The Cybernetic Rehabilitation Aid: Preliminary Results for Wrist and Elbow Motions in Healthy Subjects

Erhan Akdogan, *Member, IEEE*, Keisuke Shima, *Member, IEEE*, Hitoshi Kataoka, Masaki Hasegawa, Akira Otsuka, and Toshio Tsuji, *Member, IEEE*

***Abstract*—This paper proposes the cybernetic rehabilitation aid (CRA) based on the concept of direct teaching using tactile feedback with electromyography (EMG)-based motor skill evaluation. Evaluation and teaching of motor skills are two important aspects of rehabilitation training, and the CRA provides novel and effective solutions to potentially solve the difficulties inherent in these two processes within a single system. In order to evaluate motor skills, EMG signals measured from a patient are analyzed using a log-linearized Gaussian mixture network that can classify motion patterns and compute the degree of similarity between the patient's measured EMG patterns and the desired pattern provided by the therapist. Tactile stimulators are used to convey motion instructions from the therapist or the system to the patient, and a rehabilitation robot can also be integrated into the developed prototype to increase its rehabilitation capacity. A series of experiments performed using the developed prototype demonstrated that the CRA can work as a human–human, human–computer and human–machine system. The experimental results indicated that the healthy (able-bodied) subjects were able to follow the desired muscular contraction levels instructed by the therapist or the system and perform proper joint motion without relying on visual feedback.**

***Index Terms*—Direct rehabilitation, electromyography (EMG), human–machine–human interface, rehabilitation robot, tactile feedback.**

I. INTRODUCTION

THE DEMAND for rehabilitation related to human movement increases daily as a result of disease, occupational/traffic accidents and population growth. The evaluation and teaching of motor skills in patients represent two important aspects of motor skill training, and both areas must be addressed in order to make such training effective. However, because of the redundant degrees of freedom that exist in the human musculoskeletal system, the same joint trajectory and/or joint torque can be achieved through different muscular combinations, meaning that muscle activity as well as joint trajectory and/or joint torque must be considered. As muscle activity is closely related to the coordination of multiple muscles (a key competency in realizing motor skills), electromyography (EMG) can be used effectively to evaluate such activities on a muscular level.

A number of researchers have used EMG signals to evaluate patient performance during training or exercise sessions. Morita *et al.*, for example, used an impedance-controlled XY table for upper-limb exercises. In order to quantify the physical condition of the subjects, they measured the EMG and the position/angles of upper-limb joints during exercise [1]. Lee *et al.* developed a haptic device system for a training program. To investigate the functional effects of this system, grip position, velocity, grip force and EMG signals were measured during a reaching task [2].

Conveying therapist's instructions to patients is another important issue that remains to be resolved for effective motor skill training. This can be performed by a therapist or a computerized training system, but in either case, the provision of effective feedback channels to patients is necessary. This is not easy because in the process of motor skill teaching, the therapist cannot stimulate all the necessary limbs and muscles of the patient simultaneously due to the limited motion of the human body. In state-of-the-art rehabilitation, teaching should be performed directly by the therapist with the help of biofeedback; in the present study, this is called *direct rehabilitation*, and it allows the therapist to perform direct teaching. At this point, the study of Lieberman and Breazeal stands out [3]. They designed a wearable vibrotactile feedback suit for improved motor learning. If an error occurs while a constant trajectory is being followed on the screen, the system can stimulate the subject's body surface via tactile feedback [3].

Over the last decade, the implementation of rehabilitation robots such as human–machine systems that use intelligent techniques and aim to convey the therapist's motion capability to the patient has gained momentum [4]. However, related studies have generally been developed based on the learning of therapy motion using force and position feedback, but these techniques

Manuscript received November 15, 2011; revised March 16, 2012; accepted April 09, 2012. Date of publication June 08, 2012; date of current version September 07, 2012. This work was supported in part by the 21st Century COE Program of Japan Society for the Promotion of Science on Hyper Human Technology toward the 21st Century Industrial Revolution.

E. Akdogan is with Mechatronics Engineering, Yildiz Technical University, Istanbul 34349, Turkey (e-mail: eakdogan@yildiz.edu.tr).

K. Shima is with the Graduate School of Biomedical & Health Sciences, Hiroshima University, Hiroshima 734-8551, Japan (e-mail: shima@bsys.hiroshima-u.ac.jp).

H. Kataoka and T. Tsuji are with the Graduate School of Engineering, Hiroshima University, Hiroshima 734-8551, Japan (e-mail: kataoka@bsys.hiroshima-u.ac.jp; tsuji@bsys.hiroshima-u.ac.jp).

