Development of a support robot hand system using SSVEP

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Abstract

Recently, the Brain-Computer Interface (BCI) system could support various aspects of everyday life of elderly and disabled people. In this research, we developed a noninvasive BCI system that controls the robot hand using induced brain waves Steady-State Visual Evoked Potential (SSVEP) in order to improve the quality of life of patients with hands or arms deficient or impaired. This BCI system consists of visual stimulator, 6 degree of freedom (DOF) robot hand, an EEG recorder and a laptop for processing data. The subject induces the corresponding SSVEP signal by seeing one target in the three visual stimuli (5Hz, 6Hz, 7Hz) representing the motion: grip, pinch and arm rotation of the robot hand. The detected SSVEP signal is classified by canonical correlation analysis (CCA). The robot hand is operated by converting the SSVEP into the control signal according to the classification result. The results show that the proposed BCI system has a high performance, achieving the average accuracy of 97% in a time window length of 4 s and the use of three harmonics.

Keywords: Brain-Computer Interface (BCI), Steady-State Visual Evoked Potential (SSVEP), robot control

1 Introduction

The Brain-Computer Interface (BCI) system is a technique that analyzes human brain information, such as electroencephalogram (EEG) signals, and converts them into computer commands to control external devices without the need for peripheral nerve and muscle activity. This type of system is designed to help people with disabilities in all aspects of their daily lives. The BCI system is divided into invasive BCI and non-invasive BCI. Invasive BCI usually requires the implanted electrodes to be implanted directly into the brain to acquire signals, which means that invasive BCI has a good frequency range and high quality signals. Invasive BCI will also introduce risks associated with any type of implant surgery, which makes invasive BCI commonly used on blind and deaf patients[4, 7]. In contrast, non-invasive BCI systems typically use only surface electrodes to obtain the desired signals at various locations on the user's head surface. Safe and easy to use makes non-intrusive BCI systems a popular solution in BCI research. In recent years, a variety of non-invasive BCI systems have been developed, such as event-related out-of-step (ERD)[20] and visual stimuli such as P300[19] or Steady-State Visual Evoked Potential (SSVEP)[15] control devices.

SSVEP is an EEG signal generated by scintillation vision when people focus their attention on scintillation stimuli with a scintillation frequency above 3 Hz, which can be obtained by placing the electrodes in the head region where the primary visual cortex is located. It also has the same fundamental frequency as the flicker stimulus, as well as its harmonics. The induction range of SSVEP is divided into low ($\leq$

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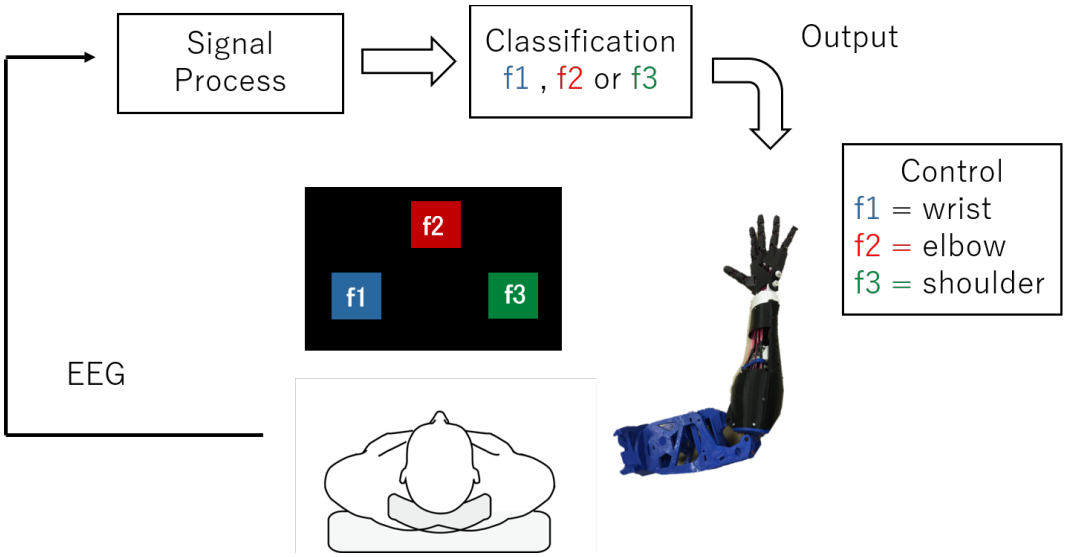


Figure 1: The structure of the proposed SSVEP-based BCI system

12 Hz), medium (12-30) and high frequency ($\geq$ 30 Hz)[17]. SSVEP-based BCI shows some advantages over other BCIs because it requires less training, high accuracy, and information transfer rate (ITR), and can only be manipulated by looking at the target.

