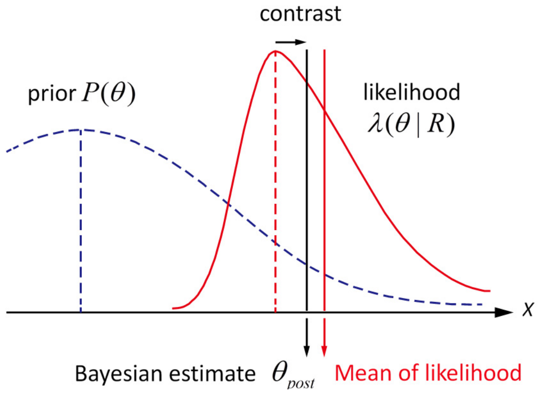

Figure 1. Contrast effect caused by the asymmetric likelihood function based on efficient coding

Figure 2 summarizes our hypothetical model of perception. Based on the efficient encoding principle, prior changes the shape of the likelihood function asymmetry while encoding the sensory stimulus of the physical variable, θ, as a firing rate of the neuron population, R. The Bayesian decoder integrates the prior distribution, $P(\theta)$, and asymmetric likelihood function, $\lambda(\theta \mid R)$, and forms posterior distributions. As a result, we perceive a peak of the posterior as an estimate of the physical variable, that is, perception.

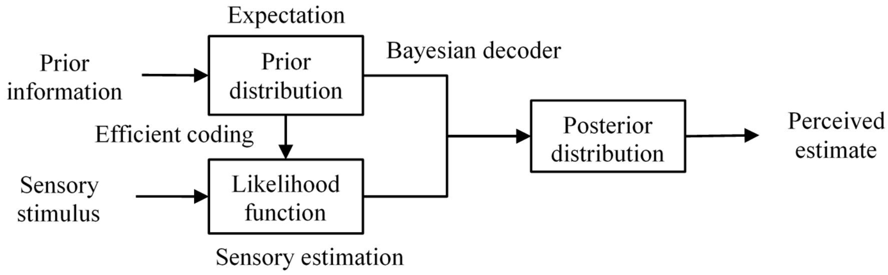

Figure 2. Hypothetical model of perception involving prior expectation

2.2 Three factors of expectation effect: prediction error, uncertainty, and external noise

Repulsion influence increases as the prediction error increases, due to asymmetry of the likelihood function. Repulsion influence involves contrast. Thus, the prediction error is a factor that decides a condition of the expectation effect.

We assume two more factors of the expectation effect: *external noise* and *uncertainty*. The shape of the likelihood function is affected by the noise of the external stimulus. An external noise modifies the shape of the likelihood function by convolving it with noise distributions. Symmetric external noise distributions do not change the mean of likelihood, but they increase its overall width. Thus, the attractive influence of prior relatively increases, and the Bayesian estimate, θ_{post}, shifts toward the peak of prior. If the attractive influence of prior exceeds the repulsion influence of asymmetric likelihood, the expectation effect may change into assimilation from contrast.

Variations of prior distributions are indicators of prediction uncertainty. The variation in prior impacts the attractive influence. In the Bayesian estimation, a small variation in prior means certain prediction and involves a strong attractive influence. Conversely, a big variation in prior means uncertain prediction and involves weak attractive influence. Thus, we define the expectation effect, ε, as a function of three factors: prediction error, Δ; variation of prior (uncertainty), σ^2_{pri}; and variation of external noise, σ^2_{noise}.

$$\varepsilon = f\left(\Delta,\ \sigma^2_{pri},\ \sigma^2_{noise}\right) \tag{5}$$

3 NUMERICAL SIMULATIONS OF EXPECTATION EFFECT

3.1 Method

Using the equation for expectation effect, we conduct a computer simulation to investigate the effects of the three abovementioned factors on the expectation effect. We focus on the conditions of contrast and assimilation and the extent of the expectation effect. We use normal distributions for prior, homogeneous likelihood, and posterior. We choose the following as conditions of the simulation parameters: prediction error of 100 steps; uncertainty, σ_{pri}^2, of ten steps within [50, 200]; and external noise, σ_{noise}^2, of ten steps within [5, 50]. The standard deviation of homogeneous likelihood is set as 0.04. We calculate the expectation effect using Equation (5) for all combinations of the abovementioned conditions for the three factors. We use MATLAB® to conduct the simulations.

