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How does expectation affect sensory experience?

– A theory of relativity in perception –

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Abstract: Prior expectation affects posterior experience and emotions. This psychological effect is called *expectation effect*. Two different patterns of expectation effect, contrast and assimilation, were observed. In this talk, I proposed a mathematical model of the expectation effect that explains the conditions of contrast and assimilation[1]. I hypothesized that perceived variable is estimated using a Bayes' inference of prior prediction and likelihood based on sensory stimuli. I formalized the expectation effect as a function of three factors: expectation error, prediction uncertainty, and external noise. Both the results of the computer simulation using the model and the experiment using Size-weight illusion (SWI) 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. Furthermore, I discussed the meanings of expectation effect from an ecological point of view.

Keywords: *Expectation, mathematical modeling, cross-modal, Bayesian estimate, efficient coding, illusion.*

1. INTRODUCTION

Prior expectations affect posterior perceived experience and emotions. Researchers from a broad range of fields have observed this *expectation effect* with regard to different cognitive processes, such as desire for rewards [2], emotions [3, 4], and sensory perceptions [5-7].

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 [8]. 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 many experimental findings exist on the expectation effect in different disciplines, the general mechanism on why and how the effect occurs is not yet clearly elucidated. A mathematical model of the expectation effect based on a fundamental mechanism enables us to estimate user perception of product and service. Two different patterns of expectation effect, *contrast* and *assimilation*, were observed [5]. 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. However, the mechanisms and conditions governing the contrasting and assimilating patterns are not yet clearly elucidated. In this study, I proposed a mathematical model of the expectation effect that explains the conditions of contrast and assimilation by applying neural coding principles, such as Bayesian decoding and the efficient encoding principles[1]. Based on the proposed model, I conducted computer simulations of the expectation effect and obtain an accurate hypothesis of the conditions of assimilation and contrast. Finally, I applied the obtained hypothesis to externalize a perceptual law behind SWI as an expectation effect from a result of an experiment with the participants.

2. MODELING EXPECTATION EFFECT

2.1 Bayesian decoding explain assimilation

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 termed the neural representation of an external physical variable *encoding*. Based on the pattern of neural signals, our brain estimates the physical variable. We termed this estimation process *decoding*. We assumed that sensory stimuli are encoded as certain firing rates of neural populations. Based on the firing rate distributions from a sensory stimulus, R, our brain forms the *likelihood function*, $P(R\mid\theta)$, of a physical variable, θ. On the other hand, a physical property has certain frequency distributions in the world. One learns such frequency distributions throughout their life. Based on such learned distributions, one predicts a physical variable, 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 defined 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. [9]). Based on Bayes' theorem, our brain estimates the distributions of perceptions or *posterior*, $P(\theta \mid R)$, using prior and likelihood.

$$P(\theta \mid R) \propto P(\theta)P(R \mid \theta) \qquad (1)$$

Namely, the posterior is proportional to the product of prior and likelihood. A peak of posterior is an estimate of a physical variable. We termed the difference between prior mean and the likelihood peak *prediction error*. We defined the *expectation effect* (i.e. contrast and assimilation) as the difference between posterior peak and the likelihood peak. Figure 1 showed a relation of prediction error and expectation effect (i.e. assimilation and contrast).

Equation (1) indicated that the Bayesian estimate always comes close to a peak of prior, form a peak of the likelihood estimate of sensory stimulus. We termed the effect *attractive influence* of prior.

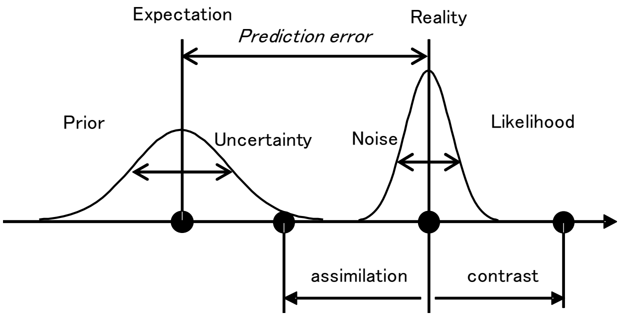

Figure 1 Prediction error and expectation effect

2.2 Efficient encoding explains contrast

The attractive influence alone involves assimilation as an expectation effect. The question then arises: How does contrast occur? Wei and Stocker proposed a neural encoding framework based on the efficient coding principle [10] 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 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. Efficient coding defines the shapes of the tuning curves in physical space by transforming a set of homogeneous neurons using a mapping, that is, the inverse of the cumulative of the prior. 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 applied this efficient encoding to explain contrast in our model. Figure 2 showed how the Bayesian estimate (perceived value), shifts from a peak of the asymmetric likelihood function away from a peak of prior. We termed the perceptual shift *repulsion influence*. The repulsion influence increases as the distance between prior distribution and peak of likelihood, that is, prediction error, increases, because the extent of asymmetry of likelihood increases away from peak of prior.