M. Hasegawa and A. Otsuka are with the Department of Physical Therapy, Prefectural University of Hiroshima, Mihara City 723-0053 Hiroshima, Japan (e-mail: m-hasegawa@pu-hiroshima.ac.jp; otuka@pu-hiroshima.ac.jp).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TNSRE.2012.2198496

cannot detect muscular activation and change the rehabilitation process accordingly. A system that directly applies the therapist's commands (i.e., muscle contractions) to the patient, combined with the ability to ascertain and evaluate the patient's muscle activation, is expected to provide a number of important benefits in motor skill training. Most previous rehabilitation studies have used human–machine or human–computer interfaces, and no research using human–human or human–machine–human interfaces appears in literature.

To solve the problems of evaluation and teaching in motor skills simultaneously within a single human–machine–human system, the authors have proposed a cybernetic rehabilitation aid (CRA) using the concept of direct teaching via tactile feedback with an EMG-based motor skill evaluation function. In the previous work, the first prototype of a conceptual CRA was developed, and the preliminary experimental results of this prototype have been published [5], [6]. In contrast, the newly developed CRA in this paper includes a human–machine–human (patient–rehabilitation robot therapist) interface known as a cybernetic interface platform (CIP) that uses biological signals not only to monitor and evaluate patients' motor skills but also to teach such skills. Direct rehabilitation can be performed even in web-based environments using the proposed CRA, enabling the difficulties inherent in transferring patients to medical centers to be eradicated. Also, the CIP can be used as a human–machine (patient–rehabilitation robot) system and a human–computer (patient–computer) system as well as a human–human (therapist–patient) system which allows direct communication and instruction transfer between therapist and patient, so that multiple patients can be treated by a single therapist. Owing to the human–machine–human interface implemented in the proposed CRA, a patient can be treated with therapist instructions and a rehabilitation robot therapy capability. So, it is simultaneously benefited from expertise of therapist and advantages of usage of a rehabilitation robot. In order to evaluate motor skills, the motions of the therapist and patient are analyzed using a log-linearized Gaussian mixture model (LLGMN) [7] that can classify motion patterns via EMG signals. Tactile stimulators that are safer than electrical stimulation (ES) are used to convey the instructions of the therapist or the system to patients. In the experiments performed in this paper, a therapeutic exercise machine known as the biodex multijoint system was integrated into the system developed to increase its rehabilitation task capacity.

II. Cybernetic Rehabilitation Aid System

A. Main Concept

The major elements of the CRA concept are the patient, the cybernetic interface platform, the therapist and a rehabilitation robot. The CRA system (shown in Fig. 1) is managed by a CIP that can be used as a human–computer (HCI), human–human (HHI) or human–machine interface (HMI). Instruction commands can be generated by the CIP or the therapist. If they are generated by the CIP and the patient performs the necessary motor functions without the rehabilitation robot, the setup works as a human–computer system. In the same situation where commands are generated by the therapist directly, it works as a human–human system. If the patient uses the rehabilitation robot to perform the instructed motor function and is rehabilitated with CIP commands, then the setup works as a human–machine system. Furthermore, the system has a flexible structure to enable its use as a human–machine–human interface. In this paper, we outline the details and experimental results for HHI, HCI, and HMI operations. Those for human–machine–human interface operation will be given in a future study.

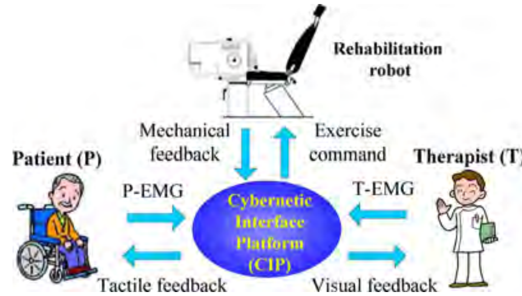

Fig. 1. Main concept of CRA. Patient, therapist, cybernetic interface platform and a rehabilitation robot are major elements of CRA. CRA system can work as a human–human (therapist–patient), human–machine (patient–rehabilitation robot), human–computer (patient–computer) and human–machine–human (therapist–rehabilitation robot–patient) system. Muscular activations of the therapist and the patient are detected using EMG signals, and instruction commands are sent to patient through tactile stimulators. In order to perform necessary movements such as isometric exercise, a rehabilitation robot is integrated into the system, which is managed by CIP.

