Economics Bulletin

Volume 31, Issue 3

The role of the orbitofrontal cortex in human adaptive learning under strategic environments

Kazuhiro Miyagawa
Graduate School of Economics, Hitotsubashi University

Tadanobu Misawa
Graduate School of Science and Engineering, University of Toyama

Tetsuya Shimokawa
School of Management, Tokyo University of Science

Abstract

This paper proposes an augmented learning model from a neuroscience perspective. This model contains brain activity data of the orbitofrontal cortex as a predictive variable of human strategic behavior. A Bayesian 3-layer perceptron, which shows the complex relationship between decision factors, was adopted to describe the learning behavior. However, the model's complexity creates the possibility of over tting. To avoid this problem, we adopt the Bayesian estimation and Akaike's Bayesian information criteria, which provide the statistical basis of the model selection, to select the model. Our experience shows that this model can better predict human strategic behavior than do existing behavioral learning models.

Citation: Kazuhiro Miyagawa and Tadanobu Misawa and Tetsuya Shimokawa, (2011) ''The role of the orbitofrontal cortex in human adaptive learning under strategic environments'', *Economics Bulletin*, Vol. 31 no.3 pp. 2284-2297.
Submitted: Mar 29 2011. **Published:** August 11, 2011.

1 Introduction

In recent years, significant changes have been introduced into the rational decision-making models that had been used in classical economics models. One trend known as behavioral economicsCamerer et al. (1995); Kahneman and Tversky (1979); Thaler (1999) tendsto change rational decision-making from a behavioral approach. Another trend is called neuroeconomics Camerer et al. (2005); Sanfey et al. (2006), which is based on rapidly developing neuroscience findings. These 2 areas are complementary and the decision-making process is elaborated by bounded rationality. Since 2000, several research groups have reported a number of attempts to refine the various decision-making biases detected by behavioral approaches by reconsidering them from a neuroscientific perspective. Two studies in particular Breiter et al. (2001); Holroyd et al. (2004) used functional magnetic resonance imaging (fMRI) and scalp electrical recordings to explore decision-making biases of the prospect theory Kahneman and Tversky (1979); Tversky and Kahneman (1992) from a brain activity perspective. In addition, with regard to time discounting Laibson (1997); Loewenstein et al. (2003); Strotz (1955), several studies have indicated a difference between the active regions involved in long and short-term activities from a neurosurgical perspective McClure et al. (2007, 2004); Tanaka et al. (2004).

In this research, based on the findings of those studies, we elaborate the behavioral learning model, a diachronic decision-making process, from the neuroscientific perspective by analyzing the adaptive aspects of decision: making with regard to: how to adjust oneself to the environment.

In the area of learning theory, several important models have already been proposed by the behavioral approach (Camerer and Foundation (2003) provides a good review). These include reinforcement learning models Bereby-Meyer and Erev (1998); Erev and Roth (1996, 1998); Sutton and Barto (1998)[1] and hybrids between reinforcement learning and fictitious behavior, such as the experience-weighted attractionlearning(EWA) model Camerer and Ho (1999). Although each has its own advantages and disadvantages, both are known to have excellent behavior describability compared to the Nash equilibrium, which predicts behaviors based on rationality. One method in particular Marchiori and Warglien (2008) has shown an excellent learning model by using an index indicative of certain forms of "regret"/ "fictive error"

The model proposed in this paper seeks to refine these behavioral models in 2 ways :
1. It refines the human learning process in strategic situations from the neuroscientific perspective. Brain activity data of the medial prefrontal cortex (MPFC) and the orbitofrontal cortex (OFC) in particular are examined as predictor variables of human behavior. Both of MPFC and OFC are thought to be related to the reward system and emotional feelings. MPFC is also considered to be related to cognitive activities.
2. It uses a statistically valid model that can demonstrate more complex relationships. Many existing learning models are defined as linear predictors, but we can expect that human decision-making is based on more complex relationships between factors. One method used nonlinear predictors Marchiori and Warglien (2008). This group used a 1-layer perceptron as a behavioral model in which the model parameters were exogenously

