FREE-ENERGY MODEL OF SENSE OF AGENCY FOR HUMAN-MACHINE INTERFACE DESIGN BASED ON COMPARATOR MODEL

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ABSTRACT

Sense of agency is the sense that one is causing an action. The increase in machine or system autonomy leads to an increase in the loss of sense of agency for the operation causing the loss of pleasure in the operation or sense of responsibility for the consequences of operations. Designing a sense of agency is necessary, especially in the context of machine autonomy. This calls for the control of the sense of agency, which requires the construction of a model to predict the sense of agency and establishing a design methodology to manipulate the factors of sense of agency. We propose the mathematical model that predicts the sense of agency in a human-machine system based on the comparator model and free-energy principle and what to design to enhance the sense of agency. Proposed model explains the effects of prediction error, prediction uncertainty, and observation uncertainty for body, machine, and environment feedback on the sense of agency. The model generally reveals the interaction effect between prediction error and prediction uncertainty and between prediction error and observation uncertainty. The model prediction can be widely applied as a design guide for enhancing sense of agency of human-machine interfaces.

Keywords: Design methodology, Sense of Agency, Mathematical model, Design for interfaces, Experience design

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1 INTRODUCTION

1.1 Importance of sense of agency in engineering design

Sense of agency is the sense that one is causing or generating an action (Gallagher, 2000). It is a factor of pleasure. For example, patients with psychosis may lose sense of agency and experience helplessness and lose pleasure as a result. Sense of agency is also a factor of sense of responsibility; people feel responsible because they perceive the consequences of their actions. Blakemore et al. (1999) investigated the effects of delay and trajectory perturbation of tactile stimulation on the tickliness rating using robotic setup. Self-produced tactile stimulation is perceived as less tickly than the same stimulation produced externally. The tactile stimulation was varied stepwise from self-produced to robot-produced by tickling the right hand with the left hand via the robot's arm and varying the delay and trajectory perturbation of the robot's arm. This means that the sense of agency changes depending on the design of the robot's behavior in engineering. In recent years, machines have become more autonomous. For example, the number of automobiles equipped with collision avoidance systems or adaptive cruise control is increasing. It is predicted that various technologies such as cameras, light detection and ranging, other sensing technologies, and deep learning object recognition will make automobiles more autonomous. Machine autonomy results in a mixture of human operation and machine assistance. It is difficult to have a sense of agency when not only human operation but also machine assistance causes machine behavior. The loss of sense of agency for the operation causes the loss of pleasure in the operation or loss of sense of responsibility for the consequences of the operation. Wen et al. (2019) state that loss of the sense of agency may cause excessive reliance on the autonomous system in the context of driving automation. The sense of responsibility is an important ethical issue in terms of human–robot collaborations (Nyholm, 2018).

1.2 How to design sense of agency

We consider that designing a sense of agency achieves an appropriate pleasure or sense of responsibility. To control the sense of agency, it is necessary to (1) construct a mathematical model to explain and predict the sense of agency and (2) establish a design methodology of human-machine interface or machine assistance to manipulate the factors of sense of agency. Yano et al. (2020) constructed a mathematical learning model of the sense of agency in which the likelihood of the sensory feedback is an indicator of the sense of agency and is used to update the prediction of the sensory feedback. This model is useful in explaining and predicting the change in the sense of agency in learning; however, is not sufficient to control the sense of agency. Legaspi and Toyoizumi (2019) constructed a mathematical model that explains the intentional binding effect in the framework of optimal Bayesian cue integration. The intentional binding effect is the subjective compression of the temporal interval between a voluntary action and its external sensory feedback, and it has been suggested that the intentional binding effect is closely related to the sense of agency (Moore and Obhi, 2012). This model explains the intentional binding effect well; however, it is insufficient to explain the sense of agency.

We proposed a mathematical model that explains and predicts the sense of agency based on the free-energy principle (Taniyama et al., 2021). This model explains the effects of prediction error, prediction uncertainty, and observation uncertainty on the sense of agency. We consider that sense of agency can be controlled by manipulating these factors. However, this model is limited in explaining the sense of agency in body movement or simple systems, such as the button-press system. The factors described in the model are abstract for manipulation. It is necessary to extend this model to the human-machine system and summarize how to manipulate the factors in the model.