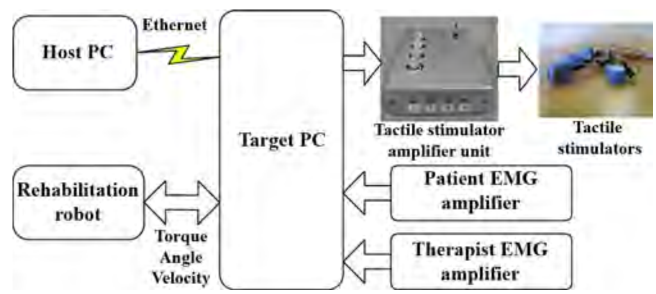

Fig. 2. CRA system setup.

B. System Implementation

The CRA system setup (shown in Fig. 2) consists of two EMG amplifiers, tactile stimulators with an amplifier unit, two DAQ cards and a rehabilitation robot. The components of the system are described as follows.

1) EMG Amplifiers and DAQ Cards: The system uses four-channel EMG amplifiers (EMG-025 with EMG-BB04, Harada Electronics Industry Ltd.) to measure the EMG signals of the therapist and the patient. A/D data conversion is performed using National Instruments NI 6024E 12-bit Multifunction Data Acquisition (DAQ) cards with a sampling time of 0.001 s.

2) Tactile Stimulators and Amplifier Unit: Teaching and/or muscle activation via tactile feedback are extremely important in rehabilitation. To this end, ES has been used in some studies [8]–[10], especially for the sensory feedback. However, electrical stimulation application may result in accidents and/or pain, and its use requires expertise. We therefore adopted tactile stimulators (VBW32C, Audiological Eng. Corp.), which are

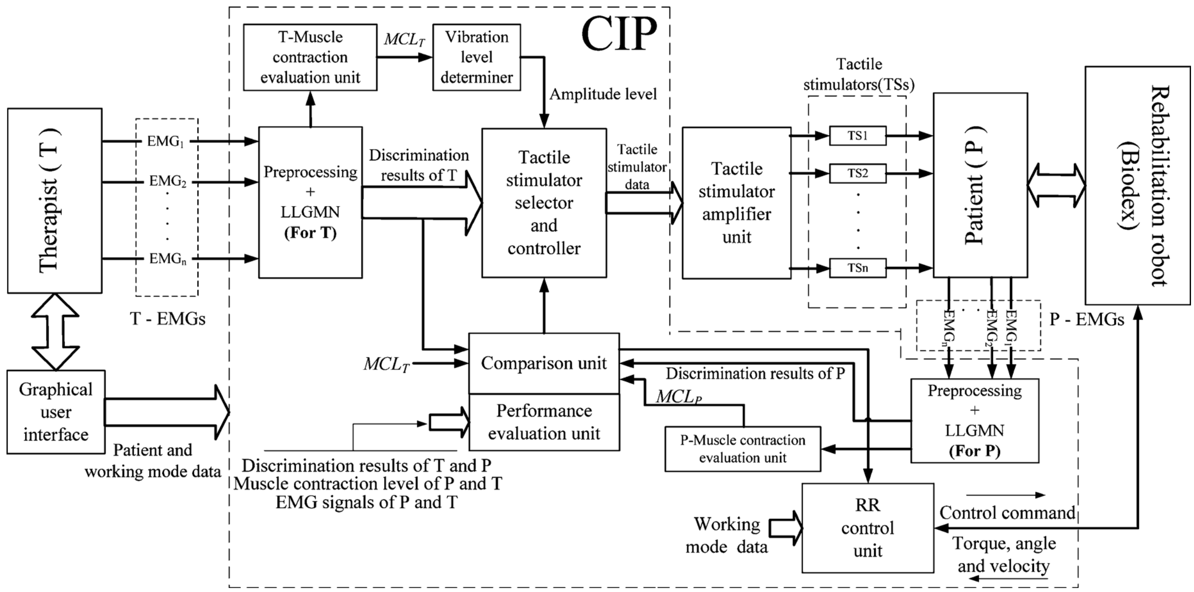

Fig. 3. Detailed block diagram of CIP.

safer than electrical stimulation. A tactile stimulator (TS) is a device that generates tactile sensations against the skin of the user. It has an ideal working frequency of 250 Hz and a nominal voltage of 2.5 V (rms). To drive the tactile stimulators, an amplifier unit encompassing a Motorola MC34119 Low Power Audio Amplifier was designed. A tactile stimulator can be driven by sinusoidal or square wave signals; with the former, the vibration level is adjusted using the signal's amplitude; with the latter, it can be adjusted using its duty cycle. In this study, we used sinusoidal signals.