Many SSVEP-based BCI systems have been developed to allow users perform certain operations independently. For example, SSVEP signal classifiers can be used for entertainment activities or video games [9, 22, 13]. Martišius et al. established an online game that allow player move or shoot target with an average precision of 80.5% by SSVEP-based BCI [12]. SSVEP-based BCI can also be used to develop spelling systems [2, 8] or perform complementary rehabilitation courses [21, 14, 5, 18]. Nakanishi et al. proposed a high-speed brain speller, which obtained an average information transmission rate (ITR) of 166.91 bits/min in 13 subjects [16]. Zeng et al. used an SSVEP-based BCI to establish an ankle rehabilitation robot. When the subject focused on one of the four flashing circles, the robot would judge the subject's intention to exercise and trigger the training [24]. These studies show that the SSVEP-based BCI has the potential to improve daily life and physical activity of physically disabled people. In a recent study, SSVEP-based BCI was used to controll the robot hand that gives the elderly or disabled people some autonomy [6, 1]. Chen et al. proposed an automatic feeding robot based on SSVEP-based BCI control. The user selects the appropriate food by looking at different visual stimuli [3]. These studies all use Commercial robot hands, which allows their systems to perform a variety of tasks well. However, this type of robot hands is generally bulky and expensive, it is difficult to apply in daily environments.

The goal of this research was to develop a simple and low cost BCI-based auxiliary system that uses sensory brainwave SSVEP to control the robotic hand to help patients with hand or arm neuromuscular control defects. The entire system includes a visual stimulator display, a 3D printed 6-DOF robotic hand, an EEG recorder, and a laptop for processing data. This system detects and analyzes the user's EEG brainwaves and classifies the detected SSVEP signals by Canonical Correlation Analysis (CCA). The robot hand is operated by converting the SSVEP into a control signal according to the classification result. The user only needs to pay attention to one of the three visual stimuli so that the robotic hand can make three actions: holding, pinching, and arm rotation. In this article, we conducted a preliminary offline experiment on three subjects to test whether our BCI system can be used in daily life.

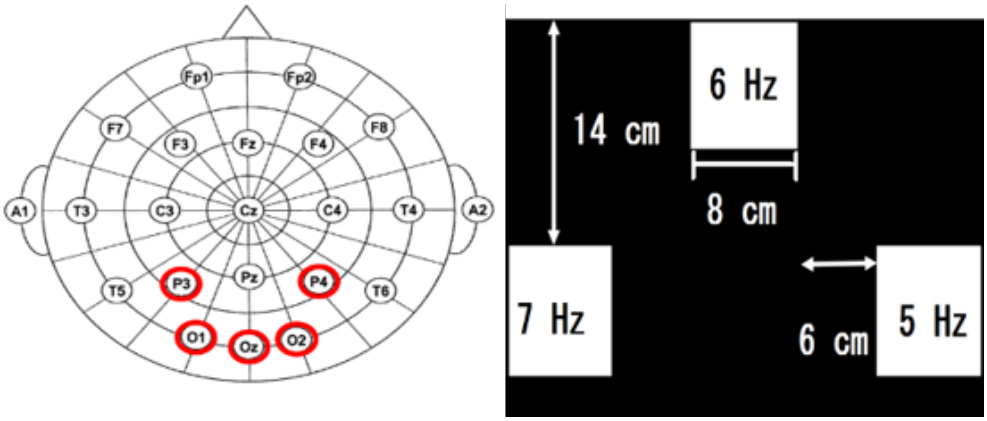


Figure 2: EEG electrodes locations(left) and layout of stimulator(right)

2 Methods

Figure 1 shows a schematic of our BCI system for robot arm control using SSVEP. It consists of a LCD monitor for visual stimulator, the right hand of InMoov robot, an EEG recorder (Avater EEG 8ch, Electrical Geodesics, Inc), and a laptop for processing data. When the subject is watching a visual stimulus, the acquisition system collects the EEG signal and transmits the data to MATLAB. Data processing and classification are done in MATLAB. Canonical correlation analysis (CCA) were used to detect corresponding frequency of the gazing stimulus in the experiment. The robot hand were controlled based on the classification results. We described details of this SSVEP-BCI system in the subsections.