1.3 Objective

Designing a sense of agency is necessary, especially in the context of machine autonomy. However, to the best of our knowledge, there is no design methodology for the sense of agency. To design the sense of agency, a mathematical model that explains and predicts the sense of agency and a design methodology to manipulate its factors are necessary. This paper aims to extend the mathematical model of the sense of agency based on the free-energy principle to the model in the human-machine system and propose a policy for the interface design by summarizing the method to manipulate the factors in the model.

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2 METHOD

We propose a mathematical model to explain and predict the sense of agency in a human-machine system based on the comparator model and free-energy principle and discuss how to manipulate the model variables. The comparator model is a fundamental model that explains the sense of agency. The comparator model states that the prediction error generated in the perceptual process of the state causes a sense of agency. The free-energy principle is an information theory of the brain that explains perception, learning, and action of organisms as minimizing the cost function called free energy. We construct the mathematical model using the framework called perceptual inference that explains the perceptual process of the state.

2.1 Comparator model

The comparator model is a qualitative model that explains the sense of agency (see Figure 1). It suggests that the predicted and the estimated actual states are compared in the motor control system to improve the forward models used to predict the consequences of actions (Frith et al., 2000). The discrepancy between the predicted state and the estimated actual state is called the prediction error. It is considered that the prediction error decreases the sense of agency.

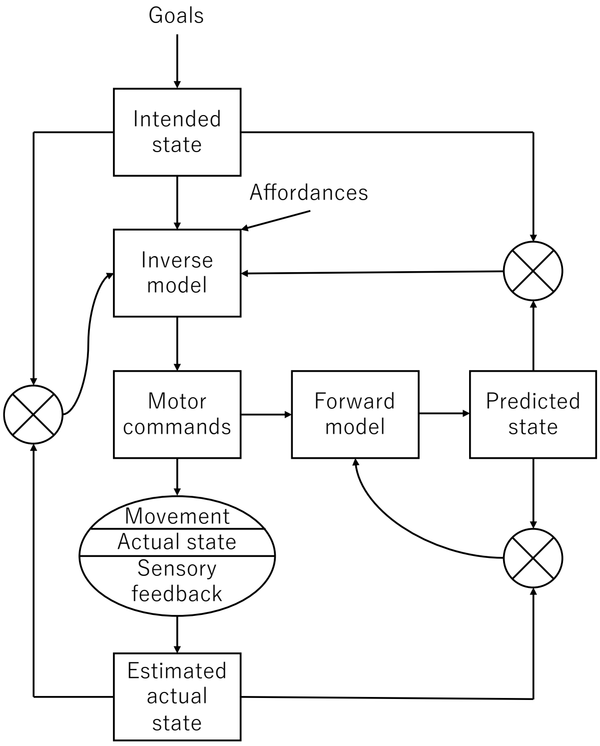

Figure 1. Comparator model

2.2 Perceptual inference in free-energy principle

The free-energy principle is an information theory of the brain that explains perception, learning, and action of organisms as minimizing the cost function called free energy (Friston et al., 2006). What makes the free-energy principle unique is that it is a unified theory that can explain both perception and action. The frameworks that explain perception and action are called perceptual and active inference, respectively. Perceptual inference is the optimization of state variables (hidden states) and parameters that constitute the internal model (generative model). Active inference is the optimization of control states (policy) and action selection. We associate the comparator model with an active inference model (see Figure 2). The inverse model in active inference differs significantly from the inverse model in the comparator model. The inverse model in active inference is the function of the prediction error, whereas the inverse model in the comparator model is the function of the intended state (Friston et al., 2010).

