The Effectiveness of Feedback Control in a HCI System Using Biological Features of Human Beings

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Abstract. The purpose of this paper is to clarify the brain activities of human beings engaged in their tasks. Response time, correctness ratios, and Event Related Potentials (ERPs) are useful indexes of the brain activities of a subject at his task in the experiments. We analyze these indexes by a method called the Principle Component Analysis. Then we characterize the brain activities while he is engaged in the task. Finally we discuss the effectiveness of feedback control in a HCI system using these indexes.

Keywords: event related potentials, feedback control, principle component analysis, and response time.

1 Introduction

The purpose of this paper is to clarify the relationship among various indexes obtained from brain activities. We examine whether the indexes may be useful to improve the effectiveness of the feedback control in a HCI (Human Computer Interaction) system. The system consists of a subject (a human being), a computer, a display and a keyboard, where Event Related Potentials (ERPs for short) [1,2,4,6-8] are used as important information extracted from the brain. ERPs are taken from electroencephalograms (EEGs for short) [5] of the subjects.

A subject is involved in a series of tasks such that he is asked to choose the correct one from three choices shown in the display. ERPs of the subject are closely related to his brain activities when he is engaged in the multi-choice tasks. The change of ERPs during the execution of the tasks may reflect the change of physiological and/or psychological conditions of the subject as well as the laboratory situation.

We consider that the display of tasks and the ERPs of a subject are an output from the HCI system and feedback signals to the HCI system, respectively. The computer in the system may try to adjust the size of characters in the display, time duration, the format of the display and others so that the subject can be comfortably engaged in the

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experiments. The HCI system is depicted in Fig. 1, where two types of feedback lines, feedback (*a*) and feedback (*b*) are mainly used.

We intend to show that the HCI system can be adaptive with the conditions of the subject as well as the situation of the laboratory. We had a number of experiments to evaluate the effectiveness of the feedback control of the HCI system. This research may be applied for the design of HCI systems coping with other types of biological information.

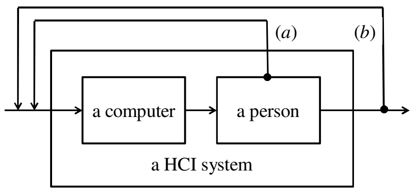


Fig. 1. An image of a feedback control HCI system

2 Experiments and Data Analysis

We repeat the following experiments from four to ten times:

1) The subjects: One is 20 years old, and the other is 21 years old. Both are male. We use "*sub* 1" and "*sub* 2" to identify them.
2) The place of the experiments: The laboratory of the first author at Hakuoh University.
3) Stimuli: We use 47 kinds of stimuli. A stimulus shown in the display is a contour of the geographical shape of a prefecture together with three choices about district capitals or prefecture capitals (see Fig. 2). We prepare three different sized stimuli for each case, a large sized one (320 ×275 pixels), a medium sized one (260×220 pixels), and a small sized one (200×160 pixels).

Fig. 2. An example of stimuli; the contour shows the shape of Tokyo, and three words of Chinese characters are *Shinjuku*, *Osaka* and *Nagano*

4) Tasks: Three types of tasks are used. These are denoted by *Task A* and *Task B*, and *Task C*. For *Task A*, a subject watches the middle sized geographical shape of a prefecture shown in the display. Then he chooses its district capital or prefecture capital from the three choices. For *Task B* and *Task C*, the actions of a subject are almost the same as the actions for *Task A*.