[1] To be precise, the reinforcement learning model used in economic models is often a reinforcement comparison model which can be referred to as its simple version (Sutton and Barto (1998)).

provided. In this research, a Bayesian 3-layer perceptron was adopted and the model parameters were estimated based on the Bayesian estimation. Three-layer perceptron was used due to the limited accuracy of 1-layer perceptrons approximation. The complexity of the model creates an overfitting possibility. To avoid the problem, we adopted Bayesian estimation and Akaike's Bayesian information criteria (ABIC), which provide a statistical basis for model selection, to select the model.

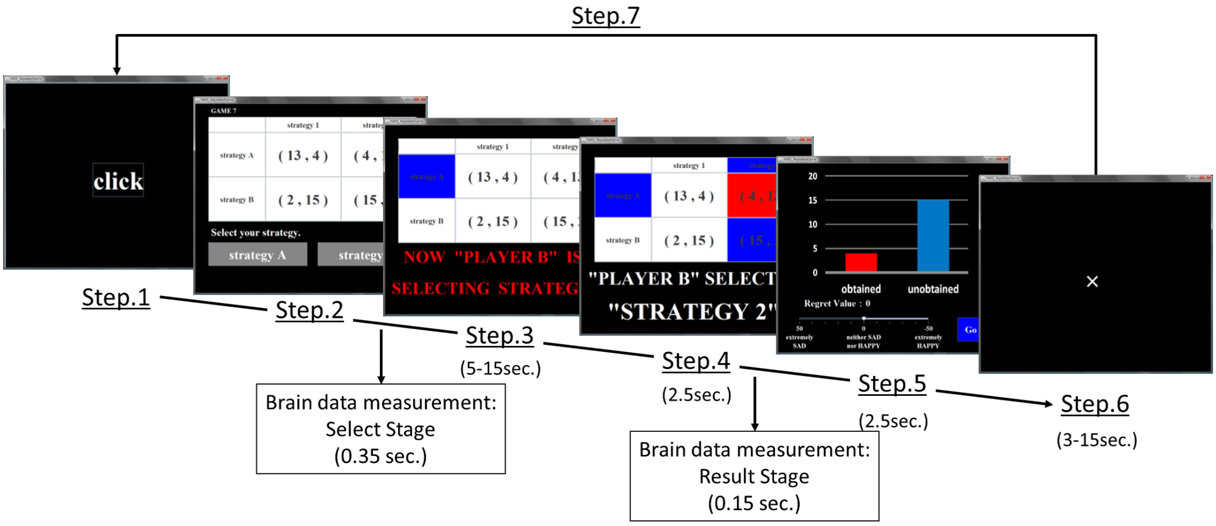

Figure 1: The detail of experimental procedure.

2 Experimental procedures

2.1 Task

In this study, the repeated game experiment (Game Task) described below was performed. Each of the games used in the experiment was 2×2 and had unique mixed-strategy equilibrium. To ensure comparability of the results, we used 3 games that were the same as the original and 1 referenced above (**?** The payoff matrices the subject faced were decided at random so the predictability results of decision-making become independent from the shape of the presented payoff function. The 29 subjects (27 men and 2 woman) were healthy individuals 19-25 years of age, and the number of valid samples was 635 [2]. In the Game Task, the subject looks at the payoff matrix and chooses 1 of the 2 strategies. A computer then chooses a strategy and the results are displayed. While the results are displayed on the payoff matrix, the resulting gains are also displayed with the difference from the gains that could have been obtained from the other choice to explicitly show the difference in gain and to put an emphasis on the fictive error. Figure:1 shows

[2]The reader should note that our examination has a limitation in the area of subject selection, i.e., the male-to-female ratio of subjects has a large bias. Although we observed the same data tendencies in females as those in males in this cohort of limited female-centric data, the effect of this bias requires further examination. We plan to examine this point in a future study.

the procedures. Please refer to the Appendix for the experimental details. condition is reached.