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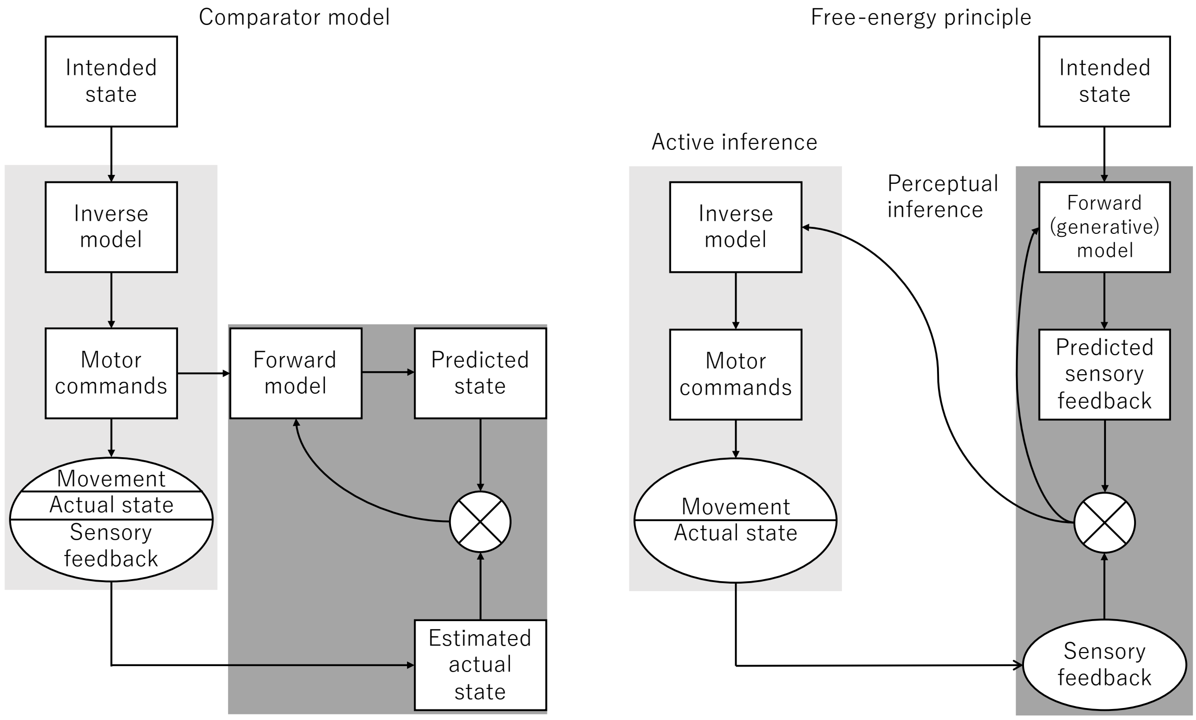

Figure 2. Mapping between comparator model and free-energy principle

To construct the model that explains the effect of the prediction error on the sense of agency, we focus on perceptual inference in the free-energy principle. The free-energy principle is based on Bayesian inference. Equation (1) shows the Bayes' theorem.

$$p(x|y) = \frac{p(y|x)p(x)}{p(y)} = \frac{p(y|x)p(x)}{\int p(y|x)p(x)dx} \tag{1}$$

In the perceptual inference, x is the hidden state and y is the sensory feedback. $p(x)$ is the probability of the hidden state before the sensory feedback is obtained (prior probability) and $p(x|y)$ is the probability of the hidden state after the sensory feedback is obtained (posterior probability). $p(y|x)$ is the joint probability of the sensory feedback viewed as a function of the hidden state (likelihood function). Given the sensory feedback, the recognition of the probability of the hidden state is updated from the prior probability to the posterior probability using the likelihood function.

However, the exact computation of the posterior probability is difficult when there are many types of hidden states or sensory feedback since the product of the likelihood function and the prior probability is required for all possible hidden states. In free-energy principle, the posterior probability is approximated by minimizing the Kullback-Leibler divergence between the posterior probability and the approximate posterior probability (recognition density).

$$D_{KL}(q(x)\|p(x|y)) = \int q(x)\log\left(\frac{q(x)}{p(y,x)}\right)dx - (-\log p(y)) \tag{2}$$

where $q(x)$ is the recognition density and $p(y,x)$ is the joint distribution of the sensory feedback and the hidden state, called generative model. The generative model is a brain mechanism that describes how sensory feedback is generated from hidden states. It is considered that the sensory feedback is predicted using the generative model (see Figure 2). The first term of the right-hand side is called free energy and the second term of the right-hand side is called surprise. The free energy is interpreted as prediction error, expected cost (Friston, 2010), novelty, uncertainty, or perceived complexity (Yanagisawa, 2021). In perceptual inference, the recognition density is optimized to minimize the Kullback-Leibler divergence. This is equivalent to minimizing the free energy.

