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EMG-based Control For a Feeding Support Robot Using a Probabilistic Neural Network

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Abstract— **This paper proposes a new manipulator control system to support the performance of eating tasks for people with severe physical disabilities, such as those with paralysis caused by cervical spine injuries. The system consists of an electromyogram (EMG) classification part, a manipulator control part and a graphical feedback display. It classifies the user's intended motions from EMG signals measured using a probabilistic neural network (PNN), and controls a robot manipulator in line with the results. Multiple subject motions can be accurately estimated based on learning of the user's EMG patterns using the PNN, thereby allowing operation of the manipulator as desired to perform eating tasks.**

To examine the performance of the proposed system, experiments were performed with five subjects, including one with paralysis from a cervical spine injury. The results demonstrated that the system could be used to accurately classify the subjects' EMG signals during motions, and that the unit could be easily controlled using EMG signals.

I. Introduction

There is widespread demand in today's world for the development of a support robot system to provide the intensive living assistance needed by physically disabled people (e.g., forearm amputees, individuals suffering from muscular dystrophy, and those with paralysis caused by cervical spine injuries). The concept of a robot that provides assistance for eating is considered to offer particularly promising options for reducing the burden of patients at mealtimes.

Systems to support eating tasks have been widely developed [1]–[9] since around 1990. By way of example, MANUS [1] is an electric wheelchair-based manipulator that allows the user to take meals in a wheelchair; Handy-1 [2] is a robot that provides assistance for eating, and consists of a robot manipulator with a spoon and a food tray; and the My Spoon feeding robot [3], [4] is a compact, lightweight robot manipulator that supports tasks involved in eating. In a previous study, Zhang *et al.* [6], [7] performed an experiment involving the control of My Spoon using EMG signals based on a thresholding method. As such signals provide a range of information on variables such as muscle condition/power and the user's intended motions, they can be utilized to control robot systems. However, it can be difficult to discriminate multiple intended user motions using simple thresholding alone because EMG signals are significantly influenced by skin condition and user ability. To assist people with severe physical disabilities (such as those with paralysis caused by cervical spine injuries) using robotics technology, it is necessary to accurately determine intended user motions from EMGs.

In the field of EMG pattern classification, probabilistic neural networks (PNNs) and support vector machines have been extensively studied and applied to various human assistance systems. In particular, Tsuji *et al.* [10] proposed a probabilistic neural network based on a Gaussian mixture model called the log-linearized Gaussian mixture network (LLGMN), and Fukuda *et al.* [11] developed an EMG-based human-assisting manipulator using this network. As the LLGMN provides high-level performance in the classification of bioelectric signals such as EMGs and electroencephalograms (EEGs), it has been used to develop a variety of support systems including electric wheelchairs and speech synthesizers [12]–[15]. Applying these developments to support for eating tasks enables the design of technologies for use in daily life by people with severe physical disabilities.

This paper proposes a novel robot control system to support eating tasks based on EMG signals and a PNN. The user's intended motions are estimated from these signals using the LLGMN, and signal differences among individuals can be taken into account thanks to adaptive learning. Robot manipulator operation commands can then be set according to the user's physical capacity. Using My Spoon as a robot manipulator to support eating tasks allows the user to hold and eat any kind of food based on simple layer-based command selection. The system may enable patients with paralysis caused by cervical spine injuries to feed themselves freely.

This paper is organized as follows: Section II outlines the proposed EMG signal-based eating support system, Section III discusses its validity in relation to the results of EMG classification and operation experiments, and Section IV gives the conclusion.