3.2 Effects of prediction error, uncertainty, and external noise on expectation effect

Figure 3 shows an example of the simulation result of the expectation effect as a function of the expectation error. Each line represents a condition of uncertainty (small: 80, big: 90) and external noise (small: 15, big: 20). A positive value represents contrast, and a negative value, assimilation. Figure 3 reveals three findings.

1. The expectation effect functions as an assimilating effect when the expectation error is small. As the expectation error increases, the expectation effect increases and changes to the contrasting condition. Around the peak of prior, where the prediction error is small, the shape of the likelihood function was close to symmetric, the repulsion influence was small, and the attraction influence of prior is dominant. Thus, assimilation occurs. As the prediction error increases, the extent of the likelihood asymmetry increases, and the repulsion influence increases. Thus, the expectation effect shifts to the contrast condition.
2. The extent of the expectation effect, $|\varepsilon|$, is bigger when uncertainty is lower for both assimilation and contrast. With respect to assimilation, the attractive influence of prior increases in the Bayesian estimation as the variation of prior (uncertainty) decreases. On the other hand, the repulsive influence increases from a certain value of prediction error as the variation of prior decreases. In other words, certain predictions involve a sharp expectation effect regardless of the condition (contrast or assimilation).
3. The prediction error at which assimilation changes to contrast increases as the external noise increases. External noise weakens the repulsive influence. In the Bayes estimation, the attractive influence of prior becomes stronger than the repulsive influence of likelihood. Thus, the area of assimilation in the prediction error increases when the external noise exceeds prediction error and uncertainty.

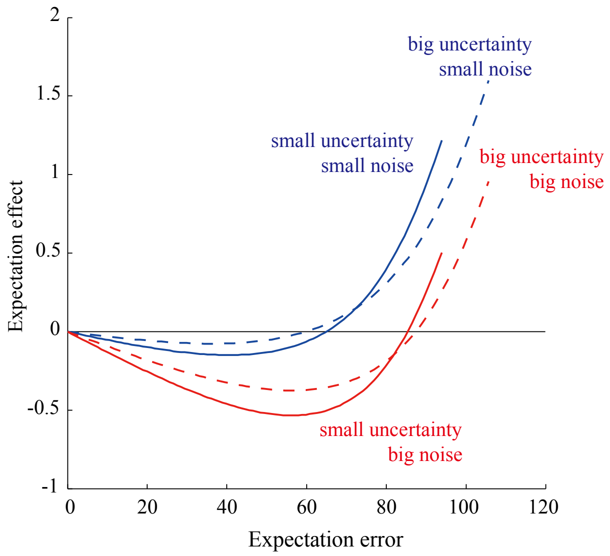

Figure 3. Simulation result of expectation effect as a function of expectation error for different conditions of expectation uncertainty and external noise

We observe the abovementioned trends for all possible combinations of conditions for uncertainty and external noise. We also observe special cases wherein patterns of only contrast and only assimilation occur. Figure 4 shows contours of prediction errors when assimilation changes to contrast for all combinations of uncertainty and external noise. The prediction error, the *z*-axis, is normalized between zero and one. Zero of the contour represents a case where only contrast occurs, whereas one of the contours represents a case where only assimilation occurs. As Figure 4 shows, the upper left-hand side of the figure, where uncertainty is high and external noise is small, denotes cases where only contrast occurs. In this area, the repulsive influence of asymmetry likelihood is dominant compared to the attractive influence of uncertain prediction. On the other hand, the area on the lower right, with low uncertainty and big external noise, shows only assimilation. The attractive influence of prior is dominant for certain predictions compared to the repulsive influence, which is weakened by the external noise.