5) Display of stimuli: For *Task A*, a sequence of middle sized stimuli is displayed in a CRT (Cathode Ray Tube) of 19 inches placed in front of a subject. A sequence of 47 stimuli is called a set of stimuli. For *Task A*, five sets of stimuli are executed in one day. For *Task B*, three sets of stimuli are executed in one day. The small sized stimuli, the middle sized stimuli, and the third sized stimuli are used in the first set, in the second set, and in the third set, respectively. For *Type C*, the size of each stimulus in a set is randomly chosen. Such a set of stimuli is repeated three times. For any sized stimulus displayed in the CRT, the subject can watch it without moving his eyes.
6) Time duration for the stimulus display: Each stimulus, such as in Fig. 2, is displayed for 1 second. The interval between two consecutive stimuli is randomly chosen within the range 400 ms to 600 ms.
7) Time duration of an experiment: About 2 minutes are spent for a set of stimuli. The subject takes a minute interval between two consecutive sets of stimuli. Consequently, for *Task A* the time duration of 5 sets of stimuli excluding the interval time is about 10 minutes. The time duration excluding the interval time for *Task B* or *Task C* is about 6 minutes.
8) EEGs: Single polar eight channels of "International 10-20 methods" are used for the measurement of EEGs. The positions of the measurement are at Fp_1, Fp_2, C_3, C_4, O_3, O_4, C_z, and P_z. The base is A_1 that is connected to A_2.
9) The sampling frequency for A/D: 1 kHz.

We process the recorded EEGs to obtain ERPs in the following way:

1) The recorded EEGs are filtered by an adaptive filter [3] designed and made by the first author.
2) The filtered data are normalized by the average and the standard deviation of the data.
3) The normalized 47 EEGs are averaged to obtain an ERP evoked by experiments of *Task A*, *Task B*, or *Task C*. We use $ERP_{kj}(t)$ to indicate the obtained ERP, where k denotes the type of tasks, j denotes the order in the repetition of stimuli sets, and t is time [ms] (k=A, B, C, j=1,2,…,5, t=1,2,…,1000).
4) Since we repeated an experiment from four to ten times, we take the average of the 4 to 10 sampling data for $ERP_{kj}(t)$ to obtain a typical value for an ERP. We use $SERP_k(t)$ to indicate the average.

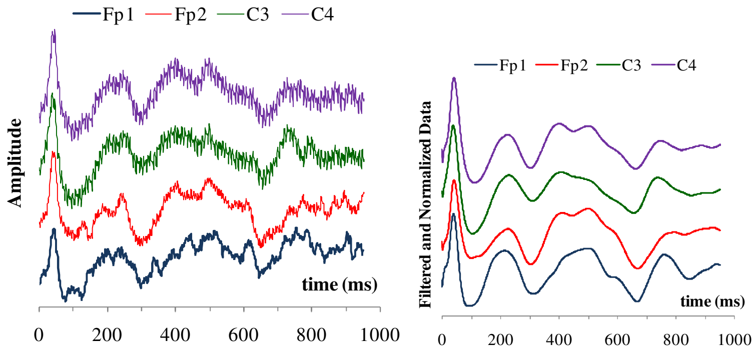
We investigate the relationship among the *response time*, the *frequency of correct answers* (i.e., the ratio of correct answers), the *latency* of ERPs, and the *amplitudes* of ERPs by analyzing the data obtained in the experiments.

3 Results

3.1 Recorded Data and Filtered Data

Examples of EEGs that are measured from *sub* 1 are shown in Fig. 3 (i). The time elapse [ms], since a stimulus is given, is shown on the horizontal axis. The amplitude of measured data is plotted in the vertical direction. In Fig. 3 (i), the lowest, the second lowest, the third lowest and the highest waveforms are plotted data from Fp_1, Fp_2,

C_3 and C_4, respectively. The measured data contain 50 [Hz] and other types of noises. These noises would be caused by electromyography, blinks or body movements of the subject and others. Before starting the experiments, the subject is asked that he should make an effort to minimize his blinks and body movements. Noises of higher frequency than frequency of EEGs are also minimized. The recorded data are filtered and normalized. These data are given in Fig. 3 (ii).



(i) Recorded EEGs (ii) Filtered and normalized data

Fig. 3. The recorded data, and the filtered and normalized data obtained from *sub* 1 during the second task (*Task A*) of the first set in the first experiment

3.2 Typical ERPs for Tasks

The results obtained from *sub* 1 are mainly described hereafter. He took the one-day experiment of *Task A* 10 times, the one-day experiment of *Task B* 4 times, and the one-day experiment of *Task C* 6 times. Consequently he took 47×5×10 stimuli of *Task A*, 47×3×4 stimuli of *Task B*, and 47×3×6 stimuli of *Task C*. First he took a one-day experiment of *Task A* once a week. Three months later after the end of the experiments of *Task A*, he took a one-day experiment of *Task B* and a one-day experiment of *Task C* in the same day once a week.