3) Rehabilitation Robot: To enable the performance of actual rehabilitation tasks and increase the system's scope of application, a Biodex Multi-Joint System 2-AP was used as a rehabilitation robot in the prototype. This model can be used in the testing and rehabilitation of knee, ankle, hip, shoulder, elbow, and wrist joints. The modes of operation cover isokinetic (concentric), isometric, eccentric and passive (continuous) movements [11]. The controller provides the three analogue outputs of torque, velocity and angle that are picked up by the CIP to enable monitoring of the patient and the process during rehabilitation.

4) Software: MATLAB/Simulink and its graphical user interface specifications were used as a platform for the development of the system and were supported by Microsoft Visual C + + 6.0 software to enable the use of MATLAB's S-function feature for complex algorithms. For rapid prototyping, the system uses xPC Target.

C. Cybernetic Interface Platform

The CIP is the central processing unit of the CRA. It receives and evaluates EMG signals from the patient and therapist as well as the output parameters of the Biodex. In line with the results of this evaluation, it controls the Biodex system and the tactile stimulators attached to the skin surface of the patient and/or the therapist. The graphical user interface (GUI) can be used to control the CIP, which permanently provides visual feedback to the therapist to enable monitoring of the patient's performance during rehabilitation. A detailed block diagram of the CIP is shown in Fig. 3, and explanations are given as follows.

1) Preprocessing and LLGMN Units: The CIP includes two preprocessing units—one for the therapist and the other for the patient. EMG signals measured from the muscles of the therapist and the patient with L pairs of electrodes positioned on the muscles dominant (see Section III-A) are amplified, rectified and filtered (using a second-order Butterworth filter with a cutoff frequency of 1 Hz) and are digitized using a DAQ card in the preprocessing unit. It should be noted that the low-pass filter here is used as an integrator of for the rectified EMG to get obtain an estimate of the muscle force. These sampled signals are defined as $EMG_i(t)$ $(i = 1, 2, \ldots, L)$. Then, the $EMG_i(t)$ values are normalized so that the sum of L channels equals one [7], [12]–[14]

$$EMG'_i(t) = \frac{EMG_i(t) - EMG_i^{\text{rest}}}{\sum_{i=1}^{L}(EMG_i(t) - EMG_i^{\text{rest}})} \quad i = 1, 2, \ldots, L \tag{1}$$

where $EMG'_i(t)$ represents the normalized EMG signals, and EMG_i^{rest} is the mean value of $EMG_i(t)$ while the arm is relaxed. The normalized EMG signals $EMG'_i(t)$ are used for motion estimation. Since the EMG signals have the nonstationary characteristics and are greatly influenced with individual differences, it is difficult to estimate accurately the intended motions from multichannel EMG patterns using a simple thresholding. Therefore, EMG signals are sent to the LLGMN unit for motion classification. LLGMN [7] is based on the Gaussian mixture model (GMM) and the log-linear model of the probability density function (pdf), and the *a posteriori* probability can be 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 motion patterns with individual differences, thereby enabling precise pat-

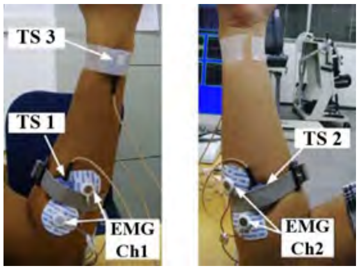

Fig. 4. Positions of EMG electrodes and tactile stimulators. In this study, tests were carried out for wrist extension and flexion motions, and instruction commands were sent to patient through tactile stimulators. To enable this, EMG electrodes were placed on extensor (Ch1) and flexor (Ch2) muscles. Tactile stimulators TS1 and TS2 were used for extension and flexion, respectively, while TS3 was placed in an independent third position on the limb. TS3 was activated when a negative difference between the MCL [see (2)] of the therapist (or system) and that of patient occurred.

tern recognition for bioelectric signals such as EMG and EEG [7], [14]. In particular, Fukuda *et al.* [14] confirmed that the LLGMN can accurately classify EMG patterns measured from forearm muscles and applied the network for human-assisting manipulator control. On the basis of this idea, the CIP allows classification of the measured EMG signals using LLGMN.