II. EMG-based robot system for feeding support

Figure 1 shows an outline of the proposed system, which involves the two processes of EMG classification and manipulator control. My Spoon [6] was used as the feeding assistance robot in this study. It includes a food tray and a robot manipulator controlled by the user via a joystick

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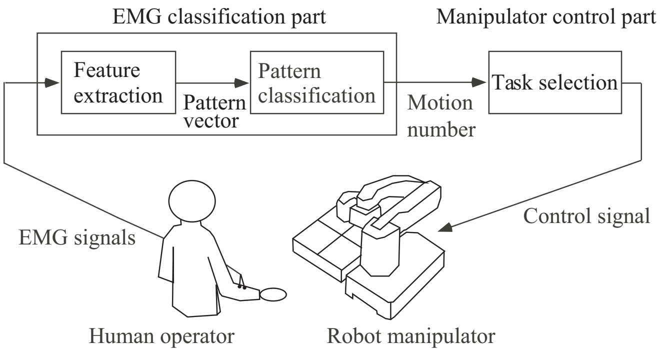


Fig. 1. System components of the mealtime support manipulator

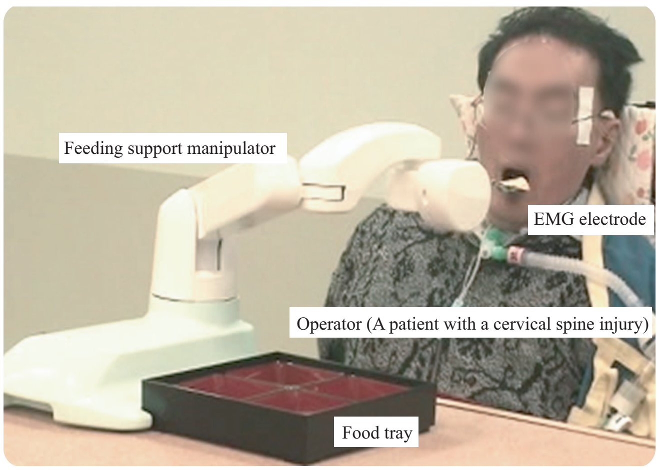


Fig. 2. Example of feeding support manipulator operation by a patient with a cervical spine injury

to pick up food from a tray. The proposed system supports movement for eating based on EMG signals using My Spoon. Figure 2 shows an example involving a patient with a cervical spine injury using the proposed method to operate a feeding support manipulator.

An overview of the prototype system developed is shown Fig. 3. It consists of a laptop, EMG electrodes, an amplifier and a robot manipulator, and can be operated using EMG signals or a joystick. The following subsection outlines the system's EMG control method.

A. EMG classification part

An overview of the EMG classification part is shown in Fig. 4. At the classification stage, EMG signals are measured and used to identify user motion features, which are then classified using the probabilistic neural network to allow estimation of intended motions. The details of each process are outlined below.

1) EMG signal measurement and feature extraction: First, EMG signals measured using L pairs of electrodes are digitized via an A/D converter (sampling frequency: 1 kHz), and are rectified and filtered out through a second-order low-pass Butterworth filter (cut-off frequency: f_c [Hz]) for each channel. These sampled EMG signals are defined

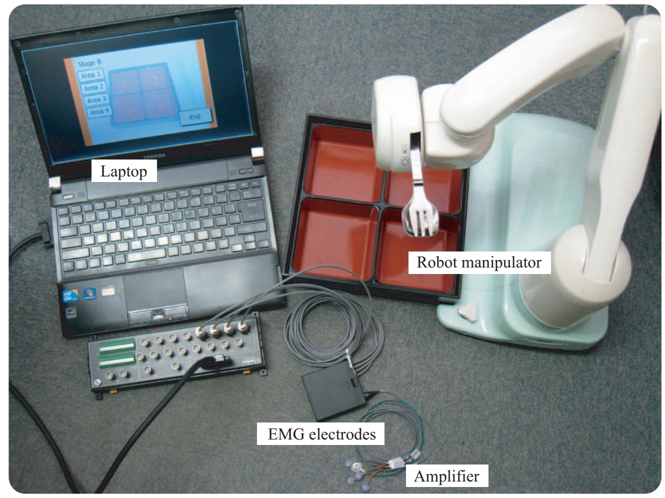
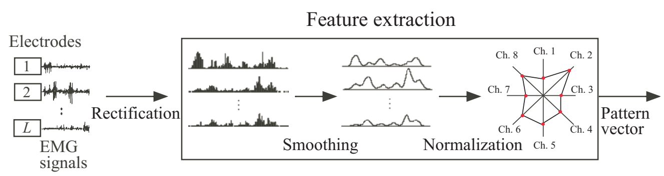
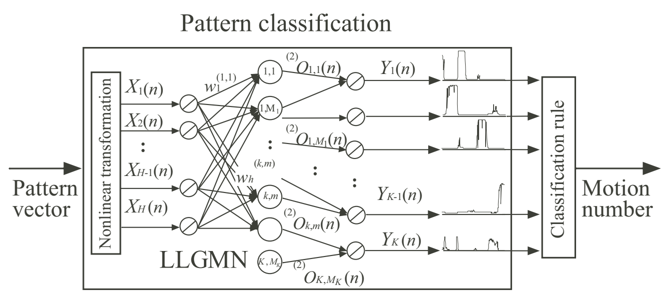