The waveforms shown in Fig. 4 are examples of $SERP_k(t)$ (k = *A, B*, *C* and t=1,2,…,1000) obtained by averaging all filtered and normalized data. These waveforms can be considered typical ERPs for *Task A*, *Task B* and *Task C*. See the potentials, P_{100}, N_{200}, P_{300} and N_{400} of the waveforms in Fig.4, where P means a positive potential and N means a negative potential. The suffix of each of these symbols indicates its latency from the start of the stimulus. Potentials P_{100}, N_{200} and P_{300} appear clearly in the waveforms for any of *Task A*, *Task B* and *Task C*. On the other hand, potential N_{400} appears clearly in the waveforms for *Task B* and *Task C* but not for *Task A*.

3.3 Comparison among Tasks

In Fig. 5, we show the tendency of how the "*average of Response time*" and "*frequency of correct answers"* for *Task A* change by repeating the experiments. Each

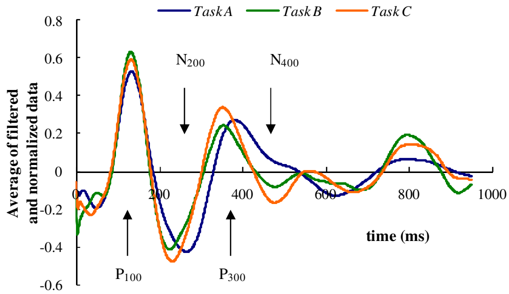


Fig. 4. Typical ERPs ($SERP_k(t)$, k=A, B, and C) for *Task A*, *Task B*, and *Task C*

point in the graph indicates a result for a set of tasks. Five consecutive points linked by lines are a result for a one-day experiment. The result for the 6th day is not shown in the graph, because we lost the experimental data for the 6th day. The "*Frequency of correct answers*" approaches 100% by repeating the experiments. It becomes about 97% during the last four days. The "*average of Response time*" is shortening by the repetition, but its tendency is not clear compared with the "*frequency of correct answers*".

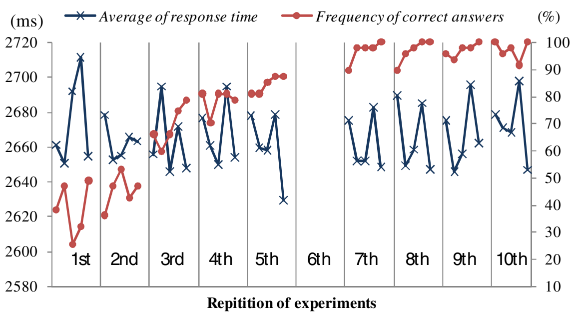


Fig. 5. Tendency of how the "*average of response time"* and the "*frequency of correct answers*" change

Let us examine how ERPs are affected by the repetition of the experiments and by the task types (*Task A*, *Task B* and *Task C*). When we use the *averaged method*, as a model of the relation between EEGs and ERPs, the following equation is widely used:

$$EEG(t) = ERP(t) + Ns(t) \quad t=1, 2, \ldots, 1000 \tag{1}$$

In equation (1) above, $Ns(t)$ is random noise including potentials caused by something unrelated to the tasks in the experiments. The average of $Ns(t)$ is 0, but it is not pure white nose. It contains EEGs caused by unexpected matters in the laboratory, the condition of the subject and others. Let us consider the EEG distribution within the whole time range. We count the number of data satisfying the following inequality (2), where the normalized values for EEGs are used:

$$\text{We count the number of positive data such that } EEG(t) > 0.5 \text{ for } 1 \leqq t \leqq 1000 \qquad (2)$$