2.1 Experiment setup and EEG recordings

Three subjects(age : 20-23 years , male only) participated in the study, all of them have had normal vision. In the experiment, the subject seated on a chair that was 60cm away from the 21 inch LCD monitor(70Hz refresh rate, 1980 x 1080 screen resolution), This display was used as visual stimulator. The visual stimulator presented three white squares as the stimuli in black board, and the stimuli were 5, 6, and 7 Hz. The subject induces the corresponding SSVEP signal by seeing one target in the three visual stimuli (5Hz, 6Hz, 7Hz) representing the motion: grip, pinch and arm rotation of the robot hand. In the experiment, subjects were randomly asked to focus on one of the three stimuli for 4 seconds, and each stimuli was asked to focus at most 20 times. In the end, each subject will perform a total of 60 trials.

The EEG signals were collected from head locations Oz, O1, O2, P3, and P4 based of the extended 10-20 international system as shown in Figure 2. GND and reference electrodes are A1 and A2. EEG signals was recorded by EEG recorder and sampling frequency was set to 500 Hz. All channels EEG signals preprocessed by the band-pass filtered between 3–50 Hz.

2.2 SSVEP-BCI system

Figure 3 shows the proposed SSVEP-BCI system, the display on the left is used to present the stimulus. The display on the right indicates the frequency of the stimulus that the user is looking at, as well as the robot hand operation instructions for each stimulus. The robot hand for this BCI system used InMoov robot[10]. InMoov robot is designed by Gael Langevin, its the first Open Source 3D printed life-size robot. The finger and wrist joint are actuated by DC servo motors. The poition of robot finger controlled by those motors are generated through fishing lines simulating a tendon and muscle for flexor