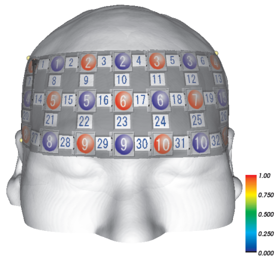

Figure 2: fNIRS prove and channel placement.

2.2 Brain data measurement

This experiment measured changes in the concentrations of oxygenated hemoglobin (oxyHb) and deoxygenated hemoglobin (deoxyHb) during task performance using functional near infrared spectroscopy(fNIRS) (fNIRStation; Shimadzu Corporation.) Instead of being absorbed by body-composing substances like water, carbohydrates, and proteins, near-infrared rays close to a wavelength of 800 nm readily pass through the skull and are readily absorbed by hemoglobin in the brain. Based on the light absorption rate, fNIRS examines changes in oxyHb and deoxyHb in the brain and thus measures brain site activation. The fNIRS used in the current study provides multichannel measurement of a continuously radiated and absorbed 3-wavelength laser (780, 805, and 830 nm).

fNIRS has the following substantial advantages not found with fMRI: subjects are less restricted and can make decisions under relatively natural conditions; the higher temporal resolution; less cost; and simultaneous measurement of multiple subjects. The environmental factors are known to control human emotions and moods and thus substantially affect economic decision-making. These advantages of fNIRS allow the measurement of brain activity accompanying economic behavior that is exhibited while a subject is normally at work.

The timings of the brain data measurement are as follows.
(1) Select stage: The concentration of oxyhemoglobin alteration was measured 0.35 sec after the payoff matrix was presented in step 2 of Figure 1. The feasible information of the subject in this stage is based on past results and a presented payoff matrix.
(2) Result stage: The concentration of oxyhemoglobin alteration was measured 0.15 sec after the result of this round was presented in step 4 of Figure 1. The newlyarrived information in this stage is on an opponent's action and is the realized payoff.

Figure 2 shows the NIRS probe and channel placement. In this experiment, the probe was placed on the forehead for focus on the PFC. The 10-20 system was used for electrode placement. The numbers in the white squares of Figure 2 are the channel numbers of the fNIRS observation. In light of earlier studies using fMRI, the following analysis especially focused on 2 areas: the MPFC, which is believed to better reflect the reward system activity(Hampton and O'Doherty (2007); Knutson and Peterson (2005);

Kuhnen and Knutson (2005)), and the OFC, which reacts to predicted gain and risk-seeking behavior in the medial area and relates to predicted loss and risk aversion in the lateral part. The sampling period was 175 msec.

The filters are sequentially adapted to Fast Fourier transforms. In most of the subjects, the threshold frequency range was 0.25-0.30 Hz. In addition, because the magnitude of the variations of the blood levels of oxyHb differs considerably between individuals, standardization between subjects (z-transformation) was conducted in order to superimpose the data from all subjects.

3 An augmented learning model

In the experiment we mentioned, by using change of concentrations of oxygenated hemoglobin (oxyHb) in cerebral blood, we examined how much we could predict subject behavior, i.e., which strategy each subject would choose. In concrete terms, we makes predictions on the subjects' next action using the currently chosen behavior and the changes oxyHb concentration in the regions corresponding to MPFC (channels 10-12 and 17, a few seconds ["time select"] after the decision-making process regarding the STEP.2 strategy as shown Figure 1) and OFC (channels $27-32$, a few seconds ["time result"] after the display of the STEP.4 result as shown in Figure 1).

As described hereinafter, these predictive factors were selected according to a statistical criterion. The sites in the prefrontal cortex/channel adopted predictive model were selected according to a statistical criterion. In light of earlier study findings, we consider the sites in the prefrontal cortex that are related to cognitive activities and emotional feelings as candidate predictive factors. The most effective site/channel was selected in each measurement stage (selection stage and result stage) according the hyperparameter marginal likelihood (HML) / Akaike's Bayesian information criterion (ABIC). The effectiveness of each candidate site in each stage is shown in Table 1 in Appendix.