In the CIP, the system first instructs the user to perform C types of motion one by one. 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 calculate the similarity between patterns in the user's motions and trained motions as *a posteriori* probabilities by inputting the newly measured (untrained) vectors to the LLGMN. Discriminating the motion with highest probability calculated as a user's intended motion, multiple motions can be estimated from the EMG signals measured.

2) Muscle Contraction Evaluation (MCE) and Vibration Level Determiner Unit: The MCE unit calculates the muscular contraction level *(MCL)* defined as follows:

$$MCL(t) = \frac{1}{N}\sum_{n=1}^{N}\frac{EMG_n(t) - EMG_n^{\mathrm{rest}}}{EMG_n^{\max} - EMG_n^{\mathrm{rest}}} \qquad (2)$$

where EMG_n^{rest} and $EMG_n^{\max}$ are the mean values of $EMG_n(t)$ while the corresponding muscle is relaxed and while the maximum voluntary contraction is maintained, respectively. Here, n $(n = 1, \ldots, N)$ is the channel number in Ξ, where Ξ is a set consisted of focused channel numbers for calculation of the MCL and N is the number of elements in the set Ξ. As an example, if Ξ includes all the channels, (2) means the average contraction level of all the recorded muscles. In the other case, the MCL can describe the specific muscle contraction level by selecting the specific channels defined as Ξ.

The control signal (CS) of the tactile stimulator is given as follows:

$$\mathrm{CS} = A\sin(2\pi f t) \qquad (3)$$

where A is the amplitude of the control signal and f is the frequency of the signal (selected as 250 Hz in this study). The value of A is determined by the vibration level determiner unit using the difference between the MCL values of the therapist (or the system) and the patient. The vibration level determined is sent to the tactile stimulator selector and controller unit.

3) Tactile Stimulator Selector and Controller Unit: First, this unit determines which tactile stimulators should work according to the classified motion data. Then, in line with the vibration level of the tactile stimulator from the vibration level determiner unit and the motion data from the LLGMN unit, it determines the driving signals for the tactile stimulators and sends the information to the tactile stimulator amplifier unit. If the LLGMN output does not activate, then the system generates a motion classification error signal and the tactile stimulators do not activate. The users can observe this situation through the graphical user interface and the tactile feedback display.

4) Comparison and Performance Evaluation Unit: In the comparison unit, the motion patterns of the therapist and patient are compared, and the tactile stimulators are controlled according to the output of the unit. The details of this process are explained in Section III-A. The performance evaluation unit is used to assess patient performance during the rehabilitation session. For a detailed explanation, see [5].

5) Rehabilitation Robot Control Unit: This unit controls the rehabilitation robot according to the working mode selected by the therapist through the GUI. It sends control commands to the actuators of the rehabilitation robot according to the selected exercise mode. Data on angles, torque and velocity generated by the patient are also received via this unit.

III. Experiments

A. Methods

A series of experiments was carried out to evaluate the performance of the developed system and human response to tactile stimulation through the CRA. Two groups of four test subjects (A, B, C, D) were selected to participate in the experiments. The test subjects were aged between 20 and 24. The first group (G1) conducted the test series without the use of the Biodex, while the second group (G2) used it. In the experiments, the system was used in HCI, HHI and HMI mode. In HHI mode, instruction commands were generated by the therapist (referred to in this case as the virtual therapist). For HCI and HMI mode, the commands were generated by the system. Furthermore, a step function and a sinusoidal function were used as test commands. During the experiments, the subjects' eyes were covered with a mask to enhance concentration, and no feedback other than tactile stimulation was provided.

The working modes were controlled with a closed-loop control system. The two parameters used to transfer commands to the patient were motion direction (or motion classification) and muscular activation level. In this study, focus was first placed on wrist motion with extension and flexion. Two EMG channels were used to gather muscular contraction data. EMG electrodes were placed on the wrist extensor (Ch. 1) and flexor (Ch. 2) muscles (see Fig. 4). For feedback, three tactile stimulators were used to convey commands to the patients. These were positioned on muscles dominant to the observed motion (i.e., the