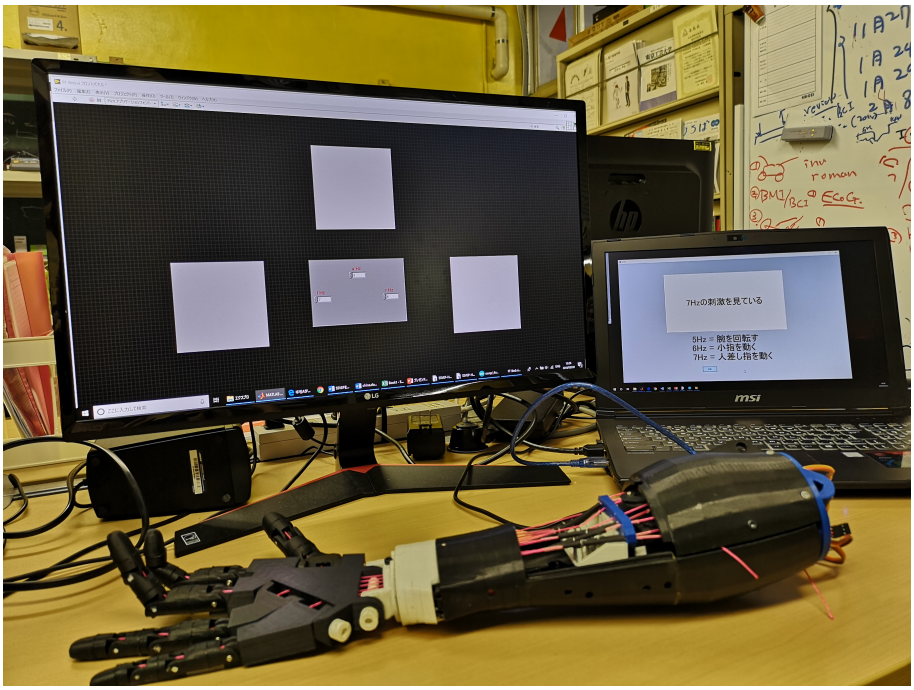


Figure 3: The proposed SSVEP-BCI system and robot hand

and extensor. By controlling the servo motor, it can accomplish some simple actions that we usually do in our daily lives such as: grab, hold. We also performed an offine simulation in order to verify the feasibility for the BCI system. We made EEG-SSVEP database at a 500 Hz sampling time for the simulator.The simulator reads 10 time points of ECoG data per cycle. We used First-In-First-Out (FIFO) method with 4 s time window length. The simulator could classify the given motion and sends it to the control robot arm using Arduino. (See this video file; `https://youtu.be/3SY4bx_C51c`)

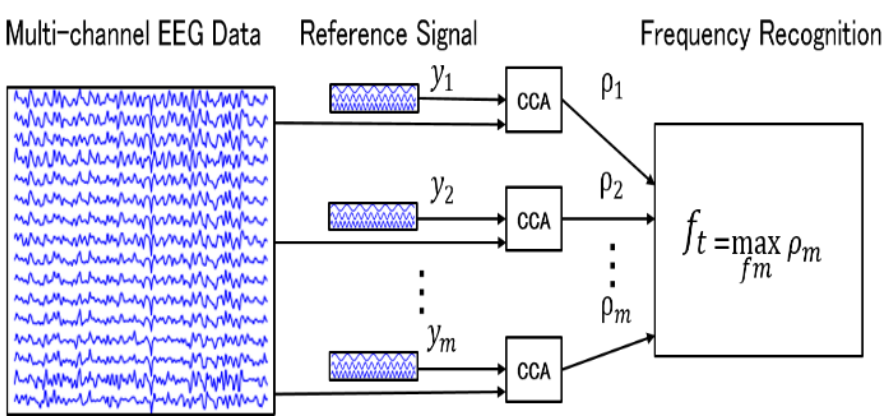


Figure 4: Image of the CCA-based method for SSVEP recognition

2.3 CCA method in the SSVEP-based BCI

CCA is a multivariate statistical method that uses the weight vector to calculate the two most relevant potential variables. For the two groups that have been normalized to have zero mean and unit variance

random variables $x \in R^{I_1 \times J}$ and $y \in R^{I_2 \times J}$CCA finds the weight vectors $W_x \in R^{I_1}$ and $W_y \in R^{I_2}$ such that the correlation between linear combinations $X = W_x^T X$ and $Y = W_x^T Y$ is maximized as:

$$\begin{aligned} \max_{W_x, W_y} \rho &= \frac{E[\tilde{x}\tilde{y}^T]}{\sqrt{E\tilde{x}\tilde{x}^T E\tilde{y}\tilde{y}^T}} \\ &= \frac{W_x^T X Y^T W_y}{\sqrt{W_x^T X X^T W_x W_y^T Y Y^T W_y}}. \end{aligned} \tag{1}$$

where ρ is called the canonical correlation, X and Y are called canonical variables.

Lin et al. first proposed to use CCA method for SSVEP detection in BCI system[11]. CCA method can perform multi-channel analysis at the same time, including more information, making SSVEP feature extraction more effective.

Figure 4 shows the CCA-based method for SSVEP recognition. When CCA is used to recognize SSVEP frequency, we set C, P, N, F to represent EEG channel number, time point number, harmonic number, and sampling frequency, respectively.EEG signal $\tilde{X} \in R^{C \times P}$ is a data set from C channels having a length of P point. The reference signal $\tilde{Y} \in R^{H \times P}$ is set with the m-th stimulation frequency $f_m (m = 1, 2, \cdots, M)$. Reference signal is defined as follows:

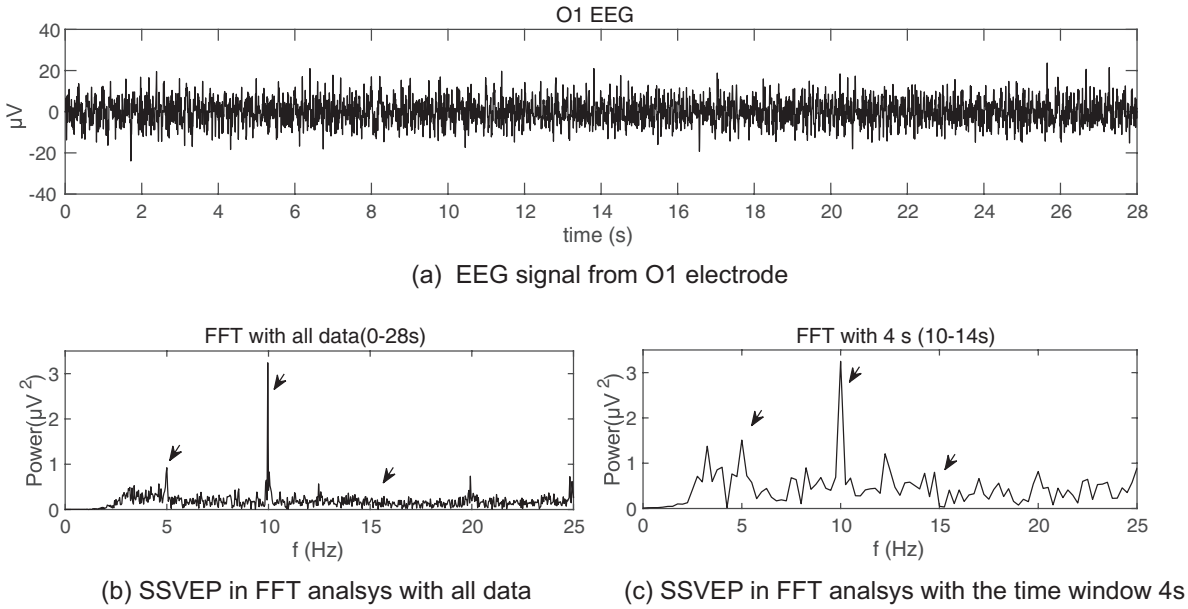
$$Y_m = \begin{pmatrix} \sin(2\pi f_m t) \\ \cos(2\pi f_m t) \\ \vdots \\ \sin(2\pi H f_m t) \\ \sin(2\pi H f_m t) \end{pmatrix}, \quad t = \frac{1}{F}, \frac{1}{F}, \cdots, \frac{P}{F} \tag{2}$$

Where H is the number of harmonics. $f_m (m = 1, 2, \cdots, M)$ is the stimulation frequency, P is the length of the EEG data, and F is the sampling frequency. Then, the maximum correlation coefficient ρ_m of the EEG signal X and the reference signal Y is calculated by the equation (1) , and the SSVEP frequency is identified as:

$$f_t = arg \max_{fm} \rho_m, \qquad m = 1, 2, \cdots, M. \tag{3}$$

3 Results

Figure 5 shows the EEG data measured during the 28 seconds of the preliminary experiment. To observe whether the subject induced SSVEP, we performed an FFT analysis of the overall (b) and 4 seconds (c) of the EEG data. It is clear from (b)(c) that our visual stimulator enables the subject to induce and stimulate the second harmonics of SSVEP and SSVEP at the same frequency. However, we did not observe the composition of the third harmonic number of the strong SSVEP. Other test sites and different subjects also had the same tendency. For BCI based on CCA determination of SSVEP, it is necessary to set the harmonic number H in advance because their identification process determines the frequency of SSVEP based on a pre-established sine-cosine wave. This may affect the best SSVEP decision rate at H = 3. In addition, we evaluated the accuracy of the SSVEP recognition of BCI systems with H = 1, 2 and 3 in the 1-4 second time-window (TW).