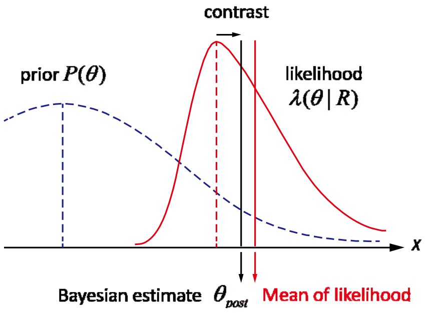

Figure 2 Contrast effect caused by the asymmetric likelihood function based on efficient coding [1]

2.3 A Model of perception with expectation

Figure 3 summarized our model of perception. Based on the efficient encoding principle, prior changed the shape of the likelihood function asymmetry while encoding the sensory stimulus of the physical variable, as a firing rate of the neuron population. The Bayesian decoder integrated the prior distribution, and asymmetric likelihood function, and formed posterior distributions. As a result, one perceived a peak of the posterior as an estimate of the physical variable, that is, perception.

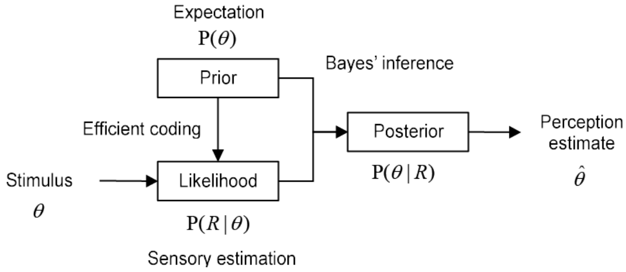

Figure 3 A model of perception involving prior expectation

2.4 A functional model of expectation effect

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 assumed two more factors of the expectation effect: *external noise* and *uncertainty* (see Fig. 1). 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, 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 defined the expectation effect, as a function of three factors: prediction error, variation of prior (uncertainty), and variation of external noise.

3. SIMULATION OF EXPECTATION EFFECT

Using the equation for expectation effect, we conducted a computer simulation to investigate the effects of the three abovementioned factors on the expectation effect. Figure 3 showed an example of the simulation result of the expectation effect as functions of the expectation error. Figure 4 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.
(2) The extent of the expectation effect is bigger when uncertainty is lower for both assimilation and contrast. 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.

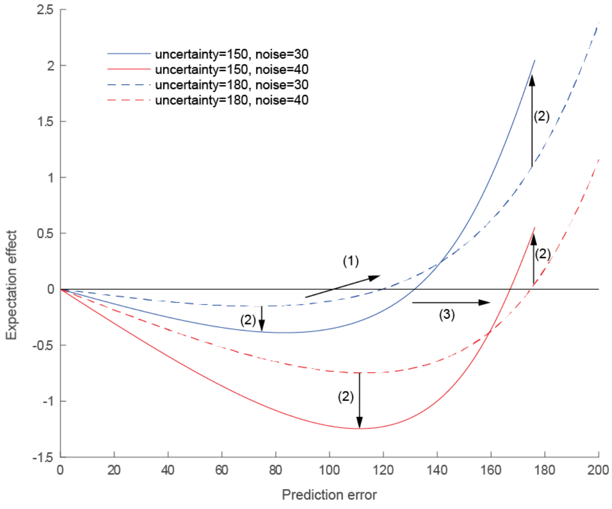

Figure 4 Simulation result of expectation effect as functions of prediction error for different condition of uncertainty and external noise. A positive value represents contrast, and a negative value, assimilation. [1]

4. EXPERIMENT USING SWI

According to conventional SWI, one perceives that a smaller object is heavier than a larger object, although both objects may have the same weight. This illusion can be viewed as a contrast of the expectation effect, where the perception of difference between the weight predicted by the object's size and its actual weight, the prediction error, is exaggerated. However, our simulation result in Fig. 4 showed that assimilation, an opposite effect to contrast, occurs when the prediction error is less than a certain value. In other words, one must perceive that a larger object is heavier than a smaller object with identical weights if the proposed model was correct.

To validate the hypothesis, we conducted an experiment where participants compared the weights for pairs of objects. The objects in each pair had identical weights but different sizes. We manipulated prediction error by adjusting the size differences in each pair. We also manipulated both uncertainty, and external noise (See [1] for the detail of the manipulation method.). We used the perceptual difference of weight for each pair as the extent of the expectation effect.

Figure 5 showed the averaged responses of the participants regarding the relative weight of each target sample for four combinations of uncertainty and external noise. The positive value represents contrast, and negative value represents assimilation. The horizontal axis denotes differences between the expected weight and the actual weight of each target, that is, the extent of prediction errors for each pair. The result showed 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 4. As we hypothesized, assimilation occurred in the presence of small prediction errors, which contradicts the idea put forth by the SWI.

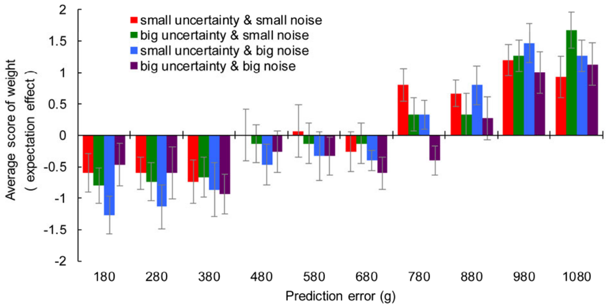

Figure 5 Experiential result of SWI as expectation effect. A positive value shows how much heavier the smaller object was than the bigger object (i.e. contrast), whereas the negative value shows the opposite (i.e. assimilation). [1]

4. DISCUSSIONS

Both the results of the computer simulation and the experiment using the SWI 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 [11] 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. 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 the proposed mathematical 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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