Internet Game Control System Based on Neuronal Signals

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Abstract. We developed a signal mapping method between brain of a rat and a computer and applied it to make a neuronal based internet game control system. The system transformed real-time neuronal activities from prefrontal cortex or hippocampus of a rat into control commands and used them to drive internet game objects of a game series called RaviDuel. The game control system was successfully implemented and the games, RaviDuel$^+$ and RaviDuel$^\#$ were operated well in real-time, which showed a possibility of a universal access to computers, internet games, or virtual realities by removing withdraw restrictions on the users.

Keywords: human-computer interaction, BCI, internet game, virtual reality

1. Introduction

The subject of human-computer interaction (HCI) is an area of science investigating the usability of an interactive computing system in terms of the design, evaluation, and implementation. Its discipline has been considered with technologies for increasing speed, miniaturization of hardware, assimilation of computation into the environment, and increasing development of network communication and distributed computing [1]. Human-computer interaction needs transformations of information between humans and machines. Its area is also expanded widely into many parts of computer science including embedded software and virtual reality, cognitive psychology, and neuroscience. Recent advances of technologies on ubiquitous computation, high functionality systems, group interfaces and information utilities made human-computer interactions more technology-sensitive. Furthermore, social concerns keep searching for widespread use of computers, especially by people who are outside of the computing profession and for the improved access to computers by currently disadvantaged groups, such as the physically disabled.

Brain-computer interface (BCI), the ultimate in development of human-computer interfaces or HCI, is a communication channel which transforms a subject's thought processes into command signals to control various devices including computer applications. Many studies have been made on the real-time prediction of human voluntary movement intention based on invasive or noninvasive methods to help severely motor-disabled persons by offering some abilities of motor controls and communications. Noninvasive method records electroencephalographic (EEG) signals and extracts intentional traits or movement-related EEG features, such as the P300 component of an event-related evoked potential (ERP), EEG mu rhythm conditioning, or visually evoked potential (VEP). Noninvasive method has low spatial resolution since it takes readings from the entire brain rather than a specific part of the brain [2, 3]. On the other hand, invasive method delivers better neuronal signal quality at the expense of its invasive characteristic. Its typical approaches include electrocorticograms [4], single neuron recordings [5], or multi-neuron population recordings [6]. Advanced researches on invasive methods are being actively pursued with the aim of recovering complex and precise movements by decoding motor information from motor related brain areas [7, 8] or by encoding motor information into non-motor related brain areas [9]. The developments and applications of signal mapping methods between brain and computer are critical issues in both the invasive and noninvasive methods in order to increase the group interfaces and the information utilities in human-computer interactions.

In this study, we developed a signal mapping method between brain of a rat and a computer and applied it to make a neuronal based internet game control system. The presented signal mapping was carried by quantization, coding, and linear combination of neuronal activities according to the averages and the standard deviations. The internet game control system, based on the BCI developed in our previous study [9], coded a series of motor functions into prefrontal cortex (PFC) or hippocampal (CA1) region of the brain of a rat (a game player; a paralyzed person or an animal such as a rat or a dog), generated real-time command signals using the signal mapping method, and controlled game objects of a game series called RaviDuel. The resulted system showed it available for a paralyzed person or a pet to play an internet game against a normal person. The resulted system also showed a possibility of a universal access to computers, internet games, or virtual realities by removing withdraw restrictions on the users and opened a probable vision for a future technology like a pet could be an aid of a paralyzed and/or aged person.

2. The signal mapping method

Figure 1 shows the block diagram of the presented internet game control system. The activities of two out of m recorded single neuronal units s_j ($j = 1,2,\cdots,m$) of a rat were used in real-time to control two-dimensional movements of game objects of the internet game series RaviDuel. The system was composed of data acquisition, signal mapping, and internet game object control units, in which the signal mapping unit was divided into feature extraction and source selection, quantization and coding, and command generation units.