In one study Marchiori and Warglien (2008), a single-layer perceptron was adopted as a predictive model, and its parameters were given deterministically on the basis of a trial-and-error process. In contrast, in this study, a 3-layer perceptron was used and its parameters were statistically learned using a hierarchical Bayesian approach MacKay (1992a,b); Neal (1996). We used standardization data (z-transformation) to make it possible to overlap the current gains with those of different games. Hierarchical Bayesian estimation was conducted to estimate the model parameters, and Markov Chain Monte Carlo methods were used in the algorithm, whereas in the model evaluation, hyperparameter marginal likelihood (HML) corresponding to ABIC was used in addition to mean squared deviation (MSD). The reason for the use of a three-layer perceptron was that the complicated nonlinear relationship between the changes in oxyHb concentration in the cerebral blood and the decision-making is possible to approximate. A 3-layer perceptron can theoretically approximate any continuous relation.

In addition, the reason for performing statistical learning was that in an analysis of noisy data such as biological data, it is suitable to use stochastic classifier, and also by learning statically, it enable to select proper robust model like considering over fitting. The parameters of the predictive model are learned through use of the first two-thirds of each subject's data. Subject decision-making was predicted using the remaining one-third of the data.

Details of the predictive model and the Bayesian estimation are as follows. With the strategy $i(t)$ for the task t as an explained variable and with the vector of the explanatory variable (or learning factor) for the task t as $x(t)$, a decision-making model is formulated as follows:

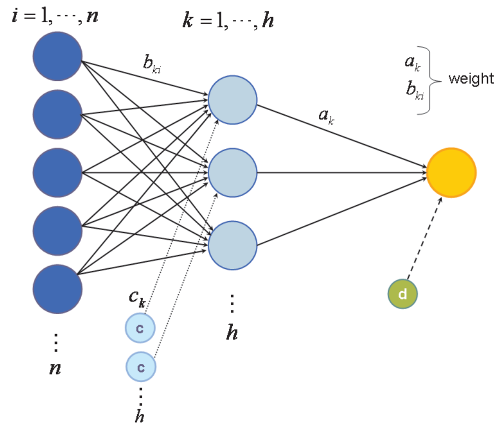

Figure 3: 3-layer perceptron.

$$i(t) = f(x(t);\theta) + \varepsilon \qquad \forall t, \tag{1}$$

where

$$\varepsilon \sim N\left(0, \frac{1}{\beta}\right), \tag{2}$$

$$f(x;\theta) = \sum_{k=1}^{h} a_k \cdot \sigma\left(\sum_{i=1}^{n} b_{ki}x_i + c_k\right) + d, \tag{3}$$

$$\sigma(u) \equiv \frac{1}{1+\exp(-u)} \quad , \tag{4}$$

$$\theta \equiv (a, b, c) \quad . \tag{5}$$

In addition to the strategy of the previous period, the extent of changes in oxyhb observed in each channel was used for the vector of the explanatory variables x. Figure3 shows the 3-layer perceptron structure. Parameter a_k is the weight with regard to output from k hidden units and represents the extent of the effect of k hidden units on explained variable. Parameter b_{ki} is the weight representing the effect of i factors on k hidden units. Parameter c_k controls the threshold for neurons in k hidden units to fire. A normal distribution with a precision of α_i is used as the prior distribution of each parameter θ_i. That is,

$$\theta_i \sim N\left(0, \frac{1}{\alpha_i}\right). \tag{6}$$

Additionally, the prior distribution of the hyperparameter α_i governing this prior distribution is assumed to be a gamma distribution. Moreover, a gamma distribution is similarly used as the prior distribution for hyperparameter β, which controls model noise.

