# CHRIS: Cybernetic Human-Robot Interface Systems


Keisuke Shima
Graduate School of Engineering
Hiroshima University
1-4-1 Kagamiyama, Higashi-Hiroshima, JAPAN 739-8527
keisuke@bsys.hiroshima-u.ac.jp

Ryota Eguchi
Graduate School of Engineering
Hiroshima University
1-4-1 Kagamiyama, Higashi-Hiroshima, JAPAN 739-8527
eguchi@bsys.hiroshima-u.ac.jp

Kenji Shiba
Graduate School of Engineering
Hiroshima University
1-4-1 Kagamiyama, Higashi-Hiroshima, JAPAN 739-8527
shiba@bsys.hiroshima-u.ac.jp

Toshio Tsuji
Graduate School of Engineering
Hiroshima University
1-4-1 Kagamiyama, Higashi-Hiroshima, JAPAN 739-8527
tsuji@bsys.hiroshima-u.ac.jp



*Abstract*

*This paper proposes cybernetic human-robot interface systems named CHRIS for operation of machines such as electric wheelchairs, home electric devices, and video game machines using biological signals. From the measured biological signals, users' intention of operation can be estimated with a probabilistic neural network (PNN), and then, control commands are generated accordingly. To verify validity of the proposed method, experiments with a healthy person and the disabled were conducted with an electric wheelchair, home electric devices, and a video game machine. From experimental results, it was shown that these machines could be manipulated skillfully, so that this system can be useful for the physically disabled.*


## 1. Introduction

It is estimated that 10 percent of the total global population of the world is disabled. This means that there are about 60 million disabled people. Besides, the population of older persons (aged 65 years and older) will reach about 80 million by the year 2025 [1].

Fields of activity of disabled and elderly people are very restricted, and it is very difficult for some of them to be self-sufficient and maintain an independent life. Nevertheless, these people have a strong will to participate in society and a desire to contribute socially as well as other reasons such as purpose of life, health maintenance, and so on. Therefore, the lack of self-sufficiency leads to physical and mental harm. If these problems can be solved, it is sure to lead to improvement in their quality of life, alleviating their physical and mental burden and allowing good health.

Recently, there has been a significant increase in the development of assistive technology based on robotics for the disabled and elderly. For example, Kitamura et al. [2] proposed a remote-operation interface for a mobile robot to work using a joystick in an environment consisting of several obstacles. Kosuge et al. [3] proposed the robot that assists the user's work using a touch-sensitive panel. M.Bergasa et al. [4] showed a guidance system of an electrical wheelchair for the physically challenged by head movements, and Rafael Barea et al. [5] presented a wheelchair guidance system based on electrooculography. Also, some products such as a meal support robot *Handy1* (Rehab Robotics Ltd. [6]) manipulated by the switch and an arm type robot manipulator *Manus* (Exact Dynamics Corp. [7]) operated with the joystick are commercially available. The users, however, have to change the device or the system whenever they do different activities because these devices and robots are often specialized for specific purposes. Additionally, some of the disabled and elderly may find it impossible to use these devices.

In this paper, a robotic agent system manipulated by biological signals, called CHRIS (for Cybernetic Human-Robot Interface Systems), is proposed. With this system, the user's intention of motion is estimated from the biological signals by using a statistical neural network, and can control various applications such as electric wheelchairs and home electric devices. The distinctive feature of the proposed system is its adaptability to various changes in the input signals. Therefore, the differences in biological signals among individuals can be covered by using adaptive learning.

This paper is organized as follows: In Section 2, the proposed system is described. Section 3 presents applications to control of an electric wheelchair, home electric devices, and a video game machine. Finally, Section 4 concludes this paper.

## 2. Cybernetic human robot interface systems

The proposed interface system called CHRIS is shown in Fig. 1. In this system, the user can use not only conventional devices but also biological signals such as electromyogram (EMG) signals and acceleration signals. The user can manipulate various applications using residual functions by combining these input channels if necessary. Generally speaking, it is difficult to discriminate the user's intentions from biological signals because of their complexity. Therefore, these problems are solved by the statistical learning technique [8], [9] adapting to the user's characteristics. Also, assignation of the manipulation such as a 2-command input mode like an on-off of a switch or a

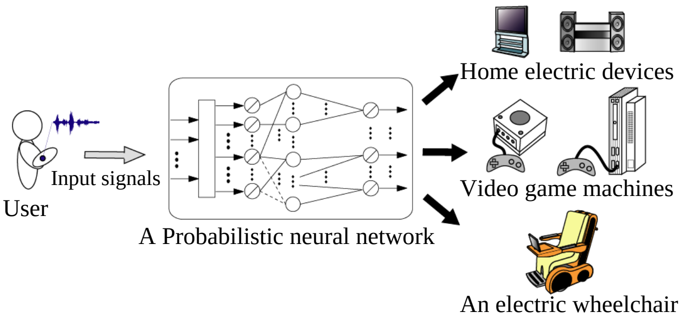


Fig. 1 Concept of the proposed system.