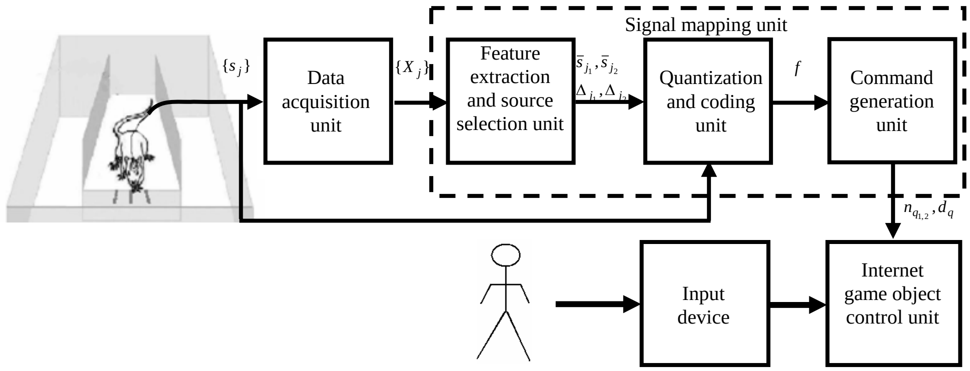

Fig. 1. Block diagram of the presented system

In the data acquisition unit, neuronal signals recorded from PFC or CA1 regions of the rat brain were amplified, filtered, sorted, and transformed into m spike trains s_j, $j = 1,2,\cdots,m$ in real-time, where $s_j = (t_1^j, t_2^j, \cdots, t_p^j, \cdots)$ and t_p^j denotes the time of occurrence of the p'th spike emitted by the j'th neuron. Each spike train during a time interval $(0\ T]$ was transformed into time series data $X_j = (x_1^j, \cdots x_i^j, \cdots, x_z^j)$ and two of them were selected based on the coefficient and the partial correlation coefficients in the feature extraction and source selection unit, where $x_i^j = \rho^j(t_i) - \rho^j(t_{i-1})$ and $z = T / \Delta t$. The time difference $\Delta t = t_i - t_{i-1}$ is the bin size of the time series data. The neuronal response function $\rho^j(t_i)$ was evaluated as sums over spikes from j'th neuron for $0 \le t \le i\Delta t$ [10]. The correlation coefficients r_{jk} and the partial correlation coefficients $r_{jk,l}$ of the time series data were then calculated using the equations given in reference [11]. The correlation coefficient r_{jk} measures the correlation between the time series data X_j and X_k. The partial-correlation coefficient $r_{jk,l}$ measures the net correlation between the time series data X_j and X_k after excluding the common influence of (i.e., holding constant) the time series data X_l. The time series data X_j were classified into two groups, correlated, and uncorrelated groups, according to the values of the correlation coefficients. Each group was again subdivided into two subgroups based on the values of the partial correlation coefficients of its elements. Two spike-trains s_{j_1} and s_{j_2} were then selected, where the corresponding time series data X_{j_1} and X_{j_2} were belong to the uncorrelated group but not in the same subgroup. In result, s_{j_1} and s_{j_2} were independent each other as well as had large difference in their correlations with other spike trains $s_{j \neq j_1, j_2}$. The quantization and command generation units coded a series of motor functions into the spike train s_{j_1} and s_{j_2} by a coding function $f(s_{j_1}, s_{j_2})$ and transformed in real-time the relative difference between the neuronal activities of the spike trains s_{j_1} and s_{j_2} into a command signal corresponding to one of the motor functions. The coding function $f(s_{j_1}, s_{j_2})$ transformed in real-time the relative difference between the neuronal activities of the spike trains s_{j_1} and s_{j_2} into a command signal corresponding to one of the motor functions. The motor functions are combinations of set {left, right, forward, and backward} for directions and the set {zero, one, two, and three} for numbers of the power element. Two different coding functions $f_1(s_{j_1}, s_{j_2})$ and $f_2(s_{j_1}, s_{j_2})$ were implemented in this study. Figure 2 represents the schematic diagram of the coding functions $f_1(s_{j_1}, s_{j_2})$ and $f_2(s_{j_1}, s_{j_2})$. Deterministic quantization was performed for both $f_1(s_{j_1}, s_{j_2})$ and $f_2(s_{j_1}, s_{j_2})$ by comparing the neuronal activity of the spike train s_{j_i} ($i = 1,2$) with set of quantization levels. Three quantization levels were set up to $\bar{s}_{j_i}$ and $\bar{s}_j \pm a_{j_i}\Delta_{j_i}$, where $\bar{s}_{j_i}$ and Δ_{j_i} are the average and the standard variation of the spike train s_{j_i} ($i = 1,2$), respectively evaluated during the preprocessing and a_{j_i} is a constant as an effective modulation coefficient which was set up to 0.5. Quantization result was the integer number n_q defined as follows:

$$\left\langle s_{j_i} - \bar{s}_{j_i} \right\rangle = n_q a_{j_i} \Delta_{j_i} \text{ and } n_{qi} = \begin{cases} 3, & s_{j_i} \geq \bar{s}_{j_i} + a_{j_i}\Delta_{j_i} \\ 2, & \bar{s}_{j_i} \leq s_{j_i} \leq \bar{s}_{j_i} + a_{j_i}\Delta_{j_i} \\ 1, & \bar{s}_{j_i} - a_{j_i}\Delta_{j_i} \leq s_{j_i} \leq \bar{s}_{j_i} \\ 0, & s_{j_i} \leq \bar{s}_{j_i} - a_{j_i}\Delta_{j_i} \end{cases}.$$

The coding function $f_1(s_{j_1}, s_{j_2})$ mapped n_{q_1} and n_{q_2} to set {left, right, forward, and backward} and set {zero, one, two, and three}, respectively after the deterministic quantization. The coding function $f_2(s_{j_1}, s_{j_2})$ subtracted n_{q_2} from n_{q_1} and mapped the resulted number $d_q \in \{d_q \mid \text{integer}, \ -3 \leq n_q \leq 3\}$ to a combination of set {left, right, forward, and backward} and set {zero, one, two, and three}. The internet game object control unit received a command signal from the command generation and/or the input device and executed it correspondingly to control game objects of RaviDuel, in which the input device directly received a signal input from a game player and transformed it to a corresponding command signal.

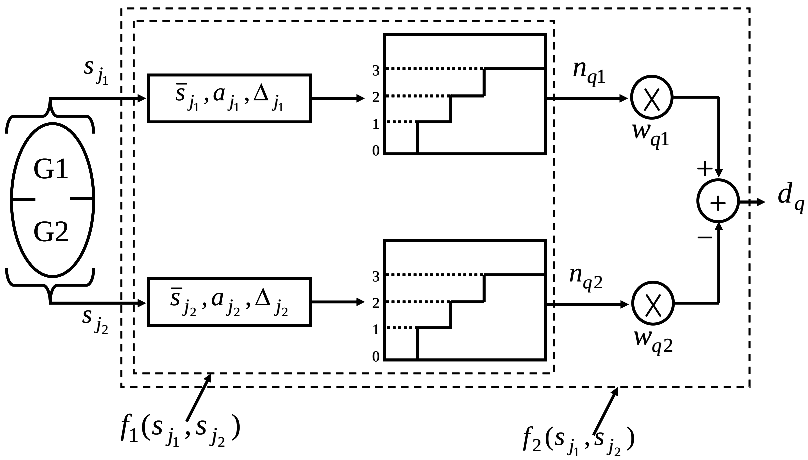

Fig. 2 . Schematic diagram of the coding functions $f_1(s_{j_1}, s_{j_2})$ and $f_2(s_{j_1}, s_{j_2})$.

3. Experiment

The game object control in two-dimensional space was accomplished through a TG task using a rat. The subject was to control the degree and the direction of the rotation of a step motor, interconnected with a water disc and linked to a game object, by using its neuronal activities of Prefrontal cortex (PFC) or CA1 region of its brain for a reward of water. The water was contained in a quarter of a circular dish positioned on top of the wheel.

3.1. Animal preparation

An animal preparation for using in the TG task was carried out with approval from the Hallym University Animal Care and Use Committee. Adult male or female SPF Sprague-Dawley rats weighing 200-220g were used. Two multi-wire recording electrodes arrays (8 channels for each array, tungsten microwire, A-M systems, USA, 75μm diameter, teflon-coated) were implanted bilaterally into Prefrontal cortex (PFC) or CA1 region of both right (RH) and left (LH) hemispheres of each rat. Four weeks after the implantations, the rats were deprived of water for 24 hrs. Each rat was then placed in the two-dimensional task space to perform a TG.

3.2. Preprocessing

A preprocessing was carried out before each TG task. In the preprocessing, the spike trains from the implanted region of the cortex were assessed by the correlations among them, two spike trains s_{j_1} and s_{j_2} were selected, and then a series of motor functions were coded into them by coding function $f_1(s_{j_1}, s_{j_2})$ and $f_2(s_{j_1}, s_{j_2})$. The bin size Δt used in the feature extraction unit was 200 ms. A critical value, r_c of the correlation coefficient was estimated at the significance level of 0.05 to categorize spike trains to the uncorrelated group, for example $r_c = 0.098$ for the sample size $n = 400$.