Fig. 3. Prototype system developed



(a) Feature extraction



(b) Pattern classification

Fig. 4. EMG classification part

as E_l $(l = 1, \dots, L)$. The force information F_{EMG} of the user is then computed as follows:

$$F_{\mathrm{EMG}} = \frac{1}{L}\sum_{l=1}^{L}\frac{E_l - \overline{E_l^{\mathrm{st}}}}{E_l^{\max} - \overline{E_l^{\mathrm{st}}}} \tag{1}$$

where $\overline{E_l^{\mathrm{st}}}$ is the mean value of E_l in a state of muscle relaxation and $E_l^{\max}$ is the maximum voluntary contraction.When F_{EMG} is greater than the threshold F_{th}, motion is judged to have occurred. Based on this process, malfunction caused by the unexpected motions can be prevented.

E_l is then normalized to make the sum of L channels equal to 1 using the following equation:

$$x_l = \frac{E_l - \overline{E_l^{\rm st}}}{\sum_{l=1}^{L}(E_l - \overline{E_l^{\rm st}})} \tag{2}$$

feature vector $\boldsymbol{x} = [x_1, x_2, \ldots, x_L]^{\rm T} \in \Re^L$ is input to probabilistic neural network, and is utilized to estimate user motion.

2) EMG classification using the probabilistic neural network: At the EMG classification stage, the LLGMN [10] is utilized as the probabilistic neural network. This network is based on the Gaussian mixture model (GMM) and a log-linear model of the probability density function (pdf), and *a posteriori* probability is estimated based on the GMM by learning. By applying the log-linear model to a product of the mixture coefficient and the mixture component of the GMM, a semiparametric model of the pdf is incorporated into a three-layer feed-forward neural network. Through learning, the LLGMN distinguishes movement patterns with individual differences, thereby enabling precise pattern recognition for bioelectric signals such as EMGs and EEGs [10], [11].

In the proposed method, the system first instructs the user to conduct C motions. The feature vectors calculated from these motions are then input to the LLGMN as teacher vectors, and the LLGMN is trained to estimate the *a posteriori* probabilities of each motion. After the training, the system can be used to calculate the similarity between patterns in the user's motions and trained motions as a posteriori probabilities by inputting the newly measured vectors into the LLGMN. In order to prevent discrimination errors, the entropy H (which shows the obscurity of the information) is calculated here from the LLGMN outputs. Since the output of the LLGMN represents the *a posteriori* probability $p(c|\boldsymbol{x})$ for each motion c ($c = 1, 2, ..., C$), entropy is defined as

$$H = -\sum_{c=1}^{C} p(c|\boldsymbol{x}) \log p(c|\boldsymbol{x}) \tag{3}$$

If H is smaller than the discrimination determination threshold value $H_{\rm th}$, the movement with the highest *aposteriori* probability becomes the result of discrimination. Otherwise, if H exceeds $H_{\rm th}$, discrimination is suspended as obscure motion to prevent the ambiguous discrimination.

B. Manipulator control part

Figure 5 shows an outline of the manipulator control part. Here, control commands (e.g., move spoon left, eat, etc.) for My Spoon are allocated to the selection menu as layer-based GUI choices. The user performs control via EMG signals and operates the manipulator while looking at command selections on the monitor.