Since we first normalize the filtered data, the average and the variance of the data distribution of EEGs are 0 and 1, respectively. If the amplitude date of EEGs show *normal distribution* $N(0, 1)$, the probability $p(x > 0.5)$ is nearly 0.3. We count the number of data that satisfy inequality (2). These numbers for the 1st day experiment and the 5th day experiment are plotted as vertical values in the graph of Fig.5. In one day experiment, 235 stimuli (47 stimuli×5 sets = 235 stimuli) are given in the display. Each stimulus lasts 1000 ms. The horizontal axis of the graph represents the elapse from the start of the stimulus (0 to 1000 ms). The arrows in the graph indicate the peak values.

Let *pt* be the time point nearest to 300 ms such that number of the EEG data is a peak at *pt* (see the time points indicated by the arrows in Fig. 6). Notation $EEG_i(t)$ means $EEG(t)$ for the *i*-th stimulus among the 235 stimuli. We categorize $EEG_i(t)$ (i = 1, 2, . . . ,235) into 3 classes according to the following rule (3):

If $EEG_i(pt) > 0.5$, then $EEG_i(t)$ belongs to *class* I
else if $EEG_i(pt) >= 0.0$ then $EEG_i(t)$ belongs to *class* II (3)
else $EEG_i(t)$ belongs to *class* III

For the 5th day experiment, the numbers of elements in *class* I, in *class* II and in *class* III are 144, 33 and 58, respectively. For each class, the averaged $EEG_i(pt)$ of the 5th day experiment is shown in Fig. 7. For each *t* (1□*t*□100), $ERP(t)$ is the weighted average of these data of $EEG_i(t)$. We first calculate the average of EEGs in each class. Then $ERP(t)$ is calculated as the weighted average of the averages of these three classes. As shown in Fig. 7, the data in *class* I has a clear peak P_{300}, but P_{300} for the data in *class* II is much lower than P_{300} for the data in *class* I. The latency of P_{300} for the data in *class* III is longer than the latency of P_{300} for other classes. In Fig. 7, we notice that there is a small positive peak after P_{300} for the data in *class* III.

We choose all $EEG(t)$'s in *class* I, and then calculate the average of these data for each type of tasks (*Task A*, *Task B*, *Task C*). The average of $EEG(t)$'s calculated in

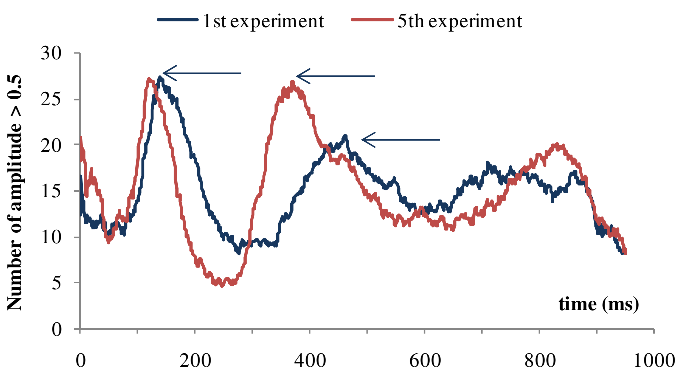


Fig. 6. The distribution of normalized EEGs greater than 0.5

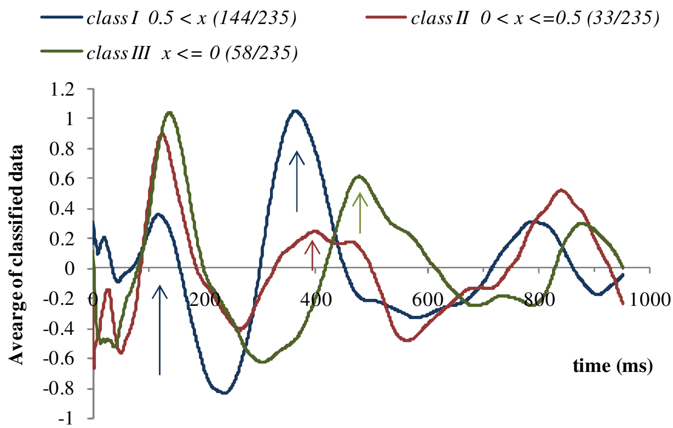


Fig. 7. The average of $EEG_i(t)$ for each of *class* I, *class* II and *class* III