3.3. Target-to-goal task

The TG task was to move the water disk from one of five target positions P_1, P_2, P_3, P_4, and P_5 to a pre-defined goal position P_0. The target positions were set to be in a limited area $-6 \le x \le +6$ and $-9 \le y \le 0$. The coordinates of the target positions were $P_1(6,0)$, $P_2(6,-9)$, $P_3(0,-9)$, $P_4(-6,-9)$, and $P_5(-6,0)$ and that of the goal position is $P_0(0,0)$. For training a rat as one of the game players, five trials for each target position were implemented for a session of the experiment. A session per a day was carried every other day for a week. Figure 3 (a) compares the variations of the distance of the water disk position from the goal position during trials t1, t2 and t3 of a TG task ($P_2 \to P_0$). Figure 3(b) compares the time durations required for the TG task ($P_2 \to P_0$) to be completed for trials t1, t2 and t3. The time duration was decreased as trials went on (in sec, t1:14.8, t2:9, t3:8.8), which reflected the increased adaptation of neuronal signals as trials went on. Figure 3 (c), (d), and (e) show the x (□) and y (■) coordinates of the water disk movements every 200ms for target positions P_2, P_3, and P_5, respectively. Average information conveyed for a trial was calculated from the observed trajectories at 200ms intervals throughout the movements. The information was conveyed within the first three to five seconds of the movements about the target positions P_2, P_3, and P_4. The information was also conveyed within the last second of the movements about most of the target positions. The degree of the modulation of the neuronal units recorded was calculated by the rate of the change of the classified group in the k-means clustering analysis. The rates of the neuronal units s_8 and s_{11} selected for the generation of the control command signals were 0.521 and 0.565%, respectively, which were almost two times as large as the average of the rates for other neuronal units ($0.205 \pm 0.210\%$). The averaged velocity of the water disk movement was the fastest from P_3 and the slowest from P_1 (in mm/sec, P_1 : 6.68±1.5, P_2 : 14.88±0.9, P_3 : 22.33±2.0, P_4 : 14.45±0.8, P_5 : 9.41±1.6). The efficiency of the system ranged from 32% to 61% (in %, P_1 : 32.49± 5.4, P_2 : 59.69±3.3, P_3 : 61.37±3.3, P_4 : 53.04±2.9, P_5 : 53.04±2.9; P_1 vs. P_2 , P_3 : $p<0.001$, P_1 vs. P_4 , P_5 : $p<0.05$) indicating the dominance of forward and right movements over backward and left, respectively.

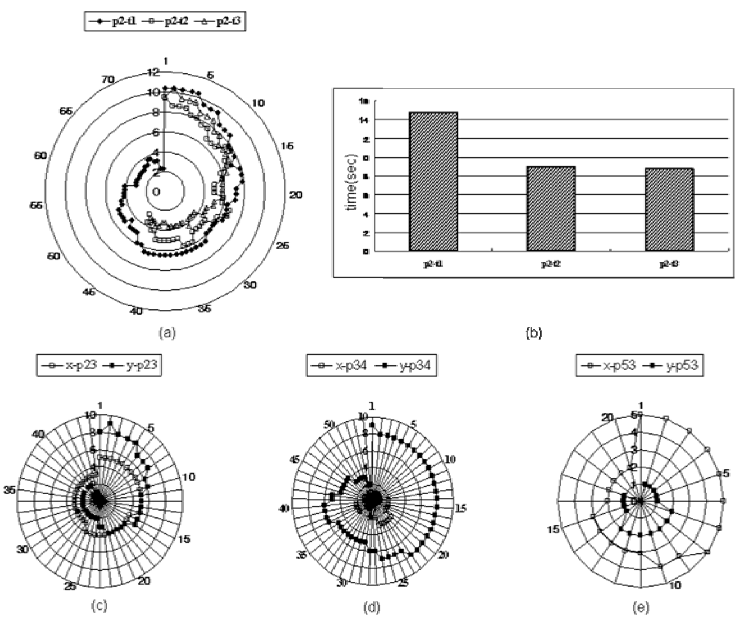

Fig. **3**. (a) The distance of the water disk position from the goal position during trials t1, t2 and t3 of a TG task ($P_2 \rightarrow P_0$); (c), (d), and (e), the x (□) and y (■) coordinates of the water disk movements every 200ms for target positions P_2 , P_3 , and P_5 , respectively; and (b) the time durations required for the TG task ($P_2 \rightarrow P_0$) to be completed for trials t1, t2 and t3.