My Spoon control consists of three stages: initialization of the spoon position for eating (Stage A); area selection from the four separate areas of the food tray (Stage B); and setting of local position and eating (Stage C). The details are shown in Table I.

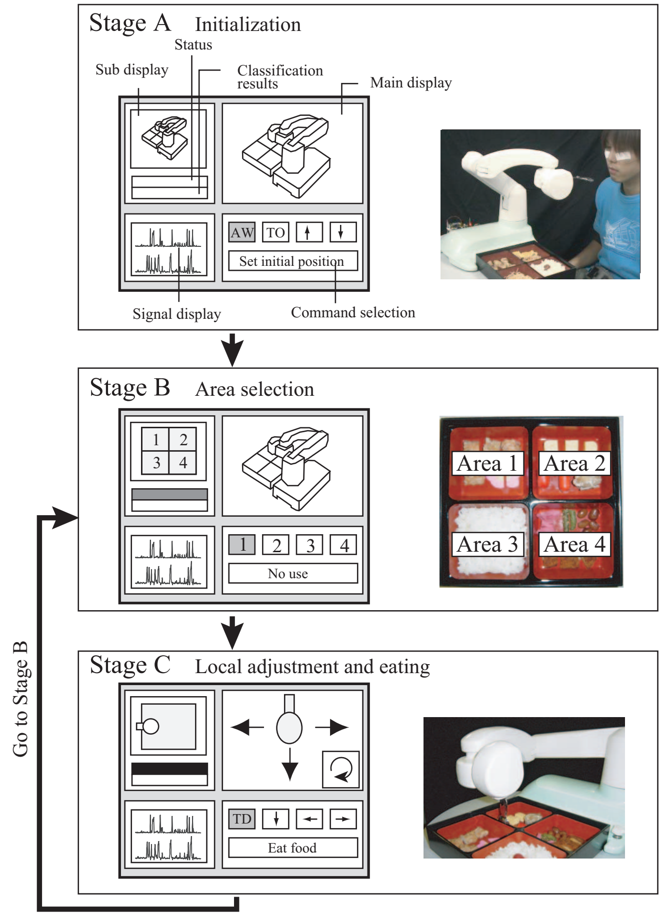


Fig. 5. Outline of manipulator control

In Stage A, the user moves the spoon (i.e., the tip of the robot manipulator) and sets the eating position according to the sitting posture and the mouth position. After this setup, the spoon is moved to the initial position automatically, and operation moves to Stage B.

The user selects the eating area of the food tray in Stage B, and the manipulator moves to the top left-hand corner of the selected area. In Stage C, the user controls the robot using adjustment commands (move left, right, closer to body and rotate spoon) to eat from the selected area. Selecting the eat command at the desired position in the selected area makes the robot pick up the food and move it to the eating position (as set in Stage A). After the user eats the mouthful, the robot returns to its initial position, and operation moves back to Stage B. The user can then select an area of the food tray and move through Stages B and C again.

Here, manipulator operation includes five commands in each layer (see Table I). The system introduces a command movement and selection method in manipulator operation, allowing the user to work it even if the number of motions (i.e., those the user can voluntarily conduct) is less than five. As an example, if the user can conduct two motions ($C = 2$), all commands can be selected by allocating the motions "command change (motion 1)" and "decision (motion 2)".

TABLE I

MY SPOON COMMAND GROUPS AND STAGES

Stage A: Initialization of eating position	
AW: Away	Move spoon away from mouth
TO: To	Move spoon to mouth
↑	Move spoon upward vertically
↓	Move spoon downward vertically
SP: Set initial position	Finish setup and move spoon to initial position
Stage B: Selection of food tray area	
Area 1	Move spoon to area 1 in food tray
Area 2	Move spoon to area 2 in food tray
Area 3	Move spoon to area 3 in food tray
Area 4	Move spoon to area 4 in food tray
No use	
Stage C: Local position setting and eating	
→	Move spoon left
←	Move spoon right
↓	Move spoon closer to body
TD: Turn direction	Rotate spoon 90 clockwise
EF: Eat food	Pick up food and move spoon to mouth