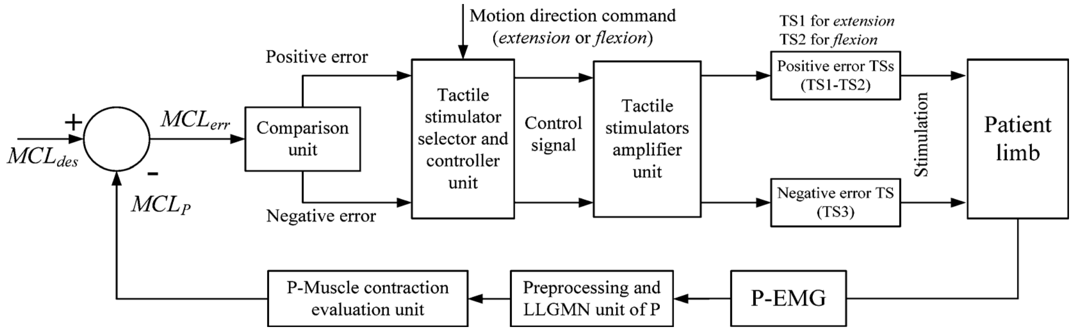

Fig. 5. Closed-loop control block diagram. Tactile stimulators are controlled by a closed-loop control system, which continuously compares the difference between muscular contraction level of therapist (or system), $\mathrm{MCL}_{\mathrm{des}}$, and that of the patient, MCL_P. If this difference is positive, the positive error tactile stimulators (TS1 or TS2) are activated in line with the motion direction command. If a negative error occurs, the tactile stimulator (TS3) is activated.

extensor and flexor muscles) and are referred to here as *positive-error tactile stimulator*s (TS1 and TS2). The third one, called the *negative-error tactile stimulator* (TS3), was placed at an independent third position on the patient's forearm (Fig. 4).

A block diagram of the closed-loop control is shown in Fig. 5. All channels are selected in the set Ξ for calculation of MCL, that is, $N = L$, in the experiments. The difference between the desired muscular contraction level $(\mathrm{MCL}_{\mathrm{des}})$ generated by the system or the therapist and the muscular contraction level of the patient (MCL_P) are continuously detected by the system. This difference $(\mathrm{MCL}_{\mathrm{err}})$ is analyzed by the comparison unit, which determines whether the error value is positive or negative. The corresponding tactile stimulator is selected according to the error value, and stimulation is initiated. The tactile stimulation amplitude is adjusted in accordance with the error signal so that the patient can actually feel the level of error.

The outlines of each working mode in the experiments are as follows.

1) HCI Mode: In this mode, commands were generated by the system and sent to the patient through the tactile stimulators without any visual feedback. In order to analyze the performance of the test subjects in HCI mode, a step function command was applied and the subjects were asked to follow the command as quickly as possible. The performance of the test subjects in the flexion and extension directions was analyzed using the trajectory-following error and steady-state error parameters. Twenty trials were carried out for each test subject. In the next step of the experiments, the responses of the test subjects to continuously changing values of desired commands were evaluated. A series of sinusoidal waves was used for the desired trajectories in the experiments. Each test had a total duration of 70 s, and the series of the sinusoidal inputs was repeated three times for flexion and three times for extension. Each test subject performed this pattern 20 times, with the task being to follow the given trajectory. The results were evaluated in consideration of the trajectory-following error and correlation.
2) HMI Mode: The patients performed rehabilitation tasks with the Biodex and commands generated by the system. Here, parameters such as joint torque, joint velocity and limb angle can be monitored by the CIP. The system was basically operated using step function commands to analyze the test subjects, who were asked to follow the commands as quickly as possible. The Biodex was used in isometric mode, and the subjects' performance in the directions of extension and flexion was analyzed using the trajectory-following error and steady-state error. Twenty trials were carried out for each test subject. Sinusoidal commands were also applied to the test subjects under a procedure similar to that applied in the HCI experiments.
3) HHI Mode: In this mode, the therapist's commands are directly transferred to the patient. In this set of tests, the therapist gave six repeated commands (three for extension and three for flexion) with a time frame of 60 s. The patients were asked to follow the trajectories given by the therapist, and each subject performed 20 trials. Evaluation of the test results again consisted of examination regarding the trajectory-following error and the correlation coefficients in the same way as for the HCI and HMI modes. The CIP receives and classifies the EMG signals of both the therapist and the patient, compares their muscular contraction levels, and generates control signals for the tactile stimulators according to the error of the muscular contraction level.

Then, direct teaching experiments were also carried out to verify the validity of the proposed rehabilitation concept in EMG pattern teaching through comparison with a teaching-by-showing approach. In this regard, another group of three test subjects consisting of healthy males aged between 20 and 24 (E, F, G) was selected. The teaching motion focused on the four movements of flexion (Motion 1: M1), extension (Motion 2: M2), supination (Motion 3: M3), and pronation (Motion 4: M4) of the right elbow joint. Electrodes and oscillators were attached to the skin surface near four muscles (Ch. 1: biceps brachii; Ch. 2: triceps brachii; Ch. 3: brachioradialis; Ch. 4: flexor carpi radialis) on each subject. The therapist's arm motions were first shown to each individual, who was then asked to repeat the motion. The EMG patterns generated from the subjects were then evaluated before and after teaching by means of tactile feedback. It should be noted that the tactile stimulation signals were prepared based on the therapist's EMG patterns and conveyed to each subject as the desired patterns.