4-command input mode like the front, back, left, and right of a joystick corresponding to the user's motions can be freely set. Moreover, this system can manipulate different applications, for example, a electric wheelchair, home electric devices, video game machines, and so on, without any change of the system and the input device.

The advantages of the proposed system is summarized as follows:

1) The user can use biological signals as input signals.
2) This system can adapt to the user's characteristic.
3) The assignation of the manipulation corresponding to input signals can be freely set.
4) The users can manipulate various applications with this system.

2.1 Hardware

The hardware of the proposed system consists of a sensor unit to measure biological signals and a main unit to receive radio wave from the sensor unit.

2.1.1 Sensor unit

The structure of the sensor unit is shown in Fig. 2, and specification of the unit is indicated in Table 1. The sensor unit consists of a head amplifier and a transmission circuit. The amplifier is used to amplify and preprocess biological signals. The preprocessed signals are sent to the main unit from the transmission circuit.

The biological signals are inputted into the head amplifiers, and transmitted to the main unit by the radio wireless module FM-RFT3-433 (IR Solution Corp.) through AD converter MAX191 (Maxim Corp.) in 12 [bits]. The signal processing is controlled by the micro controller PIC- 16877 (Microchip Corp.). The head amplifier KD128 (Oisaka Development Ltd.) shown in Fig. 2 is for EMG signals. It is possible to detach it from the transmission circuit board. For the measurement of EMG signals, the *Ag* electrodes of 8 [mm] in diameter are used. This amplifier can derive EMG signals by differential measurement and output the rectificated and smoothed signals. In addition, a first-order low-pass filter with the cut-off frequency 338 [Hz] and a first-order high-pass filter with the cut-off frequency 2 [Hz] are installed for the noise reduction. The baud rate of the transmission is 2400 [bps], the maximum input channels 6 [CH], the data length 3 [bytes], and the apparent sampling frequency 2400/144 ≒ 16.7 [Hz], where

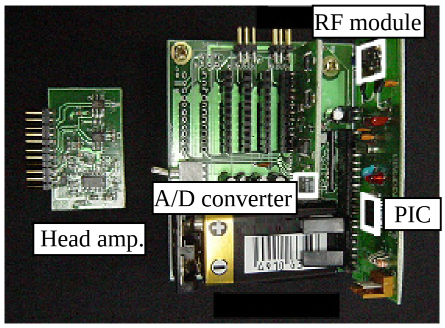


Fig. 2 Structure of the sensor unit.

Table 1 Specification of the sensor unit.

| | |
|---|---|
| Size | W110 [mm]×D140 [mm]×H45 [mm] |
| Power | Alkaline dry cell (rated 9 [V]) |
| Input channels | Max 6 [CH] |
| Modulation method | FM modulation |
| The baud rate of the transmission | 2400 [bps] |

the amount of information of one sample data are 6 [CH] × 3 [bytes]=18 [bytes]=144 [bits]. Also, in compliance of Radio Laws in Japan, the radiated emission range of this unit is restricted to approximately 500 [$\mu$ V/m] at a distance of 3 [m].

2.1.2 Main unit

The structure of the main unit are shown in Fig. 3, and the specifications of the unit is indicated in Table 2, respectively. The transmitted signals from the sensor unit are received by the radio wireless module FM-RFT3-433, and sent to a personal computer through the USB controller USBN-9604 (National Semiconductor Corp.).

2.2 Software

In this system, to discriminate operations from biological features, the probabilistic neural networks (PNNs) are used. In the study of pattern discrimination using PNNs [8], [9], several research has been carried out [10]-[13]. It is widely accepted that, due to the prominent nonlinear approximation capability, PNNs can estimate the posterior probability distribution of input patterns with arbitrary accuracy by training the network architecture and the weights appropriately. So far, PNNs have been used as an important tool for pattern discrimination, and have been proven to be efficient especially for complicated problems such as discrimination of biological signals [8], [9].

2.2.1 Feature extraction

In this paper, we consider to take EMG signals as input signals for example. The smoothed EMG signals are defined as $EMG_l(t)$ ($l = 1, \cdots, L$). Then, these EMG signals are normalized to make the sum of $L$ channels equal 1:

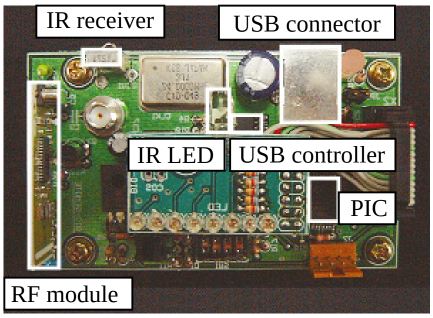

Fig. 3 Structure of the main unit.