(a) EEG signal from O1 electrode

(b) SSVEP in FFT analsys with all data

(c) SSVEP in FFT analsys with the time window 4s

Figure 5: Typical EEG plot and SSVEP

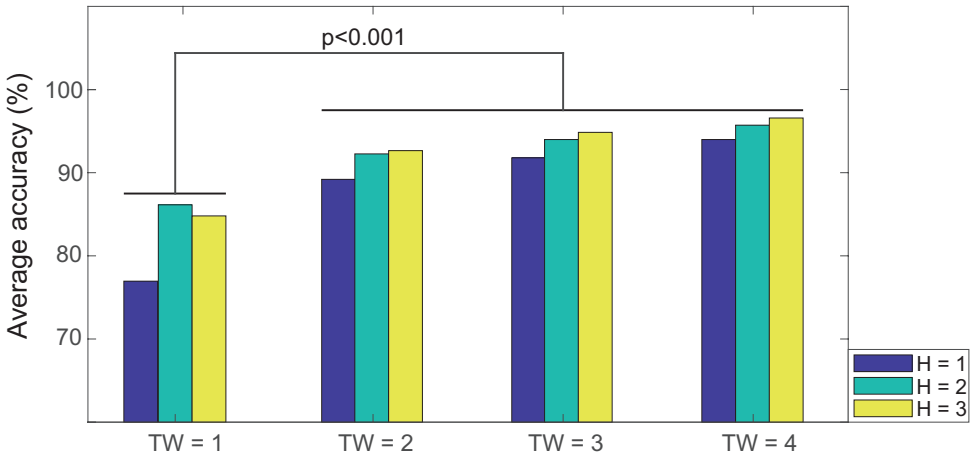
Table 1 shows the recognition accuracy of each subject for 5 Hz, 6 Hz and 7 Hz frequency stimuli at different harmonic numbers. The recognition accuracy was calculated to the number of correct target choices divided by the total count. It can be seen from the experimental results that the recognition accuracy of each subject for 5 Hz stimulation is higher than that of 6 Hz, 7 Hz stimulation.

Two way ANOVA, followed by Tukey multi-comparison test, was performed to determine the best length of TW and the best number of Harmonic frequensies. The 2-way interaction did not show any significance. Results of ANOVA showed significant main effects of TW ($F_{3,107} = 14.88$, $p < 0.001$) and of harmonic frequency ($F_{2,107} = 3.61$, $p < 0.05$). Multiple comparisons showed that the significant differences were between T1 and the others, and between H = 1 and H = 3.

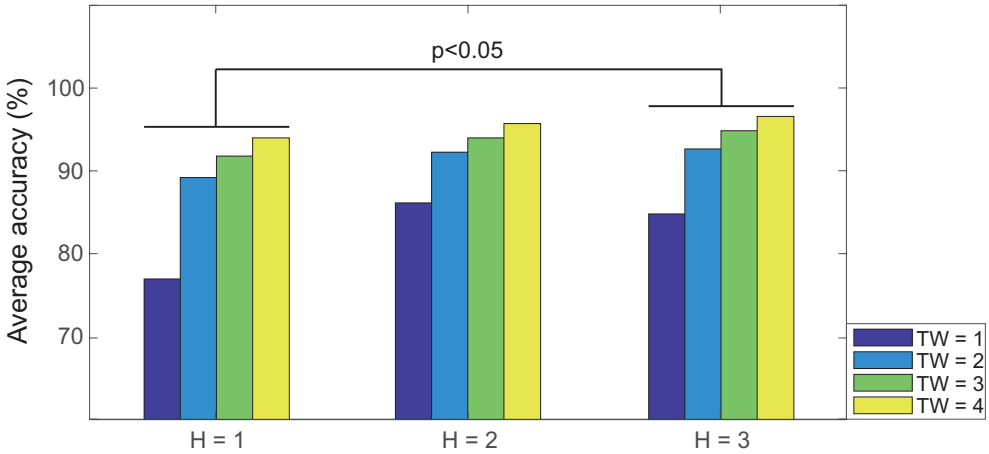
The size of H has a significant impact on the accuracy within the same TW. When the use number

Table 1: Accuracy of the SSVEP recognition

Harmonic		H = 1				H = 2				H = 3			
		TimeWindow (s)				TimeWindow (s)				TimeWindow (s)			
Subject	Frequency	1	2	3	4	1	2	3	4	1	2	3	4
Sub 1	5 Hz	70%	90%	90%	90%	85%	90%	95%	90%	95%	95%	100%	95%
	6 Hz	55%	90%	85%	95%	65%	90%	90%	95%	60%	85%	90%	95%
	7 Hz	65%	85%	90%	95%	75%	85%	90%	95%	75%	85%	90%	95%
Sub 2	5 Hz	85%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
	6 Hz	55%	65%	80%	80%	60%	70%	80%	90%	55%	70%	80%	90%
	7 Hz	80%	90%	95%	100%	85%	95%	95%	100%	85%	100%	95%	100%
Sub 3	5 Hz	90%	100%	100%	100%	100%	100%	100%	100%	95%	100%	100%	100%
	6 Hz	75%	85%	85%	90%	95%	100%	100%	100%	95%	100%	100%	100%
	7 Hz	70%	80%	90%	90%	85%	90%	90%	90%	75%	90%	95%	95%