Finally, since the achievement of muscle activation as intended does not necessarily guarantee that the desired movement will be generated, the possible use of joint kinematics in isolation or in combination with muscle activation as a control variable was explored to ensure that the desired movement was actually achieved. In this experiment, the joint trajectories seen during the motions were measured using goniometers (B2921, Biometrics Ltd.) attached to the wrists of the therapist and the patients, and the errors between these trajectories were transferred from the therapist to the patient in place of the EMG signals. That is, each tactile stimulator was activated in turn according to the joint trajectory error rather than the EMG error. The other conditions were the same as those of the experiments.

In the following section, the results of experiments in the HCI, HMI, and HHI working modes are outlined along with the details of human reactions to tactile stimulation in terms of step response, steady-state error, and trajectory-following error.

B. Results

1) *HCI Mode*: The step responses obtained from Group 1 are shown in Fig. 6(a), and the results of the analysis for 20 trials are shown in Fig. 6(b) and (c). The average trajectory-following errors obtained from the test subjects were 8.4% for extension and 8.4% for flexion. For the steady-state error, the average values for extension and flexion were 4.4% and 4.9%, respectively. According to these results, the test subjects were able to follow the desired muscular contraction level commands from the tactile stimulators.

   An example of the experimental results for the responses of continuously changing value is shown in Fig. 7. As can be seen, the CIP generates the desired command according to the parameters entered through the graphical user interface (see the fourth figure from the top in Fig. 7). These parameters are the muscular contraction level, the activation time for repetition, the number of repetitions and the interval between two commands. The CIP receives and classifies the measured EMG signals of the patient (the first three figures from the top), compares the desired muscular contraction level specified by the system and the resulting muscular contraction level of the patient (the fifth figure from the top) and uses the results to generate control signals for the tactile stimulators (the last three figures).

   In the experiments, the test subjects were able to follow the desired trajectory with an error of less than 12.1% (A1: mean $= 8.6\%$, SD $= 1.4\%$; B1: mean $= 10.0\%$, SD $= 1.0\%$; C1: mean $= 12.1\%$, SD $= 1.0\%$; D1: mean $= 10.0\%$, SD $= 0.9\%$), while their average correlation constants for trajectory following were between 0.85 and 0.92 $(\mathrm{A1} = 0.93,\ \mathrm{B1} = 0.92,\ \mathrm{C1} = 0.85,\ \mathrm{D1} = 0.92)$. These results indicate that the test subjects were able to follow the sinusoidal commands generated by the system with a high level of accuracy.

2) *HMI Mode*: The step responses of the test subjects using Biodex are shown in Fig. 8(a). Their performance in the directions of extension and flexion was analyzed using the trajectory-following error and steady-state error. The results of 20 trials are shown in Fig. 8(a) and (c) The average trajectory-following errors obtained from the test subjects were 6.4% for extension and 7.9% for flexion. For the steady-state error, the average values for extension and flexion were 2.2% and 2.9%, respectively. As can be seen from these results, the test subjects using the Biodex were able to follow the desired MCL commands from the tactile stimulators.

   An example of the experimental results for the sinusoidal commands is shown in Fig. 9. The subjects were able to follow the desired trajectory with an error of less than 16% (A2: mean, SD $= 12.7\%, 3.3\%$; B2: mean, SD $= 16.0\%, 4.1\%$; C2: mean, SD $= 13.8\%, 2.3$; D2: mean, SD $= 12.3\%, 1.9\%$). The average correlation constants for trajectory following were between 0.84 and 0.89 $(\mathrm{A2} = 0.88, \mathrm{B2} = 0.84, \mathrm{C2} = 0.84, \mathrm{D2} = 0.89)$. These results indicate that the CIP is able to classify patients' EMG