Table 2 Specification of the sensor unit.

| | |
|---|---|
| Size | W110 [mm]×D140 [mm]×H40 [mm] |
| Power supply | Supply by USB bus (5 [V]) |
| USB communication method | USB full speed mode (USB 1.1) |
| Infrared rays transmission distance | Approximate by 8 [m] (Directivity having) |
| AD converter | Resolution 12 [bits] |
| MPU | PIC16F877-20P (Microchip Corp.) |
| Input-Output channels | Input 6 [CH] (A/D), Output 1 [CH] (TTL) |
| Wireless communication method | FM modulation method (433 [MHz]) |

$$x_l(t) = \frac{EMG_l(t) - EMG_l^{st}}{\sum_{l'=1}^{L}(EMG_{l'}(t) - EMG_{l'}^{st})} \quad (1)$$

where $EMG_l^{st}$ is the mean value of $EMG_l(t)$ which is measured while relaxing the muscles. Feature vector $\boldsymbol{x}(t) = [x_1(t), x_2(t), \cdots, x_L(t)]^T$ is used for pattern discrimination.

Also, this paper assumes that the amplitude level of the EMG signals changes in proportion to muscle force, and the proposed system uses the EMG amplitude information to use timing when the user's motion begins. The force information $F_{EMG}$ for the input vector $\boldsymbol{x}(t)$ is defined as

$$F_{EMG}(t) = \frac{1}{L}\sum_{l=1}^{L}\frac{|EMG_l(t) - \overline{EMG_l^{st}}|}{\overline{EMG_l^{\max}} - EMG_l^{st}} \quad (2)$$

where $\overline{EMG_l^{\max}}$ is the mean value of $EMG_l(t)$ are measured under an average contraction level that is determined by the user. The $F_{EMG}(t)$ is set as [0,1] to simplify the data representation. When $F_{EMG}(t)$ is more than 1, $F_{EMG}(t)$ is adjusted to 1. Then, $F_{EMG}(t)$ is compared with a threshold $M_d$. When $F_{EMG}(t)$ is more than $M_d$, intention of operation would be discriminated.

2.2.2 Pattern classification

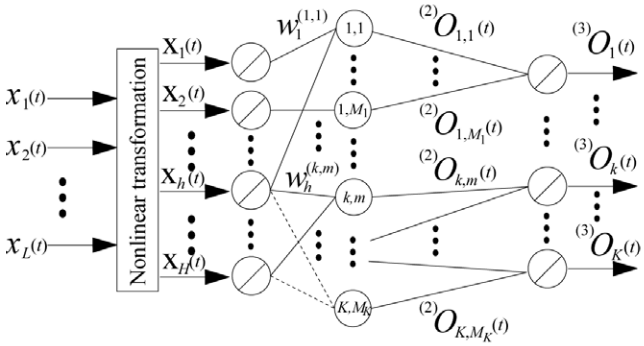

Fig. 4 EMG pattern discrimination using LLGMN [8].

In the proposed system, a log-linearized Gaussian mixture network (LLGMN) [8] is used in order to estimate the use's intensions. LLGMN is based on a Gaussian mixture model (GMM) and a log-linear model of probability distribution function (pdf). By applying the log-linear model to a product of the mixture coefficients and the mixture components of GMM, a semiparametric model of pdf is incorporated into a three-layer feedforward NN, as shown in Fig. 4. LLGMN estimates probability distribution from the input vector $\boldsymbol{x}(t)$, and outputs posterior probability of operation $k$ ($k = 1, \cdots, K$).

The entropy of the output of LLGMN is used to avoid misdiscrimination [10]-[13]. The entropy is defined as

$$E(t) = -\sum_{k=1}^{K} {}^{(3)}O_k(t) \log {}^{(3)}O_k(t) \quad (3)$$

where ${}^{(3)}O_k(t)$ indicates the posterior probability of operation $k$. If $E(t)$ is less than a threshold $E_d$, an operation, which has the largest posterior probability, is determined. In contrast, when $E(t)$ is more than $E_d$, discrimination should be suspended, since large entropy suggests that the output is ambiguous.

## 3. Applications

In this section, examples of possible applications of CHRIS are shown, in which the operation experiments of an electric wheelchair, home electric devices, and a video game machine using the EMG signals were conducted.

In the proposed method, misdiscrimination can be reduced using the force information $F_{EMG}$ and the entropy $E(t)$ [8]. However, during the transient phases of the user's motions, some misdiscrimination can still be found. Therefore, in the experiments, commands corresponding to the user's operations are executed when the same discrimination continues $\alpha$ times. Using this rule, a stable operation can be achieved.