Increasing a model's complexity has the advantage of increasing its explanatory ability, but there is a substantial risk of decreasing its extendability due to overfitting. In particular, special attention is required for the data that have a relatively large amount of noise, like those from a live subject. Selection of a model using HML in a hierarchical Bayesian framework is a way to manage this problem. Using this criterion, the model is assessed with HML.

Table 1: Results of prediction by using 3-layer perceptron Model.

	selection stage	result stage	h	HML	MSD
				improvement rate	
without Hb	-	-	2	-306.1936	0.4103
				-	-
with Hb	channel 11	channel 32	2	-286.9153	0.2482
				6.30%	39.51%

$$\begin{aligned} & P(\{i(t), x(t)\}_t|\alpha, \beta) \\ = & \int P(\{i(t), x(t)\}_t|\theta, \beta)P(\theta|\alpha)d\theta \end{aligned} \tag{7}$$

This value is the amount corresponding to ABIC and is sometimes also called "evidence." When specifically calculated in the current design with N as the number of observed dat

$$\begin{aligned} & P(\{i(t), x(t)\}_t|\alpha, \beta) \\ = & (\frac{\beta}{2\pi})^{\frac{N}{2}} \int \exp\left\{-\frac{\gamma}{2}\right\}d\theta, \end{aligned} \tag{8}$$

where

$$\gamma = \beta \sum_t (i(t) - f(x(t); \theta))^2 + \sum_c \alpha_c \|\theta_c\|^2. \tag{9}$$

This reveals that factors and hidden units with a large estimated α cause a substantial decrease in hyperparameter marginal likelihood (and are thus invalid).That is, in this criterion α functions as a penalty with regard to the number of factors and hidden units. Normally, penalty weight is often controlled exogenously, but in a hierarchical Bayesian framework penalty weight α can be endogenously determined.

The results of the prediction on strategies using a 3-layer perceptron are shown in Table 1. The second column of the table shows the channel that was used for the MPFC data after the strategic decision-making occurred, while the third column shows the channel that was used for the OFC data after the results are displayed. Moreover, "h" depicts the number of hidden units while "improvement rate" shows how much the model that adopted the change in concentration of blood oxyHb improved compared with the model that did not adopt it. "Without Hb" in the second row shows the results from the models that did not consider blood oxyHb, whereas the third row shows the results of the models in which oxyHb level was taken into consideration.

As shown in Table 1, it could be understood that by including the blood oxyHb levels relevant to MPFC (channel 11) and OFC (channel 32) among the factors for the predictive model, HML showed a 6.3% improvement compared to the 3-layer perceptron models in which those factors were not used. The MSD was approximately 0.248 in the predictive power test using the latter one-third of the data, and there was 40% improvement compared to the models in which the data on the concentration of oxyHb in the blood was not taken as a factor. From the correspondence between HML and MSD shown in the table, it was found that our predictive model did circumvent the overfitting problem.

Table 2: Results of prediction by using Nash Equilibrium and Random Strategy Model.

	Our model (with Hb)	Nash	Random	EWA	Fictitious play
MSD	0.2482	0.485	0.495	0.271	0.3578

Table 3: Results of prediction by using 3-layer perceptron Model(limited subjects who achieved all 30 trials).

	selection stage	result stage	h	HML	MSD
				improvement rate	
without Hb	-	-	2	-152.9894	0.4823
				-	-
with Hb	channel 11	channel 32	2	-139.2313	0.24202
				8.99%	49.82%

Moreover, MSD is defined as follows:

$$MSD \equiv \sum_{t}^{T} \frac{\{i(t) - f(x(t); \theta)\}^2}{T}, \tag{10}$$

where $i(t)$ is the next strategy (observed value) in task t, $f(t)$ is the next strategy (theoretical value) predicted on the basis of the learning model in task t, and T is the number of decision-making used for verification.