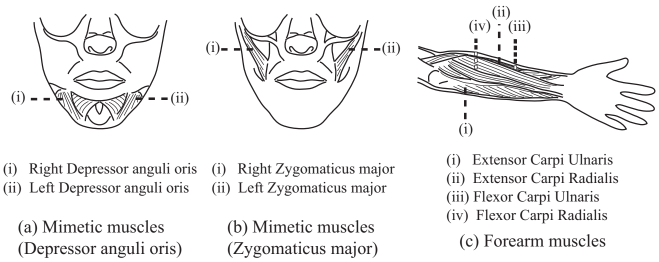


Fig. 6. Electrode locations

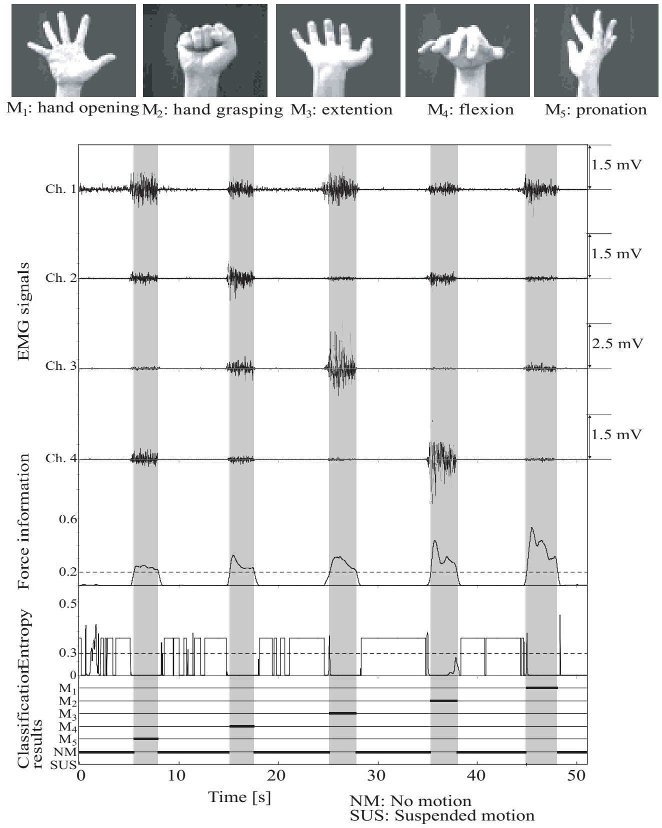


Fig. 7. Examples of measured EMG signals and classification results (Subject A)

III. Experiments

To verify the validity of the proposed method, EMG classification experiments and operation experiments were conducted.

A. Experimental conditions

The subjects were four healthy males (A – D; average age: 22.7 ± 0.58) and a patient with paralysis resulting from a cervical spine injury (E; 51 years old). Subject E, who was injured at the fifth cervical vertebra, had function C5 (ADL total assistance level due to quadriplegia). He usually needs full assistance for eating at mealtimes. Informed consent was obtained from all subjects.

In the experiments, electrodes were attached to three different locations for the EMG measurement: (a) the depressor anguli oris muscles ($L = 2$; on the right and left sides); (b) the zygomaticus major muscles ($L = 2$; on the right and left sides); and (c) the forearm muscles ($L = 4$; right hand; extensor carpi ulnaris, extensor carpi radialis, flexor carpi radialis and flexor carpi ulnaris), as shown in Fig. 6. This paper assumes that the patients with cervical spine injuries select to use from these muscles according to their physical conditions. Using the depressor anguli oris muscles and the zygomaticus major muscles, three motions ($C = 3$; muscle contraction on the right side, the left side and both sides) were discriminated. For the forearm muscles, there were six motion classes ($C = 6$; right hand: hand grasping/opening, wrist flexion/extension, and pronation/supination). Each subject conducted the individual motions for a period of about 1 s, and the system measured the EMG patterns. For Subject E, operation with the forearm muscles was not conducted due to paralysis.