### 3.1 An electric wheelchair with CHRIS

The specification of the electric wheelchair is indicated in Table 3. An overview and the structure of an electric wheelchair with CHRIS is, respectively, shown in Fig. 5 and in Fig. 6. The signals assigned in the output of LLGMN are converted into the analogue signals with the 12 [bits] D/A converter (Interface Corp.), and these signals are sent to the motor driver circuit of the electric wheelchair. The discrimination results of the user's intention are sent to the

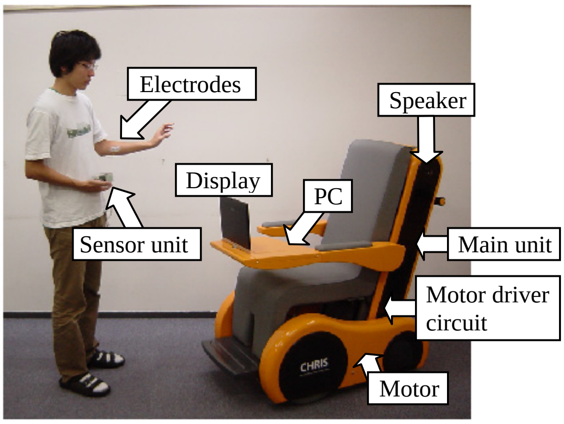


Fig. 5 An overview of an electric wheelchair with CHRIS.

Table 3 Specification of the electric wheelchair.

| | |
|---|---|
| Size | W1,000 [mm]×D750 [mm]×H1,400 [mm] |
| Weight | 70 [kg] |
| Diameter of wheels | Front 380 [mm],Rear 200 [mm] |
| Battery | DC24 [V] |
| Motor | Permanent Magnet Gear Motor 150 [W]×2 |
| Speed | Forward 2.5 [km/h], Backward 1.8 [km/h] |
| Turning radius | 600 [mm] |

feedback display and speakers. This wheelchair allows movement with 3 degrees of freedom (right/left, forward/backward, and up/down).

### 3.1.1 Operation system

Two control methods of an electric wheelchair are proposed: the analogue control mode and the command control mode. The analogue control mode assigns each body motion of the user to a different operation such as forward, backward, left, and right. Therefore, an electric wheelchair can be intuitively operated. However, in the analogue control mode, it is difficult for people with severe physical disabilities to operate because this mode requires a different motion by the user for each operation.

In the command control mode, the user can select one of the possible commands on the operation screen using fewer motions. Consequently, the number of motions, which can be changed according to the disabled level and preference of each user, is extremely few comparing to the analogue control mode. In this paper, the details of about the command control mode are explained.

The operation screen of the command control mode is shown in Fig. 7. The control commands consist of (1) forward (the wheelchair moves forward), (2) right (the wheelchair rotates right), (3) left (the wheelchair rotates

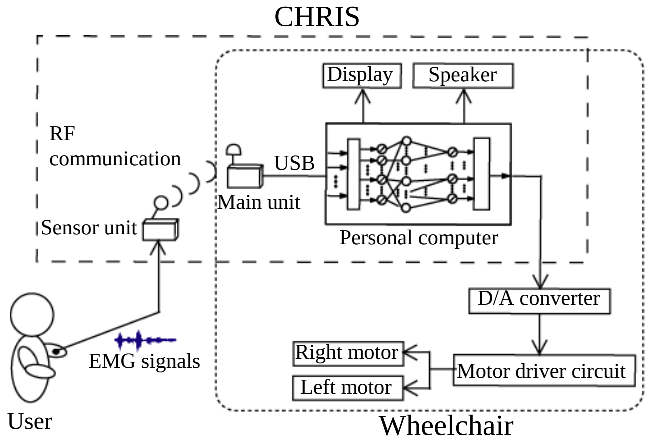


Fig. 6 Structure of the proposed control system for an electric wheelchair with CHRIS.

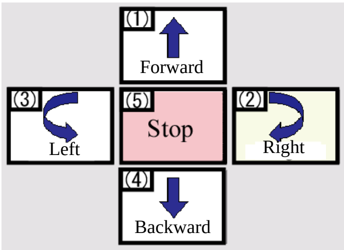


Fig. 7 Menu of the control commands.

left), (4) backward (the wheelchair moves backward) and (5) stop (the wheelchair stops).

The user inputs the control commands by repeating the body motion assigned to “Operation” twice as explained below, in order to execute the intended control command.

When the user begins the operation, the stop command has been always selected. Then, the color of the one command among the possible ones on the screen shown in Fig. 7 starts changing from white to yellow automatically in order of (1), (2), (3) and (4) by doing the “Operation” motion. The user can operate the wheelchair by doing the “Operation” motion while the color of the desired control command is yellow. Therefore, this mode can be operated by using only one body motion.