Here, the predictions based on the 3-layer perceptron models were compared with the Nash equilibrium, which represents rational decision-making models adopted in classical economics with predictions of the subjects' strategies based on the Random strategy, which assumes that people are not rational at all, and with the predictions on the traditional behavioral learning models (EWA and Fictitious play). Table 2 shows the MSDs, which is the same to what was defined earlier, are derived from these behavioral hypotheses. We can observe that our model provided a good description of strategic behavior compared to other models.

Lastly, we should address a robustness of our result to sample data selection. In our experience, the frequency of trials of a subject is theoretically 30. However, when the concentration of deoxyhemoglobin in a subject's blood largely surpassed that of oxyhemoglobin, we removed these data from the sample analysis because cognitive deterioration of the subject is expected. In addition, the experiment was interrupted at that time when the subject declared that his or her physical condition was unfavorable. To show that our analytical results are robust for this non-uniform trial frequency, we tried to re-examine the results of limited subjects who achieved all 30 trials. Table 3 shows the re-examination results. Our model still exceeds the benchmark models and the brain data provide additional information.

References

Bereby-Meyer, Y. and I. Erev (1998). On learning to become a successful loser: a comparison of alternative abstractions of learning processes in the loss domain. *Journal of Mathematical Psychology 42*(2), 266–286.

Breiter, H., I. Aharon, D. Kahneman, A. Dale, and P. Shizgal (2001). Functional imaging of neural responses to expectancy and experience of monetary gains and losses. *Neuron 30*(2), 619–639.

Camerer, C. and R. Foundation (2003). *Behavioral game theory: Experiments in strategic interaction*. Princeton University Press Princeton, NJ.

Camerer, C. and T. Ho (1999). Experience-weighted attraction learning in games: A unifying approach. *Econometrica 67*(4), 827–74.

Camerer, C., J. Kagel, and A. Roth (1995). *The handbook of experimental economics*. Princeton University Press.

Camerer, C., G. Loewenstein, and D. Prelec (2005). Neuroeconomics: How neuroscience can inform economics. *Journal of Economic Literature 43*(1), 9–64.

Erev, I. and A. Roth (1996). On the need for low rationality cognitive game theory: reinforcement learning in experimental games with unique mixed strategy equilibria. *University of Pittsburgh*.

Erev, I. and A. Roth (1998). Predicting how people play games: Reinforcement learning in experimental games with unique, mixed strategy equilibria. *American economic review*, 848–881.

Hampton, A. and J. O'Doherty (2007). Decoding the neural substrates of reward-related decision making with functional MRI. *Proceedings of the National Academy of Sciences 104*(4), 1377.

Holroyd, C., J. Larsen, and J. Cohen (2004). Context dependence of the event-related brain potential associated with reward and punishment. *Psychophysiology 41*, 245–253.

Kahneman, D. and A. Tversky (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society*, 263–291.

Knutson, B. and R. Peterson (2005). Neurally reconstructing expected utility. *Games and Economic Behavior 52*(2), 305–315.

Kuhnen, C. and B. Knutson (2005). The neural basis of financial risk taking. *Neuron 47*(5), 763–770.

Laibson, D. (1997). Golden Eggs and Hyperbolic Discounting*. *Quarterly Journal of Economics 112*(2), 443–477.

Loewenstein, G., T. O'Donoghue, and M. Rabin (2003). Projection Bias In Predicting Future Utility*. *Quarterly Journal of Economics 118*(4), 1209–1248.

MacKay, D. (1992a). A practical Bayesian framework for backpropagation networks. *Neural computation 4*(3), 448–472.

MacKay, D. (1992b). The evidence framework applied to classification networks. *Neural Computation 4*(5), 720–736.

Marchiori, D. and M. Warglien (2008). Predicting human interactive learning by regret-driven neural networks. *Science 319*(5866), 1111–1113.

McClure, S., K. Ericson, D. Laibson, G. Loewenstein, and J. Cohen (2007). Time discounting for primary rewards. *Journal of Neuroscience 27*(21), 5796.

McClure, S., D. Laibson, G. Loewenstein, and J. Cohen (2004). Separate neural systems value immediate and delayed monetary rewards. *Science 306*(5695), 503–507.