In the LLGMN learning process, 20 EMG patterns were extracted from the signals for each operation, and the teacher signals consisted of $C \times 20$ patterns (where C is the number of motions). In addition, the threshold of F_{th} was 0.3, and that of H_{th} was 0.2 determined by preliminary experiments. The learning processes were finished within a few seconds in all cases.

B. EMG classification experiments

The EMG patterns measured during the user motions were discriminated using the LLGMN. Examples of these signals and the classification results (Subject A; forearm motion) are given in Fig. 7, which shows measured EMG signals, force information, entropy and classification outcomes. The shaded area indicates the time during which F_{EMG} was greater than F_{th}. It can be seen that EMG patterns with different features were observed in each motion, and that the system was able to classify the user's intended motion accurately.

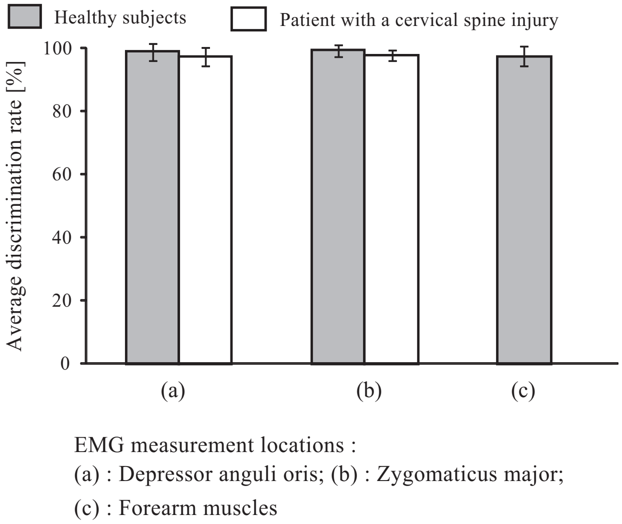


Fig. 8. EMG pattern discrimination rates

Figures 8 shows the EMG pattern classification rates calculated from 1000 test samples in each class for the three measurement locations, and indicates relatively high values in all cases. A high level of discrimination accuracy can be achieved using the LLGMN, and the approach can be considered applicable to practical feeding-robot operation even if the experimental conditions (e.g., the number of operations and the measurement positions) are changed. These results lead us to conclude that the system can be used to estimate intended motions (including for patients with paralysis) with a high level of accuracy.

C. Operation experiments

In the experiments, the subjects were asked to select from areas 2 and 3, and to eat freely. For manipulator control using facial muscles, the motions were allocated as M_1: move to next command selection; M_2: move to previous command selection; and M_3: execute selected command. In operation using forearm motion, five motions were allocated directly to each command. All subjects were allowed to practice with the proposed system for a few minutes in advance.

An example of the operation results (for Subject A) based on the use of EMG signals measured from the zygomaticus major muscles are shown in Fig. 9. The figure plots smoothed and filtered EMG signals, force information, classification results, and stages and selected commands. The shaded area shows the time during which F_{EMG} was greater than F_{th}. The photographs in Figs. 9 (a)–(c) highlight each stage of operation.

The figure shows that the subjects were able to perform voluntary EMG signal control and select individual commands using only three eye motions. For example, position initialization finished at 12 s, and operation moved to Stage 2. Area 2 was then selected (Stage 2; 15.5 s), and the manipulator tip was used to pick up food (Stage 3; from 16 to 28 s). In response to EMG operation by the user at 28 s, the manipulator moved to the eating position and the subject ate the mouthful. No command input errors were observed during the experiments.