In consideration of safety, two kinds of automatically stopping functions are installed. While the wheelchair is running, it stops immediately according to any input command by the user. Also, when there is no input within the time limit, the wheelchair does so. Moreover, for anticipating emergencies, the “Stop” motions are prepared. Whenever one of the “Stop” motions is done, the wheelchair stops as quickly as possible.

The selected command returns to (5) when the wheelchair stopped, and the command scanning is repeated automatically from (1). Also, the motion speed of the wheelchair and the time until automatic stopping can be freely changed by the users.

### 3.1.2 Operation experiment

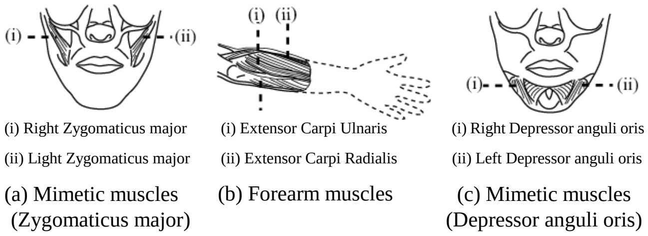


Fig. 8 Locations of electrodes.

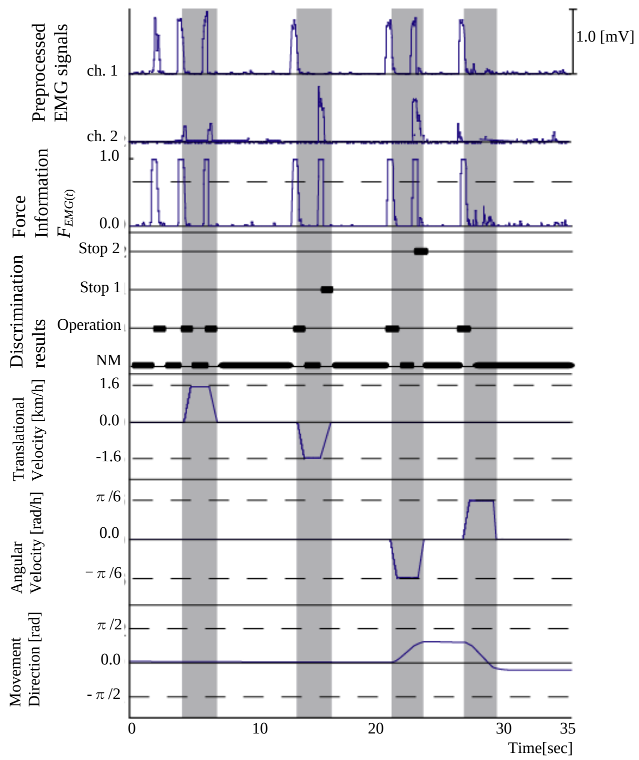


Fig. 9 An example of the experimental results during the EMG control of the electric wheelchair.

To verify validity of the proposed method, an operation experiment using EMG signals was performed with a healthy person.

In this experiment, electrodes were attached to the zygomaticus major muscles ($L$ = 2; on the right and left sides), as shown in Fig.8 (a), and three motions ($K$=3; contracting muscles on the right side, the left side, and both sides) were discriminated by LLGMN, where one is for the "Operation" command, and the others for the "Stop" command.

The feature pattern, $\boldsymbol{x}(t)$, was used to train LLGMN. In the learning process of LLGMN, 20 EMG patterns were extracted from EMG signals for each motion, and the teacher signals consisted of $K \times 20$ patterns. In addition, the threshold $\alpha$ was set as 20, the threshold $M_d$ as 0.6, the threshold $E_d$ as 0.2, and the time until automatically stopping was set as 5 [sec].

The experimental results are shown in Fig. 9. In this figure, two channels of the preprocessed EMG signals, the force information $F_{EMG}$, the discrimination results, the translational velocity, and the angular velocity are plotted.

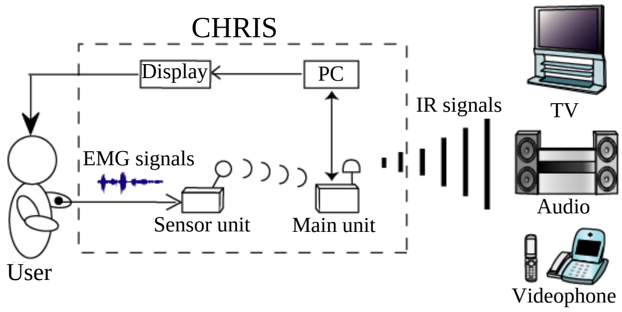


Fig. 10 Structure of the proposed control system for home electric devices with CHRIS.