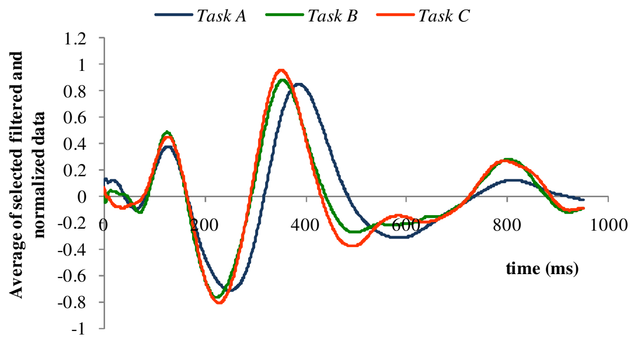
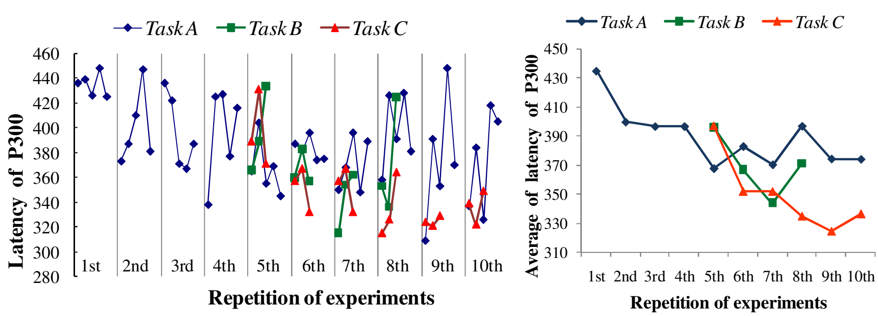


Fig. 8. Typical *SERP*(t)'s calculated from *EEG*(t)'s in *class* I



i) Change of the latency of P_{300} ii) Average latency of P_{300}

Fig. 9. The change of the latency of P_{300} through all the experiments. The horizontal axis is the order of the experimental days, and the vertical axis is the latency of P_{300}.

this way is denoted by *SERP*(*t*). An example of *SERP*(*t*) for each type of tasks is shown in Fig. 8. A peak potential P_{300} is considered to be caused by brain activities for recognition and judgment. The feature of the *SERP*(*t*) is the clear appearance of P_{300}. Through all the experiments, the change of the latency of P_{300} for each type of tasks is shown in Fig. 9 (i). The average latency for each day and for each type of tasks is shown in Fig. 9 (ii). We carried out the experiments for *Task A* before the experiments for *Task B* and *Task C*. For the first three or four days, the latency of P_{300} for *Task A* is longer than the corresponding latency for every type of the experiments after 4th day. From this tendency, we consider that the subject needs a few days to improve his skill for recognition and judgment in the experiments. The shorter latency of P_{300} reflects the better ratio of correct answers.

4 Considerations

4.1 Categories of the Human System Status

The relation between the latency and the amplitude of P_{300} is shown in Fig. 10 and Fig. 11. The horizontal axis and vertical axis in Fig. 10 are the amplitude of the average of normalized data and the averaged latency of P_{300}, respectively. Each of small circle points, small square points and small rectangle points show the result for a task of *Task A*, *Task B* and *Task C*, respectively. In Fig. 10, S_1 contains the result for *Task A* obtained in the first experiment, circle S_2 contains the results for *Task A* in the next three-days experiments, and so on. The arrows connecting these circles show the order of the experiments. Circle S_1' contains the results obtained in the first experiment for *Task B* and *Task C* (i.e., in the 5th day experiment). Circle S_2' contains other results. The results in S_2 *and* S_2*'* are resemble each other. *The results in* S_3 and S_2*'* are resemble each other. However, for the latency, the results in S_2, and S_4 are not much different. We can consider that the path indicated by the arrows in Fig. 10 shows the process of the change of the brain status. From such consideration of the categories, the learning process of the subject for *Task B* and *Task C* seems to be different from the learning process for *Task A*.