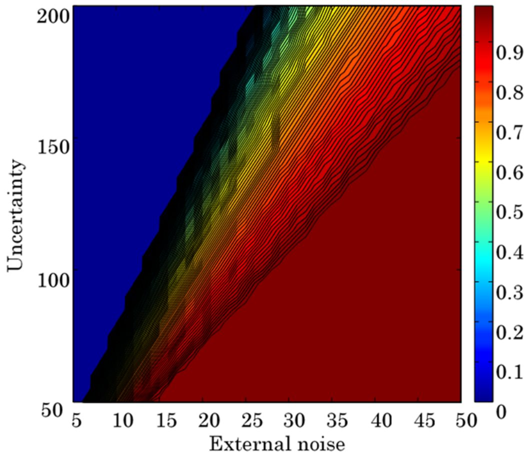

Figure 4. Contours of expectation errors when assimilation shifts to contrast for different conditions of uncertainty and external noise

4 EXPERIMENT

4.1 Method

To validate the simulation result shown in Figure 3, which is based on the hypothetical model, we conducted an experiment with participants using the SWI as a case of the expectation effect. We manipulated prediction error, uncertainty, and external noise as experimental factors of the expectation effect. For each condition, we obtained responses of participants with respect to perceptions of weight and evaluated the extent of weight illusions as expectation effects. We presented participants with pairs of cubic metal objects. The objects in each pair had identical weights but different sizes. We asked participants to compare the weights and obtained their responses for the difference in weights. We used the perceptual difference of weight as the extent of the expectation effect.

Control of prediction error

According to the SWI, human beings perceive that a smaller object is heavier than a larger one although both objects may weigh the same. This illusion can be viewed as a contrast of the expectation effect, in which the perception of difference between the weight predicted by the object's size and its actual weight, namely the prediction error, is exaggerated. However, our simulation result in Figure 3 shows that assimilation, an opposite effect to contrast, occurs when the prediction error is less than a certain value. To validate the simulation results for various conditions of assimilation and contrast, we controlled the prediction errors in the experiment. As Figure 5 shows, we prepared pairs of objects, called *target* and *reference*. Participants evaluated the weight of the target by comparing it with that of the reference. The target was bigger than the reference for each pair. We adjusted both the actual weights to be the same. We prepared different weights for each pair to control the extent of the expectation error (difference between the predicted and actual weights) ((c) in Figure 5). In other words, the differences in size between the target and reference differed between the pairs.

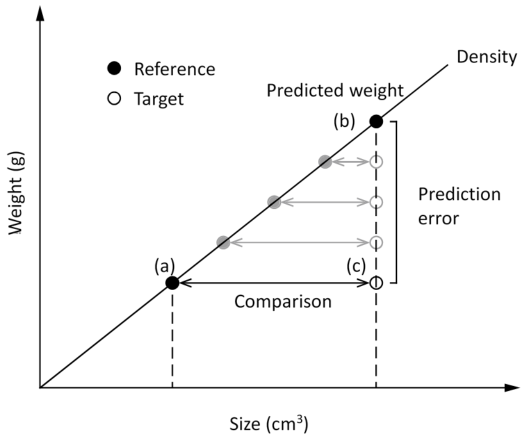

Figure 5. Method for manipulating expectation error. Participants compared weights of the reference (a) and target (c). The difference between the predicted weight (b) and actual weight (c) of the target were controlled as prediction errors for each reference–target pair.

Control of uncertainty and external noise

To control uncertainty of visual predictions, we used a fogged glass so that transparency between the participants and target object was manipulated. We assumed that fuzzy visual images of the targets would increase the uncertainties of size and weight predictions. To control the external noise of somatosensory sensation while lifting an object, we asked participants to add a weight to the wrist he/she used for lifting the samples. According to the Weber–Fechner Law, the difference threshold increases as the intensity of stimulus increases. We assumed that the additional weight of each participant's wrist serves as the external noise of weight perception due to the increasing difference threshold.