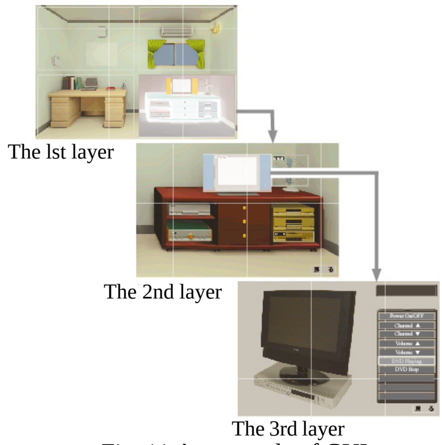


Fig. 11 An example of GUI.

The gray areas indicate the time while the wheelchair was moving. The discrimination results were set as no motion (NM) when the force information $F_{EMG}$ was less than $M_d$.

From the experimental results, the command control mode was proven to be functionable and practical. Also, by paying attention around 30 [sec], it was confirmed that the wheelchair stopped automatically when there was no input within the predetermined time.

### 3.2 Home electric devices with CHRIS

The proposed control system for home electric devices is shown in Fig. 10. In this system, in the output of LLGMN are sent to the main unit, and the infrared (IR) signals to corresponding to home electric devices are transmitted from the infrared LED of the main unit to the devices.

#### 3.2.1 Operation system

It is difficult for the disabled and elderly to operate a lot of home electric devices using biological signals during the EMG control of the electric wheelchair. Therefore, the operation commands are arranged with a hierarchical structure as explained as follows, and various operations can be done by repeating a command selection and execution.

Examples of the operation screen based on a graphical user interface (GUI) is shown in Fig. 11. In this figure, the operation menus in three hierarchical layers are shown, each menu of which is displayed separately on the screen. The user switches the menu from one to other, and can

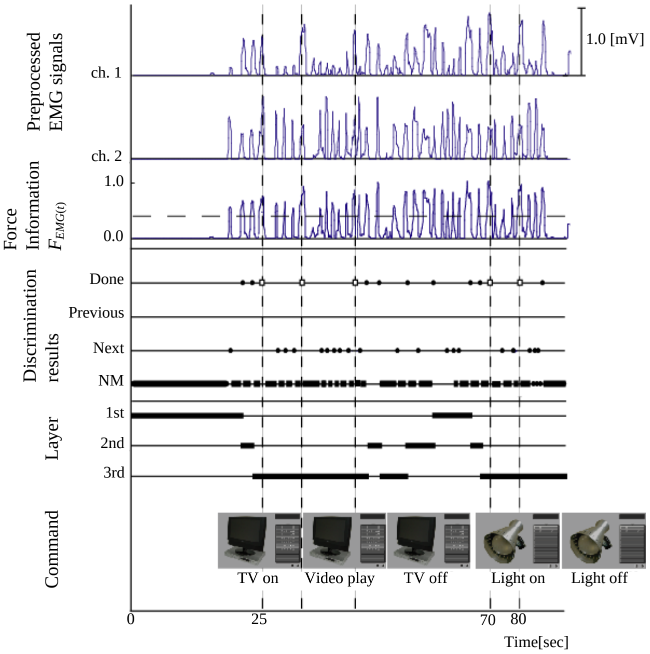


Fig. 12 An example of experimental results during the EMG control of the home electric devices by the forearm amputee.

execute the intended operation. When the control command of the home electric device is determined in the third layer, the IR signals are transmitted from the infrared LED of the main unit to the corresponding home electric devices.

### 3.2.2 Operation experiment

An operation experiment using EMG signals was performed with an amputee. The amputee is a 45 year-old man whose forearm was amputated when he was 41 years old. Two pairs of electrodes were attached to the forearm muscles ($L$ = 2; on the extensor and flexor), as shown in Fig. 8 (b)). The subject was asked to perform three motions (K=3; flexion, extension and grasp of the amputated arm and hand), that are corresponding to the "Previous" command, the "Next" command, and the "Done" command, respectively. Other experimental conditions are the same as the ones described in section 3.1.2.

An example of experimental results is shown in Fig. 12. In this figure, two channels of the preprocessed EMG signals, the force information $F_{EMG}$, the discrimination results, the selected layers, and the IR commands are plotted.

From the experimental results, it can be seen that the subject could operate the home electric devices by skillfully switching the layered menus based on GUI. It should be noted that there was no malfunction at all, and the home electric devices could be operated according to subject's intention. Therefore, it could be confirmed that even the subject with an amputated forearm and hand was able to operate the home electric devices using the proposed system.

## 3.3 A video game machine with CHRIS

The control system for a video game machine system is

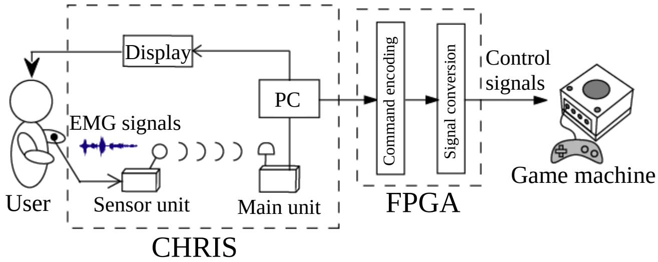


Fig. 13 Structure of the control system for a video game machine with CHRIS.