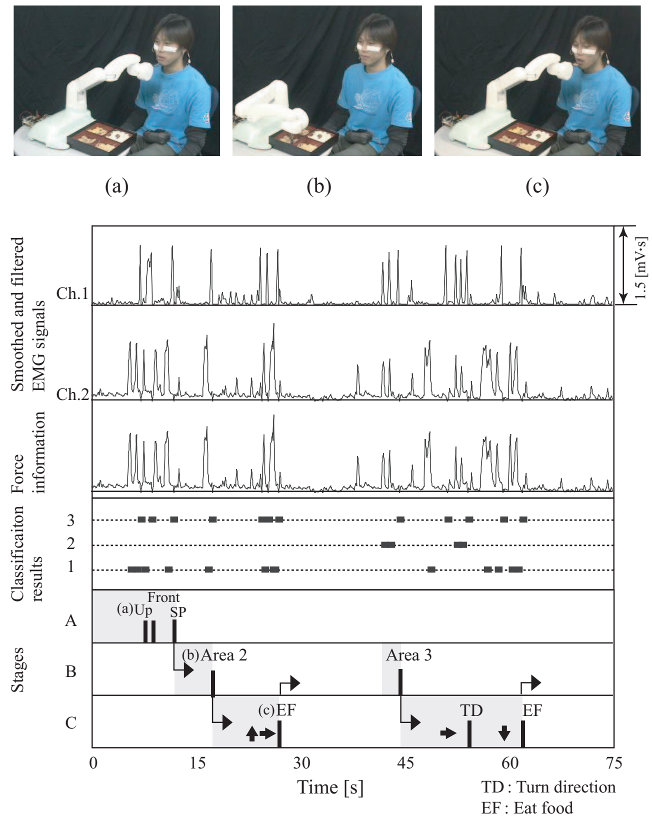


Fig. 9. Example of experimental results

As all subjects (including the one with paralysis) were able to control the manipulator and eat using the proposed method, we conclude that the system supports feeding for individuals with severe physical disabilities such as paralysis caused by cervical spine injuries.

Finally, operability with the proposed method was compared with that seen in experiments on joystick-based manipulator operation involving Subjects B and C. Standard joystick and manual mode [3] was utilized for joystick operation. In the manual mode [3], by moving the joystick in four directions (up, down, left, right), any food item within the included tray can be eaten in any desired order. Details of joystick-based operation are almost same as the proposed method, and are outlined as follows: 1. select the compartment from the included tray; 2. after the spoon reaches the compartment, use the joystick to fine-tune its position near the item; 3. instruct the spoon to grasp the food; and 4. the spoon grasping the item automatically approach the mouth.

The subjects were asked to eat the food in areas 1, 3 and 4. In EMG signal-based operation, electrodes were set on the zygomaticus major muscles (Fig. 6 (b)), and three eye motions ($C = 3$; muscle contraction on the right side, the left side and both sides) were utilized. The other parameters

TABLE II

RESULTS OF COMPARISON EXPERIMENTS

		Subject B	Subject C	Subject D
Joystick	Mean [s]	84.4	89.4	87.0
	Standard deviation [s]	1.14	0.89	2.12
EMG switch	Mean [s]	94.6	94.8	95.6
	Standard deviation [s]	2.61	1.10	2.41

of the proposed method were the same as those outlined in III-A. Five trials were performed, and the experiments lasted about an hour.

The results are shown in Table II, in which each value represents the average for all the trials. It can be seen that the difference between the operation methods was small, although EMG operation took longer. These outcomes indicate that operability with the proposed method does not differ greatly from that of joystick operation. Further investigation of the capabilities of each method will be necessary in future work.

IV. CONCLUSION

This study investigated a novel control system for the My Spoon feeding robot based on EMG classification. The system measures the user's EMG signals during various motions such as wrist flexion/extension and eye motion, and estimates intended motions using a probabilistic neural network. The user can voluntarily control the manipulator to support eating tasks by selecting operation commands using EMG signals.

EMG classification accuracy and operability with the proposed method were verified in experiments involving five subjects. The results showed that EMG signals measured from healthy individuals and a patient with paralysis caused by a cervical spine injury could be classified accurately, and that the subjects were able to control the manipulator to eat as desired.

In future work, we plan to investigate operability using the proposed method with an increased number of subjects (including forearm amputees and muscle dystrophy patients) and a wider range of eating-related tasks and EMG measurement locations. We also plan to discuss the optimal electrodes locations for individuals, mental workload and risk and safety of the proposed method for subjects.

V. ACKNOWLEDGMENT

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