4.2 Material

We prepared ten solid cubic shapes made of duralumin (A2017) as a set of reference samples. The weights of the reference samples ranged from 350 g to 1250 g. Their sides were 50 mm to 76.5 mm long. For the target samples, we prepared hollow cubes made of duralumin (A2017), with sides of 80 mm. We inserted additional weights into the hollow cubes so that weights of both samples were identical for each pair. We attached a wire to the top of each target and reference sample and hung them from a steel framework to straighten the wires without tension. We placed a ring in the middle of each wire to enable the participants to lift the samples using their index fingers.

4.3 Participants

Fifteen (twelve male and three female) volunteers aged 21 to 24 years served as experiment evaluators. They were undergraduate or graduate students studying mechanical engineering at the University of Tokyo. All the participants were physically healthy.

4.4 Procedure

The participants were invited individually into the isolated test room. Each participant was seated on a chair in front of the framework, which was set on a table. After obtaining informed consent, the participants received written instructions for the procedure. Before starting the comparison of the pairs, we asked the participants to lift up the ten reference samples with their index fingers using the wired ring in order to perceive the density of the duralumin. After the learning session, participants compared the weights of the target and reference samples under four different combinations of external noise and uncertainty (Table 1). To simulate the condition of big uncertainty (B and D in Table 1), we put a fogged glass between the target and participant so that the visual image of target was fuzzy. For the big external noise condition (C and D in Table 1), a participant added a weight to the wrist he/she used for lifting the samples. For each condition, we randomly presented each pair of the ten pairs of the target and reference samples with identical weights. We asked participants to alternately lift the target sample and reference sample with the index finger of the dominant arm using the wired ring. After they had lifted both samples, we asked them to rank the target weight as "very much heavier," "heavier," "kind of heavier," "almost the same," "kind of lighter," "lighter," and "very much lighter" in comparison to the reference sample in that pair. We repeated the paired comparisons of sample pair weights for all ten pairs for the four conditions.

Table 1. Experimental conditions regarding uncertainty and external noise

		External noise	
		Small	Big
Uncertainty	Small	A	C
	Big	B	D

4.5 Data analysis

We used the participants' responses regarding the relative weights of the target samples in comparison to those of the reference samples as an index of the expectation effect. As explained previously, the physical weight of the target and reference samples in each pair were identical. If the response was "almost the same," we can say that no expectation effect was observed. Due to the combination of learned density of the material and the visually estimated volume, all the target samples were actually lighter than the expected weight, whereas the reference samples, which were solid and had congruent expected and actual weights, were heavier. Thus, participants' responses that the target samples were heavier than the reference samples denote contrast. Conversely, participants' responses that the target samples were lighter than the reference samples represent assimilation. We compared the participants' responses of the expectation effect for different combinations of prediction error, uncertainty, and external noise. We compared the simulation results (Figure 3) and experimental results in order to validate the appropriateness of our hypothetical model of the expectation effect.

5 RESULTS

5.1 Effect of prediction error on expectation effect

Figure 6 shows the averaged responses of the participants regarding the relative weight of each target sample for four combinations of uncertainty and external noise. A positive value shows how much heavier the target (smaller object) was than the reference (bigger object), whereas the negative value shows the opposite. In other words, the positive value represents contrast, and negative value represents assimilation. The horizontal axis denotes differences between the expected weight ((b) in Figure 5) and the actual weight of each target, that is, the extent of prediction errors for each pair. The result shows that under all combinations of uncertainty and external noise, the expectation effect began with assimilation and then shifted to contrast as the prediction error increased. This trend corresponds to the simulation results shown in Figure 3. As we hypothesized, assimilation occurred in the presence of small prediction errors, which contradicts the idea put forth by the SWI.