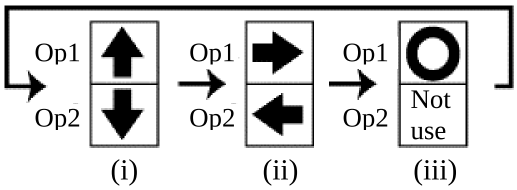


Fig. 14 Command groups.

shown in Fig. 13. In this system, the output of LLGMN are converted into the control signals corresponding to the video game machine by a field programmable gate array (FPGA), and these converted signals are transmitted to the video game machine [14].

### 3.3.1 Operation system

In the proposed method, both a direct mapping and a shift-group method can be used. The direct mapping assigns each body motion to a different command. As for the shift-group method, commands are divided into several groups. In each group, the body motions are directly mapped into commands. By shifting these groups, the execution of multiple commands can be achieved with a smaller number of the motions. In this paper, the shift-group method was used for the operation experiment.

In the signal conversion shown in Fig. 13, the control signals are determined based on the selected commands, and then transmitted to the target game machine following the communication protocols. However, since the communication protocols vary largely among amusement machines, the signal conversion part needs to be reconstructed whenever the game machine is changed. In the prototype system, an FPGA chip is used. FPGA is chosen since it allows easy reprogrammability and fast development times. When the game machine is changed, FPGA can be reconfigured easily. Consequently, a variety of amusement machines can be operated with a single hardware device.

We implemented the signal conversion part on a development board (Xtreme DSP Development Kit-2, Nallatech), which hosts a Xilinx Vertex family FG676 FPGA chip (XCV3000-4FG676). The signal conversion circuit was described in Verilog-HDL.

### 3.3.2 Operation experiment

An operation experiment using EMG signals was performed with CHRIS. For the subject who is a patient with a cervical spine injury and his whose arms are comple-

Fig. 15 Subject with electrodes attached on his face.

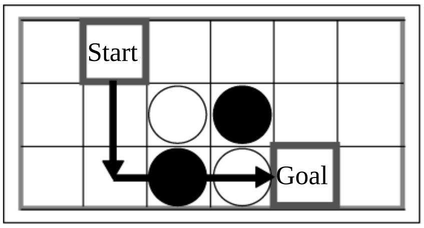


Fig. 16 The desired route given to the subject.

tely paralyzed, any operation with forearm muscles could not be performed. Therefore, electrodes were attached to depressor anguli oris muscles ($L$ = 2; on the right and left sides), as shown in Fig. 8 (c), and the subject was asked to perform three motions ($K$ = 3; contracting muscles on the right side, left side and both side). Command groups (i), (ii), (iii) are shown in Fig. 14. Three motions are corresponded to the "operation 1" command, the "operation 2" command, and the "shift-group" command, respectively. The operation threshold $\alpha$ was set as 30, and other experimental conditions are the same as the ones shown in section 3.1.2.

An overview with electrodes attached on his face is shown in Fig. 15. In this experiment, the game machine was the PlayStation2 (Sony Computer Entertainment Inc.), and the "Othello" game (SUCCESS Corp.) were used. The subject was asked to follow a predefined route and place the stone at a goal (see Fig. 16) using the shift-group method for game control.

An example of operations by the subject is shown in Fig.17. In this figure, two channels of the preprocessed EMG signals, the force information $F_{EMG}$, the discrimination results, and the control commands are plotted. The gray areas indicate the operations the subject made in the Othello game. It should also be mentioned that since the shift-group method was utilized, some additional commands could be added easily if it would be necessary.

From the experimental results, it could be confirmed that the proposed system could work properly according to the subject's intentions even when the number of motions were very small.

## 4. Conclusion

In this paper, we have proposed cybernetic human-robot interface systems, CHRIS, and three kinds of prototype systems for controlling an electric wheelchair, home electric devices, and a video game machine have been developed. In this system, a variety of biological signals can be used as input signals. The users can choose input signals