3.4 The control of game objects

The internet game series RaviDuel was constructed to be driven by the command signal output of the presented system. Figure 4 shows the block diagram of the internet game control unit consisting of switching unit and more than one internet game object controllers. The switching unit received a command signal (n_{q1}, n_{q2}, or d_q) from the command generation unit and/or the input device and transformed it to one of the internet game object controllers which executed it correspondingly to control one of game objects of RaviDuel. The input device directly received a signal input from a game player and transformed it to a corresponding command signal. The internet game RaviDuel consisted of two versions, a betting game RaviDuel^{+} and a competitive game RaviDuel$^{\#}$. In RaviDuel^{+}, players bet on the time taken in completing a mission or on one of the subjects who competed with each other for completing a mission. The mission was animated like that a rat finds a water spring, which was linked to a TG task in the presented system.

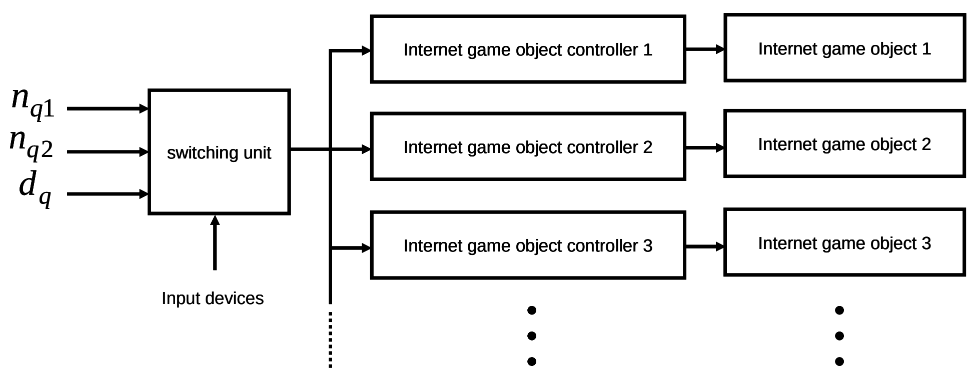

Fig. 4. Block diagram of the internet game object control unit.

The rat was the animated character of the subject of a TG task; the water spring was the animation of the water disc. A competitive internet game RaviDuel$^{\#}$ was programmed and tested. RaviDuel$^{\#}$ was a player vs. player hitting game, where one of the players was supposed to be a rat, a pet, or a paralyzed person. Each player had a bowling ball (or a bomb) at the beginning of each game. The player continually encountered new randomly moving animated opponents throughout a session of the game until she/he/it lost. The player got a designated score if she/he/it hit one of the opponents with the bowling ball. The player could adjust the speed and the direction of the bowling ball (or a bomb) by using the mouse of his/her system or by using its relative neuronal activity differences and generating a command signal for a combination of the directions and the powers. The player lost when he/she/it was hit by the opponents or got lower scores than other player within a session of the game. The game was over when either player lost.

4. Conclusions

We developed a signal mapping method between brain of a rat and a computer and applied it to make a neuronal based internet game control system. Activities of two single neuronal units recorded from PFC or CA1 region of SD rats were used in real time to control two-dimensional movements of a game object. The results of this study suggest that rats were able to use the 2-D movement by differentially modulating CA1 hippocampal single neuron activities according to predicted routes from different targets. A betting game RaviDuel^{+} and a competitive game RaviDuel$^{\#}$ were programmed and tested. The constructed game system linked to the BCI system was successfully implemented and the games, RaviDuel^{+} and RaviDuel$^{\#}$ were operated well in real-time. The resulted system showed it available for a paralyzed person or a pet to play an internet game against a normal person. The resulted system also showed a possibility of a universal access to computers, internet games, or virtual realities by removing withdraw restrictions on the users and opened a probable vision for a future technology like a pet could be an aid of a paralyzed and/or aged person.

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