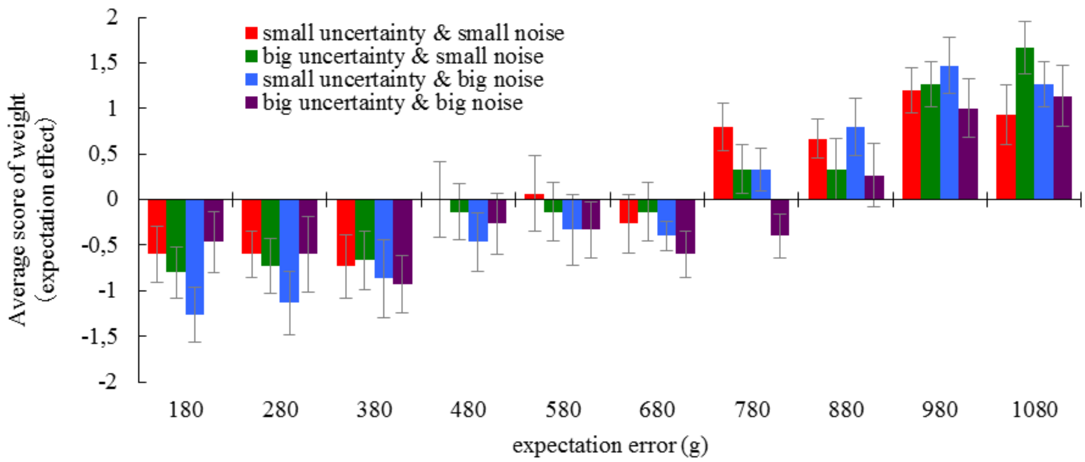

Figure 6. Experimental results of expectation effects as functions of expectation error for each condition of uncertainty and external noise. Each bar represents the average responses of the relative weight of each target. The error bars denote standard errors.

5.2 Effects of uncertainty and external noise on expectation effect

We compared expectation effects for different conditions of uncertainty and external noise. For each prediction error, we conducted a two-way repeated measure ANOVA with *uncertainty* and *external noise* as independent variables and the response of the relative weight of the target sample as the dependent variable for each target sample. The results indicate statistical significance at the prediction errors of 180 g for assimilation and of 780 g for contrast.

With respect to the prediction error of 180 g (assimilation), the main effects of *uncertainty* [F = 2.25, p = 0.16] and *external noise* [F = 0.38, 0.55] were not significant. However, we observed marginally significant interaction between *uncertainty* and *external noise* [F = 2.92, p = 0.1]. Figure 6 shows a prominent negative response, namely assimilation, for small uncertainty and small noise at a prediction error of 180 g. We also observed a similar trend at 280 g (Figure 6). We compared the responses for the prediction error of 180 g for different conditions of uncertainty and external noise using Bonferroni-corrected paired comparisons. We found that the negative response (assimilation) for small uncertainty and big noise was significantly bigger than the response for big uncertainty and small noise. For the prediction error of 780 g (contrast), we found significant main effects for both *uncertainty* [F = 5.18, p = 0.0391] and *external noise* [F = 7.88, p = 0.0140]. The interaction between *uncertainty* and *external noise* is not significant [F = 0.25, p = 0.62]. Figure 7 shows the comparison of average expectation effects for different levels of uncertainty and external noise. We observed that smaller uncertainty involves a significantly bigger expectation effect, namely contrast, than bigger uncertainty. Regarding external noise, smaller noise involves significantly bigger contrast than bigger noise.