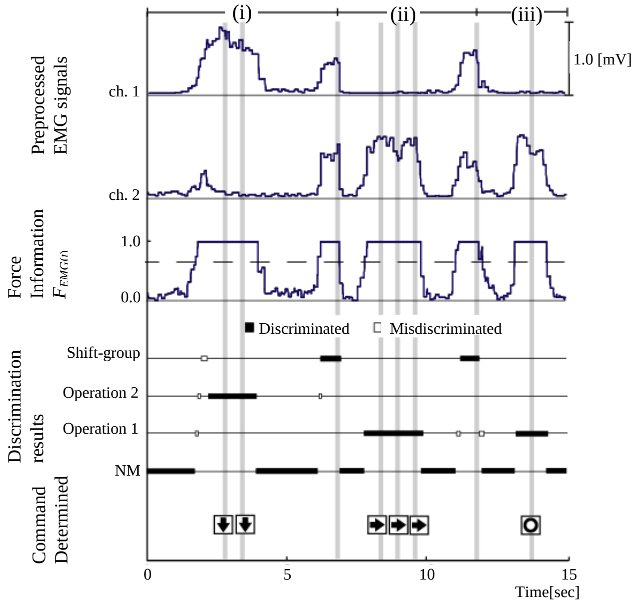


Fig. 17 An example of the experimental results during the EMG control of the video game machine by the patient with a cervical pine injury.

with respect to their conditions, so that a lot more people are able to operate the proposed system. Also, the user's intention of motion is estimated from the input signals using LLGMN. Due to the adaptive learning capability of LLGMN, a high discrimination accuracy was achieved.

To verify validity of the proposed system, experiments with a healthy person and the disabled were carried out. From the experimental results, validity of the system was confirmed. In future research, we would like to improve the GUI of the proposed system, and apply the method to other input signals and other machines.

## 5. Acknowledgment

This research is carried out as part of the NEDO Project for the Practical Application of Next-Generation Robots. The authors would like to thank Mr. Kazuyuki Fujita and Mr. Hiromi Koseki for their kind cooperation.

## #. REFERENCES

[1] The World Health Organization, http://www.who.int/net/

[2] S. Yamashita, K. Asami and T. Kitamura, "Human Interface for Navigation Using a Mobile Robot," *The Japan Society of Mechanical Engineering, Robotics and Mechatronics Division'01* CD-ROM, 2P1-H7, Sunmesse Kagawa, 2001. (in Japanese)

[3] S. Aizawa, K. Kosuge, "Mobile Assistant Robot for You-MARY-" *The 20nd Annual Conference of the Robotics Society of Japan CD-ROM*, 3D25, 2002. (in Japanese)

[4] L. M. Bergasa, M. Mazo, A. Gardel, M. A. Sotelo and J. C. Garcia, "Guidance of Wheelchair for Handicapped People by Head Movements," *Proceedings of the International Field and Service Robotics.FSR'99*, pp. 150-

155, 1999.
[5] R. Barea, L. Boquete, M. Mazo and E. Lopez, “System for Assisted Mobility using Eye Movements based on Electrooculography,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, Vol. 10, No. 4, pp. 209-218, 2002.
[6] Refab Robotics Limited, http://www.rehabrobotics.com/
[7] Exact Dynamics Corporation, http://www.exactdynamics.nl/
[8] T. Tsuji, O. Fukuda, H. Ichinobe, and M. Kaneko, “A Log-Linearized Gaussian Mixture Network and Its Application to EEG Pattern Classification,” *IEEE Transactions on Systems, Man, and Cybernetics-Part C: Application and Control Engineers*, Vol. 29, No. 1, pp. 60-72, 1999.
[9] T. Tsuji, N. Bu, M. Kaneko, and O. Fukuda, “A Recurrent Log- Linearized Gaussian Mixture Network,” *IEEE Transactions on Neural Networks*, Vol. 14, No. 2, pp. 304-316, 2003.
[10] T. Tsuji, H. Ichinobe, K. Ito, and M. Nagamachi, “Discrimination of Forearm Motions from EMG Signals by Error Back Propagation Typed Neural Network Using Entropy,” *Transactions of the Society of Instrument and Control Engineers*, Vol. 29, No.10, pp. 1213-1220, 1993. (in Japanese)
[11] O. Fukuda, T. Tsuji, M. Kaneko and A. Otsuka, “A Human-Assisting Manipulator Teleoperated by EMG Signals and Arm Motions, ” *IEEE Transactions on Robotics and Automation*, Vol. 19, No. 2, pp. 210-222, 2003.
[12] N. Bu, O. Fukuda, and T. Tsuji, “EMG-Based Motion Discrimination Using a Novel Recurrent Neural Network,” *Journal of Intelligent Information Systems*, Vol. 21, No. 2, pp. 113-126, 2003.
[13] T. Tsuji, O. Fukuda, M. Kaneko and K. Ito, “Pattern Classification of Time-series EMG Signals Using Neural Networks,” *International Journal of Adaptive Control and Signal Processing*, Vol. 14, No. 8, pp. 829-848, 2000.
[14] K. Shima, N. Bu, M. Okamoto, and T. Tsuji, “A Universal Interface for Video Game Machines Using Biological Signals,” *Proceedings of 4th International Conference on Entertainment Computing –ICEC 2005*, pp. 88-98, 2005.