2.3 Free-energy model of sense of agency

The free-energy model is the mathematical model of the sense of agency based on the perceptual inference in free-energy principle (Taniyama et al., 2021). The free energy can be interpreted as a

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prediction error. The free energy is minimized when the recognition density sufficiently approximates the posterior probability.

$$\int q(x) \log\left(\frac{q(x)}{p(y,x)}\right) dx \geq -\log p(y) \tag{3}$$

We consider that the minimized free energy (surprise) is an indicator of the prediction error that affects the sense of agency and quantifies the sense of agency with the negative surprise (log-probability of the sensory feedback).

$$(sense\ of\ agency) = \log p(y) = \log \int p(y|x)p(x)dx \tag{4}$$

where $\log p(y)$ is interpreted as model evidence. If the generative model sufficiently approximates reality, the value of the model evidence is large, and the obtained sensory feedback is exactly as likely as the predicted sensory feedback. The model evidence can be computed by the product of the likelihood function and the prior probability. The likelihood function and prior probability can be approximated by various distributions depending on the problem.

We show the approximation of the likelihood function and prior probability in the simplest case using Gaussian distributions.

$$p(y|x) = \frac{1}{\sqrt{2\pi\sigma_l^2}} \exp\left(-\frac{(x-\mu_l)^2}{2\sigma_l^2}\right) \tag{5}$$

$$p(x) = \frac{1}{\sqrt{2\pi\sigma_p^2}} \exp\left(-\frac{(x-\mu_p)^2}{2\sigma_p^2}\right) \tag{6}$$

The negative surprise as the indicator of the sense of agency is calculated using equation (7).

$$(sense\ of\ agency) = \frac{1}{2}\left(\frac{1}{\sigma_p^2+\sigma_l^2}\left|\mu_l - \mu_p\right|^2 + \log 2\pi\left(\sigma_p^2 + \sigma_l^2\right)\right) \tag{7}$$

where $\left|\mu_l - \mu_p\right|$ is the difference between the averages of the prior probability and likelihood function and means the prediction error, σ_p^2 is the variance of the prior probability and means the prediction uncertainty, and σ_l^2 is the variance of the likelihood function and means the observation uncertainty. The sense of agency is described as the function of these three variables.

2.4 Extension to free-energy model in human-machine system

We consider applying the free-energy model to the human-machine system. Figure 3 shows the outline of the human-machine system (based on Chapanis, 1965). For example, humans move their hands or legs or sometimes talk as the input to the operation elements of the interface. The operation elements output the body information, which is input to the machine. The machine outputs the machine information, which acts on the environment. The body information, machine information, and environment information are output to humans through the information display elements of the interface as sensory feedback. We extend the free-energy model to the model in a human-machine system by describing the three types of prediction errors for the body feedback, machine feedback, and environment feedback.