Neal, R. (1996). *Bayesian learning for neural networks*. Springer.

Sanfey, A., G. Loewenstein, S. McClure, and J. Cohen (2006). Neuroeconomics: cross-currents in research on decision-making. *Trends in Cognitive Sciences 10*(3), 108–116.

Strotz, R. (1955). Myopia and inconsistency in dynamic utility maximization. *The Review of Economic Studies*, 165–180.

Sutton, R. and A. Barto (1998). *Reinforcement learning: An introduction*. MIT press.

Tanaka, S., K. Doya, G. Okada, K. Ueda, Y. Okamoto, and S. Yamawaki (2004). Prediction of immediate and future rewards differentially recruits cortico-basal ganglia loops. *Nature Neuroscience 7*, 887–893.

Thaler, R. (1999). Mental accounting matters. *Journal of Behavioral Decision Making 12*, 183–206.

Tversky, A. and D. Kahneman (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of risk and uncertainty 5*(4), 297–323.

Appendix: The role of the orbitofrontal cortex in human's adoptive learning under strategic environments.

August 11, 2011

1 Game Design

The gains from the 2-by-2 games - which had unique mixed strategy equilibrium used in the Game Task -, and the Nash equilibrium (N.E.) were as described below. In order to make it possible to compare the results, games $No.1-3$ were the same as those used in Marchiori and Warglien's work (2008), whereas game No.4 was an original one.

GAME1

computer / player	strategy 1	strategy 2	player's N.E.
strategy A	3 , 7	8 , 2	3/8
strategy B	4 , 6	1 , 9	5/8
computer's N.E.	7/8	1/8	

GAME2

computer / player	strategy 1	strategy 2	player's N.E.
strategy A	3 , -3	1 , -1	6/7
strategy B	9 , -9	3 , -3	1/6
computer's N.E.	1/7	6/7	

GAME3

computer / player	strategy 1	strategy 2	player's N.E.
strategy A	1 , 0	0 , 1	1/2
strategy B	0 , 1	1 , 0	1/2
computer's N.E.	1/2	1/2	

GAME4

computer / player	strategy 1	strategy 2	player's N.E.
strategy A	13 , 4	4 , 13	13/22
strategy B	2 , 15	15 , 2	9/22
computer's N.E.	1/2	1/2	

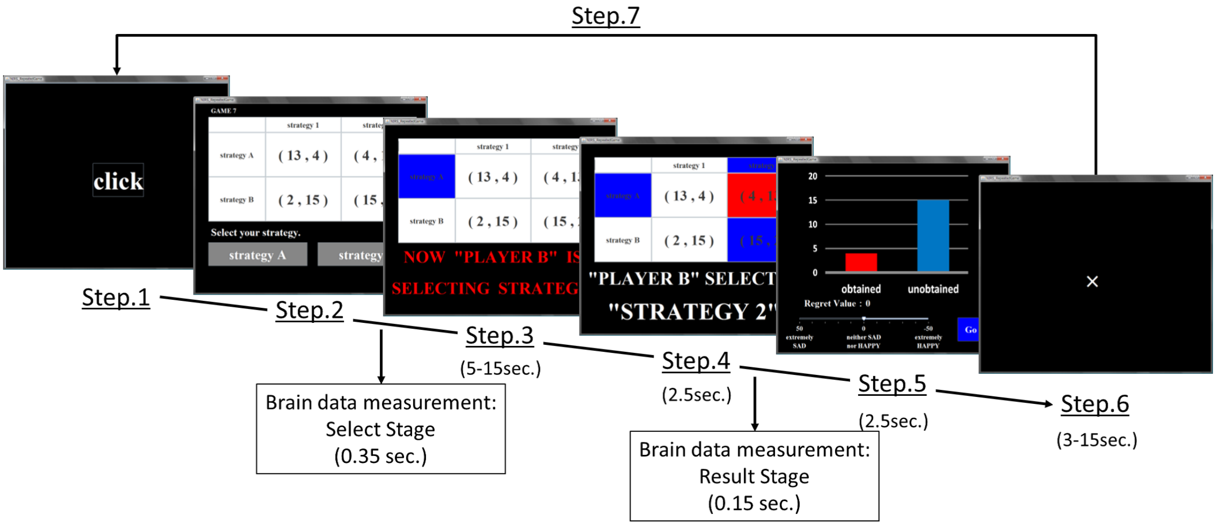

Figure 1: The detail of experimental procedure.