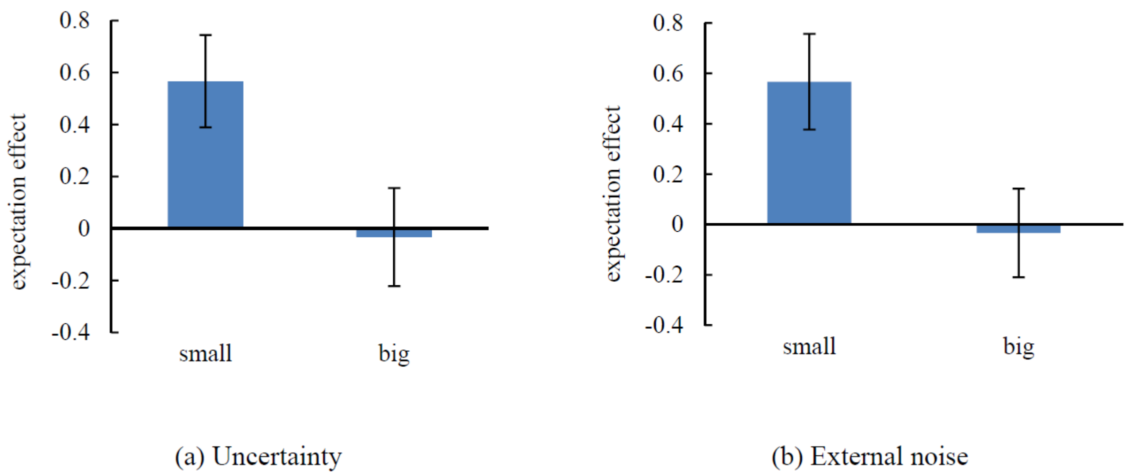

Figure 7. Expectation effect for each condition of uncertainty and noise when the expectation error is 780 g

6 DISCUSSION AND CONCLUSION

Both the results of the computer simulation (Figure 4) and the experiment using the SWI (Figure 6) show that prediction error affected the extent of the expectation effect and worked as a factor of either the assimilation or the contrast condition. The pattern of expectation effect shifted from assimilation to contrast as the prediction error increased. This correspondence between the simulation and experiment supports our hypothesis, namely that the prediction error increases the likelihood repulsive influence against prior attractive influence during Bayesian estimation (decoding). We discuss the meaning of the psychological phenomenon from an ecological viewpoint. Contrast exaggerates expectation disconfirmation so that human beings pay attention to novel stimuli with surprise (Itti and Baldi 2009) and try to gain information from unexpected phenomena. This biological function may provide an opportunity to learn novel information and renew prior knowledge, that is, prior distributions. However, due to limitations of cognitive resources, such as short-term memory content and energy, human beings cannot pay attention to each unexpected phenomenon. Assimilation may work as a filter to select which unexpected phenomena should be paid attention to. In other words, human beings ignore marginal prediction error. This biological function is reasonable in that it saves the energy resources of the human brain.

The second hypothesis was that the trend in the relationship between the expectation effect and prediction error depends on uncertainty and external noise. The simulation results in Figure 4 show that uncertainty decreased the extent of the expectation effect and external noise increased the assimilation due to the decreasing repulsive influence during the Bayesian estimation. The experimental results supported the simulation result. The condition of small uncertainty with big external noise involved prominent assimilation. Figure 7 shows that the extent of contrast with smaller noise significantly exceeded that with bigger noise. Smaller uncertainty involved a significantly bigger contrast than bigger uncertainty. We can explain these phenomena with our hypothetical model as follows. Prior distributions of low variation, namely certain predictions, attracted a Bayesian estimate against the likelihood function of noisy stimuli when the prediction error and likelihood asymmetry are small. The repulsive influence decreased as uncertainty and external noise increased. The contrast weakened with big uncertainty and big noise. Human beings rely on their prior distributions when the external stimulus is noisy. Certain prior predictions may increase this dependency, and thus, the extent of assimilation becomes prominent. On the other hand, human beings should pay attention to big prediction errors of certain predictions and clear external stimuli. Therefore, contrast increased with small uncertainty (certain prediction) and small external noise (clear stimulus).

This discussion suggests that our simulation model of the expectation effect is reasonable from the viewpoints of both neuroscience and ecology. In general, one of the biggest advantages of computer simulation is its ability to estimate responses of huge parametric space including untouched area. Traditional modeling based on experiments with human subjects always suffers the limitation of sample size regarding the stimuli that participants can process efficiently during evaluation. The proposed simulation model can potentially apply estimations of user perceptions of physical properties to design a product during the early design stage.

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