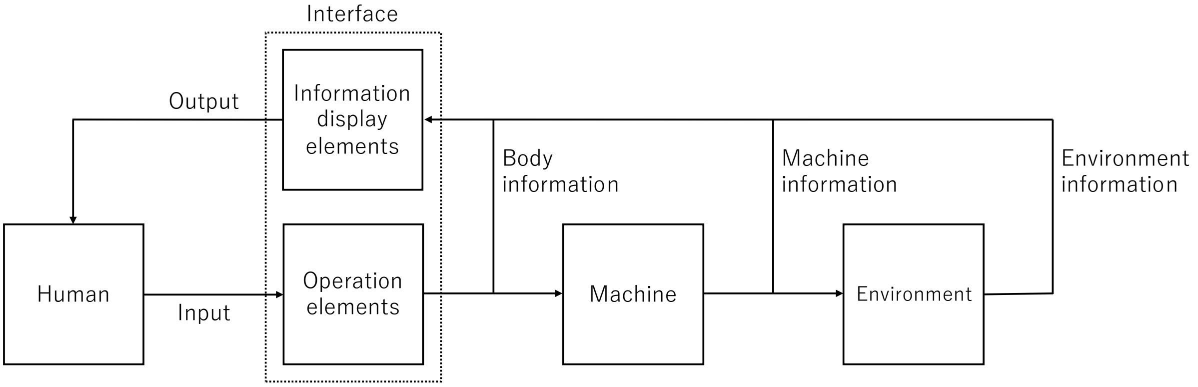

Figure 3. Human-machine system

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3 RESULT

3.1 Free-energy model in human-machine system

We described three types of prediction errors for the body feedback, machine feedback, and environment feedback. We derived an extension of the comparator model (Figure 1) in human-machine system (Figure3) according to the framework of the free-energy principle (see Figure 4). When the human-machine system is learned by receiving the body information, machine information, and environment information, humans acquire the body forward, machine forward, and environment forward models. The body, machine, and environment feedback are predicted using the body forward, machine forward, and environment forward models in the generative model, respectively. The body, machine, and environment states are changed by outputting the motor commands. As shown in Figure 2, according to the free-energy principle, the predicted sensory feedback is compared to the actual sensory feedback. In the human-machine system, the three types of predicted sensory feedback are compared to the three types of actual sensory feedback.

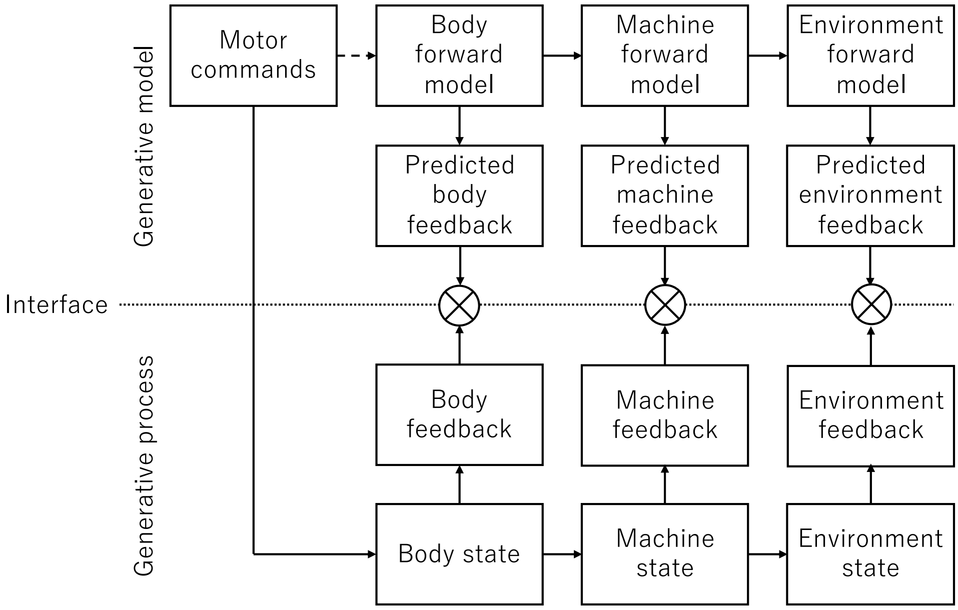

Figure 4. Extension to comparator model in human-machine system

In the human-machine system, Bayes' theorem can be described as equation (8).

$$p(x_B, x_M, x_E | y_B, y_M, y_E) = \frac{p(y_B, y_M, y_E | x_B, x_M, x_E) p(x_B, x_M, x_E)}{p(y_B, y_M, y_E)} \tag{8}$$

The subscripts B, M, and E mean body, machine, and environment, respectively. We considered that the sense of agency in the human-machine system is quantified as equation (9) as well as equation (4).

$$(sense\ of\ agency) = \log \int p(y_B, y_M, y_E | x_B, x_M, x_E) p(x_B, x_M, x_E) dx_B dx_M dx_E \tag{9}$$