2 Details of the Experiment Procedure

Each step of experiment showed in Figure1 is as follows.

STEP.1: Start
The changes in haemoglobin concentration in the cerebral blood were measured in a situation where the subjects were given no encouragement for a certain length of time; and then, the game was started.

STEP.2: The subject's decision-making
The subjects look at the 2-by-2 payoff matrix, and choose whether to take action according to strategy A or according to strategy B.

STEP.3: Rest (5-15sec.)
The strategy chosen by the subject is marked (blue), and the subject rests until the data on the changes in haemoglobin concentration in the cerebral blood from 50 previous samples (8.75 seconds) fall from their mean value to within $\pm\sigma$ (the standard deviation of the data on the changes in haemoglobin concentration in the cerebral blood obtained in STEP 1) (stable condition).

STEP.4: Display of Results 1 (2.5sec.)
A computer selects an action from either strategy 1 or strategy 2, and the resulting gains are displayed on the payoff matrix (red).

STEP.5: Display of Results 2 (2.5sec.)
The obtained gains ("obtained") are displayed, along with the gains which could have been obtained if the other alternative had been chosen ("unobtained"). That is, in the example in Figure 1, assuming that the computer took the behavior corresponding to strategy 2, and that the gain from strategy A chosen by the subject is "obtained", the gains that could have been obtained from strategy B which was not chosen by the subject are displayed as "unobtained". This "unobtained" is some sort of opportunity cost, and the difference between the obtained and unobtained is also called a fictive error.

STEP.6: Rest (3-15sec.)
The sign (x) is displayed, and like in STEP.3, the subject rests until a stable condition is reached.

STEP.7: Repeat
STEP.2 to STEP.6 are repeated to a maximum of 30 times (with consideration for the subject's physical condition).

Table 1: The effectiveness of all candidate cites in each stage.

channel	selection stage	result stage
ch1	-290.4766	-294.3243
ch2	-301.5592	-327.5683
ch3	-290.9134	-305.1513
ch4	-290.6657	-289.2597
ch5	-300.9882	-296.1476
ch6	-317.0926	-310.7114
ch7	-289.2811	-292.2114
ch8	-289.1663	-309.6956
ch9	-290.8586	-298.5074
ch10	-292.0314	-290.8465
ch11	-288.6281	-289.3001
ch12	-291.9021	-289.3260
ch13	-364.2536	-296.3957
ch14	-288.9639	-324.0938
ch15	-290.0176	-289.6878
ch16	-325.9317	-290.2845
ch17	-288.8450	-289.0319
ch18	-291.9057	-307.9741
ch19	-290.4226	-290.5160
ch20	-294.5828	-294.5828
ch21	-291.6889	-291.9336
ch22	-289.3562	-314.3330
ch23	-289.1478	-291.4767
ch24	-298.3892	-308.0825
ch25	-289.9938	-296.1303
ch26	-295.5469	-289.3074
ch27	-298.2945	-289.8746
ch28	-311.9935	-290.4932
ch29	-289.3037	-294.3163
ch30	-289.4415	-289.6579
ch31	-296.0695	-303.0191
ch32	-320.4847	-289.0230

3 Brain data selection

This table shows the hyperparameter marginal likelihood (HML) when each channel's data is involved in model. The most effective site/channel was selected in each measurement stage (selection stage and result stage) according HML / Akaike's Bayesian information criterion (ABIC).