(a) Average accuracy along with the length of time window



(b) Average accuracy along with the use number of harmonics

Figure 6: Average accuracy of the SSVEP recognition

of harmonics are larger, the accuracy is also higher. At H = 3, the accuracy of the three subjects was significantly higher than H = 1. When TW $\geq$ 2 s, all subjects with all H achieved good recognition accuracy. Subject 3 showed the highest accuracy under all conditions, especially, the accuracy for 5 Hz stimulation was 100% (H = 2) as shoen in Table 1. The accuracy of subject 2 for 6 Hz stimulation at each TW was significantly lower than 5 Hz and 7 Hz.

We calculated the average accuracy of the three subjects under the same harmonic as TW 1-4 seconds, and summarized results as written in Table 2. From the results of Table 2, the average accuracy increased to depend on the length of TW, and the average accuracy at TW 4s reaches 97%. In the case of H=3, except the TW 1s case, the accuracy is better than the others. However, the difference in accuracy between the two is almost same ($\pm$ 1%).

Table 2: Average accuracy of the SSVEP recognition results

TimeWindow(TW)		1	2	3	4
Average accuracy	H = 1	72%	87%	91%	93%
	H = 2	83%	91%	93%	96%
	H = 3	82%	92%	94%	97%

4 Discussion

Our BCI system runs the classfication on a laptop with a 2.60GHz CPU. When using TW 4s, the calculation times for H = 1, 2, and 3 were 0.018 seconds, 0.020 seconds, and 0.021 seconds, respectively. In the case of comparing various aspects, we achived the higher SSVEP judgment accuracy and the smaller standard deviation setting at H = 3, and the difference in calculation time could be negligible. Therefore, we believe that H = 3 would be sufficient our BCI system to determine SSVEP quickly and efficiently.

According to the results in Table 1, there are personal errors in our experiments. Subject 3 performed better than the other two subjects at each time period. Subject 3 achieved 100% accuracy at H=2 and H=3. When using FFT to analyze the evoked results of SSVEP in subjects, we found that the third harmonics of all subjects could not be induced or little induced. Since the used visual stimulus could not evoke the third harmonic of SSVEP, the recognition accuracy of SSVEP shows not much different ($\pm$ 1 %) between H = 2 and H = 3. The frequency and brightness of the stimulus would affect the strength of SSVEP. The proposed method may not enable each subject to induce strong SSVEP because each person's SSVEP characteristics are different [23].

So far, we have only considered the scintillation stimulation and the stimulation placement on monitor. In order to improve the accuracy of our BCI system, it may be necessary to further improve the above proposed issues, such as changing visual stimuli, frequency or sequence layout. In addition, the low frequency stimulation (5-7 Hz) used in this study brought about physical discomfort or visual fatigue during the experiment. In order to make the system more secure, it may be applicable high frequency as the stimulation frequency[25]. We will improve these issues in future research.

5 Conclusions

We developed a BCI system based on CCA to determine the SSVEP frequency in this study. We used it as a basic action to control the robot arm. The results of our BCI system showed the average accuracy of 97% when the length of time window set up at 4s and the used number of harmonics is at H=3. It also has good performance in other time windows. We successfully demonstrate the feasibility of our BCI system, so that it could help patients and the disabled to improve their quality of life. For real life applications, the system needs to be further improved in the following directions. First, it may be desirable to optimize individual characteristics such as electrode position, stimulation frequency, in order to improve the performance. Second, we have to use more higher stimuli frequencies than 30Hz for the user comfortability as possible. Finally, we hope to apply our BCI system to a commercial wheelchair mounted a seven-degree-of-freedom manipulator which can perform some tasks such as picking up or grabbing items.

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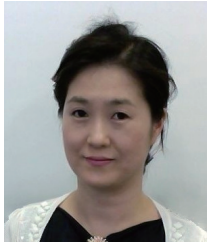

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