The likelihood function and prior probability in the human-machine system are described as equation (10) and equation (11), respectively.

$$p(y_B, y_M, y_E | x_B, x_M, x_E) = p(y_B | x_B) p(y_M | x_M) p(y_E | x_E) \tag{10}$$

$$p(x_B, x_M, x_E) = p(x_B) p(x_M | x_B) p(x_E | x_M) \tag{11}$$

The likelihood function in the human-machine system is described as the product of the likelihood functions of the body, machine, and environment states. The prior probability in the human-machine system is described as the product of the prior probability of body state, the probability of machine state given body state, and the probability of environment state given machine state. The likelihood functions of the body, machine, and environment states can be approximated by the following observation equations.

$$y_B(t) = g_B\big(x_B(t)\big) + \epsilon_{y_B}(t) \tag{12}$$

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$$y_M(t) = g_M(x_M(t)) + \epsilon_{y_M}(t) \tag{13}$$

$$y_E(t) = g_E(x_E(t)) + \epsilon_{y_E}(t) \tag{14}$$

The prior probability of body state, the probability of machine state given body state and the probability of environment state given machine state can be approximated by the following state equations.

$$Dx_B(t) = f_B(x_B(t)) + \epsilon_{x_B}(t) \tag{15}$$

$$x_M(t) = f_M(x_B(t)) + \epsilon_{x_M}(t) \tag{16}$$

$$x_E(t) = f_E(x_M(t)) + \epsilon_{x_E}(t) \tag{17}$$

The functions $f, g,$ and the noise ϵ can be configured depending on the problem.
When the likelihood functions and probabilities of body, machine, and environment states are approximated using Gaussian distributions, the sense of agency in the human-machine system can be described as a function of the prediction error, prediction uncertainty, and observation uncertainty for body feedback, machine feedback, and environment feedback.
The negative surprise as the indicator of the sense of agency is calculated using equation (18).

$$(sense\ of\ agency) = \frac{1}{2}\left(\frac{1}{\sigma_{pB}^2+\sigma_{lB}^2}\left|\mu_{lB} - \mu_{pB}\right|^2 + \frac{1}{\sigma_{pM}^2+\sigma_{lM}^2}\left|\mu_{lM} - \mu_{pM}\right|^2 + \frac{1}{\sigma_{pE}^2+\sigma_{lE}^2}\left|\mu_{lE} - \mu_{pE}\right|^2 + \log(2\pi)^3\left(\sigma_{pB}^2 + \sigma_{lB}^2\right)\left(\sigma_{pM}^2 + \sigma_{lM}^2\right)\left(\sigma_{pE}^2 + \sigma_{lE}^2\right)\right) \tag{18}$$

where $|\mu_{lB} - \mu_{pB}|$, $|\mu_{lM} - \mu_{pM}|$, and $|\mu_{lE} - \mu_{pE}|$ are prediction errors, σ_{pB}^2, σ_{pM}^2, and σ_{pE}^2 are prediction uncertainties, and σ_{lB}^2, σ_{lM}^2, and σ_{lE}^2 are observation uncertainties for body, machine, and environment feedback, respectively.