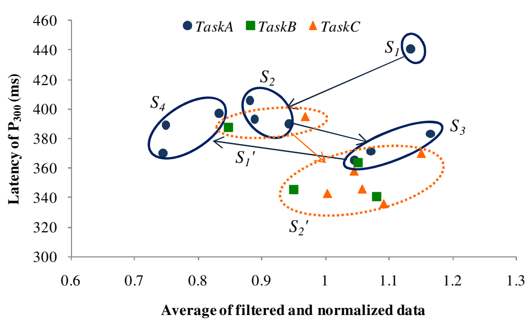


Fig. 10. The change of the average and the latency of P_{300} during the experiments

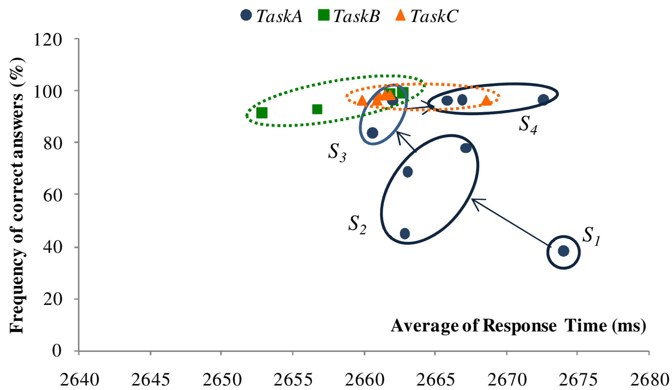


Fig. 11. The relation between the average *response time* and the *frequency of correct answers* for each of the task types (*Task A*, *Task B* and *Task C*)

The relation between the average *response time* and the *frequency of correct answers* for each of *Task A*, *Task B* and *Task C* in Fig. 11. The path indicated by the arrows in Fig. 11 shows the tendency of how the relation changes through the experiments. As shown in Fig. 11, we cannot simply say that the *response time* for *Task A* monotonically decreases by iterative learning. If we only use the data such that the *frequency of correct answers* is less than 90%, the correlation between the *response time* and the *frequency of correct answers* is about – 0.596. On the other hand, for the data such that the *frequency of correct answers* is greater than 90%, the correlation between them is about 0.502.

By applying the *Principal Component Analysis* to the values for four indexes (response time, frequency of correct answers, latency, amplitude of ERPs), we obtain the results given in Fig. 12.

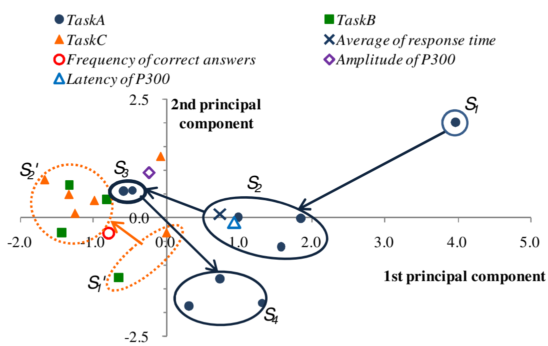


Fig. 12. The Results obtained by the *Principal Component Analysis*

5 Concluding Remarks

A HCI system can be considered a closed controlled system consisting of human beings and a computer system. The computer system is relatively stable compared with human beings. The brain activities are sensitive to the change of various factors. To realize a comfortable HCI or to improve the stability of a HCI system, stimuli and instructions given to human beings from the compute system should be well adapted to the brain status of the human beings. From our experiments and data analysis given in this paper, we can say that ERPs would be useful information to adjust stimuli and/or instructions from a computer system to human beings. ERPs calculated from EEGs of human beings could be used as feedback signals in a HCI system.

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