3.2 Application of the free-energy model to interface design

The sense of agency is described as a function of prediction errors, prediction uncertainties, and observation uncertainties. The analysis of equation (7) reveals the interaction between prediction error and prediction uncertainty (see Figure 5) and the interaction between prediction error and observation uncertainty (see Figure 6). The interaction between the prediction error and prediction uncertainty was observed in the button-press experiment in which the prediction error and prediction uncertainty were manipulated by delay and learning, respectively (Bamba and Yanagisawa, 2021). The interaction between the prediction error and observation uncertainty was observed in the button-press experiment in which the prediction error and observation uncertainty were manipulated by delay and number of sensory feedbacks, respectively (Taniyama et al., 2021). These interactions observed in previous studies are evidence for the free-energy model. Equation (18) shows that the free-energy model in the human-machine system also predicts the interaction between the prediction error and prediction uncertainty and the interaction between the prediction error and observation uncertainty for body, machine, and environment feedback.
Previous studies have shown that the sense of agency is modulated in various ways, such as delay (Wen et al., 2015; Haering and Kiesel, 2015; Kataoka et al., 2017; Bamba and Yanagisawa, 2021; Taniyama et al., 2021; Yang and Yanagisawa, 2022), space discrepancy (Yang and Yanagisawa, 2022), learning (Spengler et al., 2009; Moore et al., 2012; Bamba and Yanagisawa, 2021), priming (Haggard and Chambon, 2012; Sidarus et al., 2017), and number of sensory feedbacks (Taniyama et al., 2021).
Wen (2019) summarized the effects of delay on sense of agency and stated that delay produces prediction errors, graded response, worse task performance, motor-based computation of agency, an excess of the time window of sensory pre-activation, or breakdown of causal relations. The effect of the delay on the sense of agency for body movement is explained by the prediction error, however, in the sense of agency for external events, the weight of factors other than the prediction error is significant. This implies that delay can be interpreted as a prediction error under the condition of sufficiently learned forward models. Yang and Yanagisawa (2022) interpreted space discrepancy as a prediction error and manipulated the discrepancy between the object movement referred to by the operation and intervened visual feedback. However, in addition to delay, space discrepancy affects factors other than the prediction error, such as task performance or causal relations. We can argue that space discrepancy is a prediction error under the condition of a sufficiently learned forward model.

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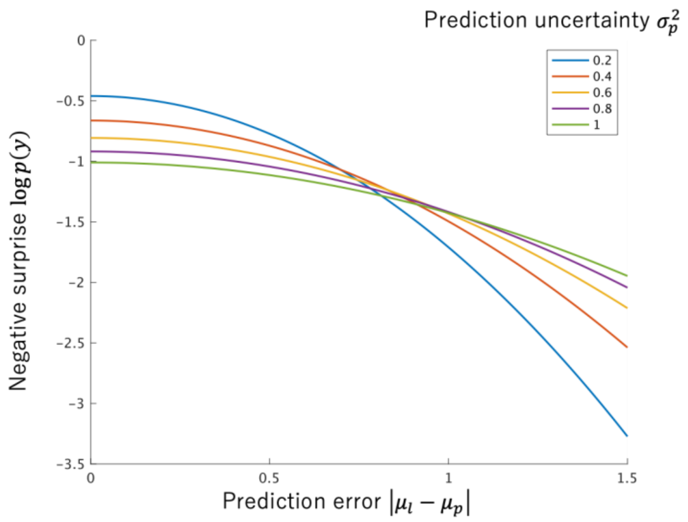

Figure 5. Effect of prediction error and prediction uncertainty on negative surprise (interaction between prediction error and prediction uncertainty)

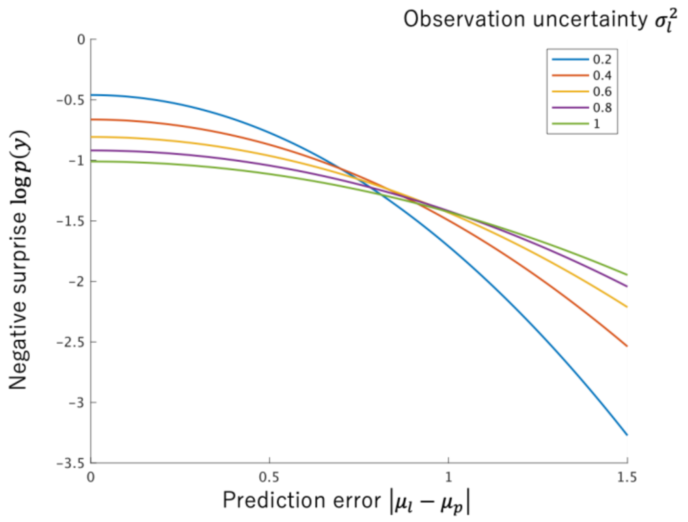

Figure 6. Effect of prediction error and observation uncertainty on negative surprise (interaction between prediction error and observation uncertainty)

In previous studies (Spengler et al., 2009; Moore et al., 2012; Bamba and Yanagisawa, 2021), the effect of learning was investigated and the idea that learning builds prediction is the foundation. Yano et al. (2020) constructed a mathematical learning model of the sense of agency based on Bayesian inference. Therefore, we consider that learning is within the scope of the free-energy model. Learning can be interpreted as a prediction uncertainty. Priming is also used to modulate the sense of agency (Haggard and Chambon, 2012; Sidarus et al., 2017). In previous studies, it was considered that priming affects action selection; however, priming can be interpreted as a cue (feedforward information) for sensory signals. In Posner paradigm (Posner, 1980), it is known that cue enhances predictability and attention for sensory signals. Priming is also interpreted as prediction and observation uncertainty. The cue integration model (Moore and Fletcher, 2012) states that variance of the sensory estimate decreases when sensory information from different sources refers to the same feature of the environment. The number of sensory feedbacks that refer to the same feature is interpreted as observation uncertainty.

To apply the free-energy model to interface design, the relationship between model variables and potential design variables or constraints discussed above can be summarized as shown in Table 1. We propose to optimize model variables for the body, machine, and environment feedback to maximize the negative surprise in equation (9) by manipulating design variables in Table 1.

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Table 1. Relationship between model variables and design variables or constraints

Model variables	Design variables or constraints
Prediction error	Delay, Space discrepancy
Prediction uncertainty	Learnability, Feedforward information
Observation uncertainty	Reliability of feedback information, Feedforward information

Based on the free energy model, we propose a design methodology that uncertainty is reduced under small prediction error and increased under large prediction error to increase the sense of agency. For example, if there is a large unpredictable delay from steering wheel rotation to wheel rotation due to friction in the car's gears, the uncertain force feedback from the steering wheel, which is information about the wheel-road interaction, enhances the sense of agency.

DISCUSSION

We constructed a mathematical model to explain and predict sense of agency in the human-machine system and suggested how to manipulate the model variables. The interaction between the prediction error and uncertainty for body, machine, and environment feedback was predicted by constructing the free-energy model in the human-machine system. This implies that large prediction and observation uncertainty enhance sense of agency under the condition of a large prediction error. For example, in the limitation of a large prediction error due to a long delay, such as in remote operations, no feedforward information or low reliability feedback information can be designed to increase the prediction or observation uncertainty. By constructing a mathematical model of the sense of agency, we could predict the interaction between prediction error and uncertainty and propose a method for interface design.

However, the free-energy model is limited in explaining part of the sense of agency. Synofzik (2008) suggested a two-step account as a new framework for sense of agency. This framework classifies sense of agency into the feeling and the judgement of agency. The feeling of agency is a non-conceptual, low-level feeling of being the agent of an action. The judgement of agency is a conceptual, interpretative judgment of being an agent. The feeling of agency has feedforward cues, proprioception, or sensory feedback as factors. The judgment of agency has the feeling of agency, intentions, thoughts, and social or contextual cues as factors. Non-conceptual factors explains the feeling of agency, which is processed by conceptual factors in the second step. It is considered that prediction error is the dominant factor of the feeling of agency. Therefore, the free-energy model is limited in explaining the feeling of agency.

Wen (2019) specified that the sense of agency contains two layers and called the sense of agency over one's own action and that over external events as the body agency and external agency, respectively. With respect to the body agency, the feeling of agency is dominant because no prediction error is default when moving the body. However, with respect to the external agency, conceptual factors cannot be ignored because it is not default that there is no prediction error when causing the external events.

The free-energy model is useful under the condition that the user is familiar with the system.

4 CONCLUSION

Designing a sense of agency is necessary, especially in the context of machine autonomy. However, there is no design methodology for the sense of agency. We proposed the mathematical model that explains and predicts the sense of agency in a human-machine system based on the free-energy principle and what to design: delay, space discrepancy, learnability, feedforward information, reliability of feedback information in body, machine, and environment feedback. The unique feature of the free-energy model is the interaction between prediction error and uncertainty. These interactions derive a design methodology that uncertainty is reduced under conditions of small prediction error and increased under conditions of large prediction error to increase the sense of agency. In future, an extension to the mathematical model that explains the effects of conceptual factors on the sense of agency is required.

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