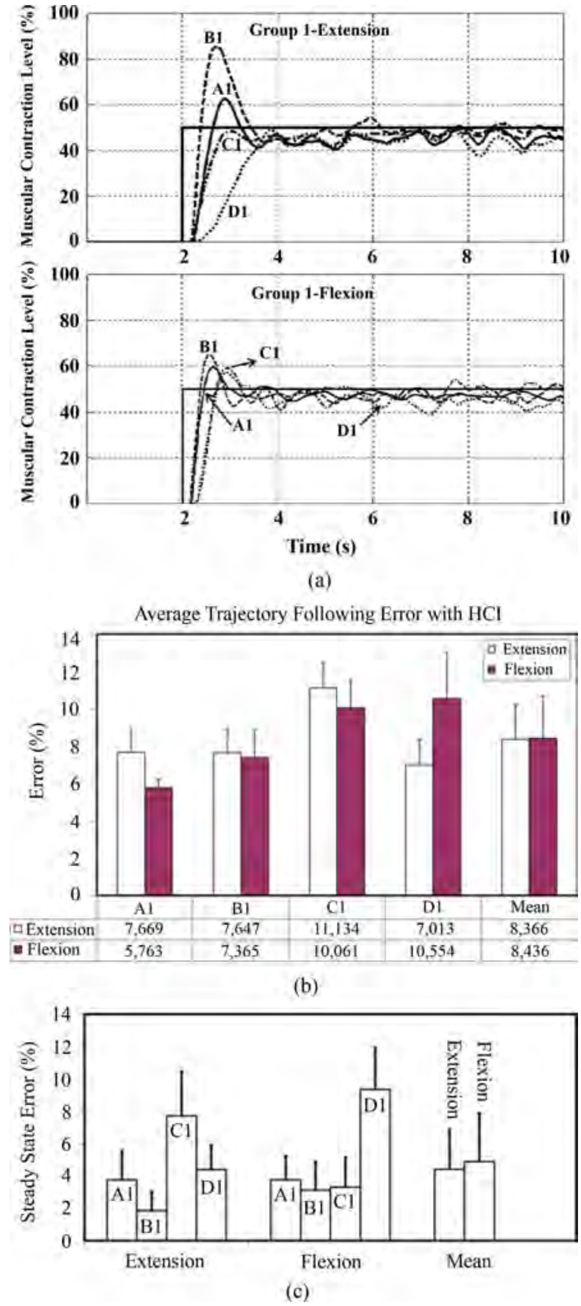

Fig. 6. (a) Step response of test subjects with HCI. (b) Average trajectory-following error. (c) Steady-state error. Mean values and standard deviations of all subjects for extension and flexion are shown in (b) and (c).

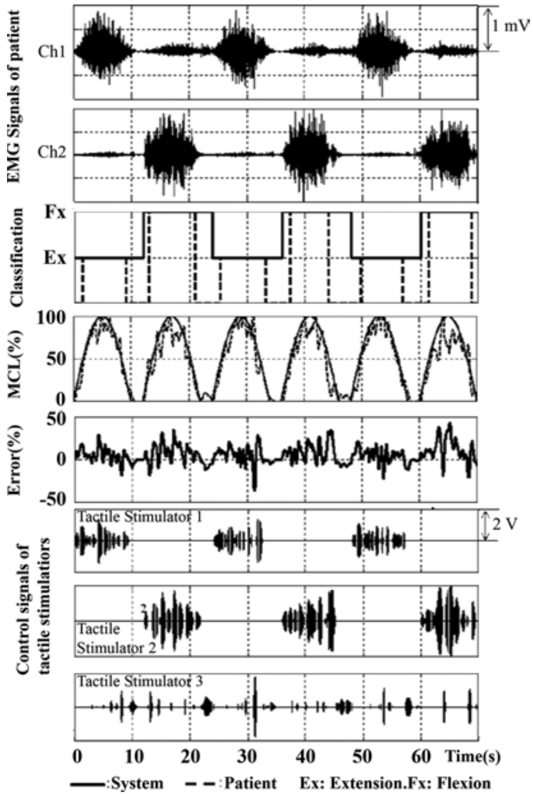

Fig. 7. Example of experimental results with HCI. This figure shows (from top to bottom) EMG signals of patient (test subject), motion classification results, desired and resulting muscular contraction levels ($\mathrm{MCL}_{\mathrm{des}}$ and MCL_P), MCL error and control signals for tactile stimulators. In the motion classification results, there are no signals from test subject at the beginning and end of motion for a short time because there is a threshold that prevents misclassification in the LLGMN algorithm. Tactile stimulators send vibrations to patient according to MCL error signal. As can be seen from bottom three figures, if the error is positive and direction is extension, then TS1 is activated; if error is positive and direction is flexion, then TS2 is activated; and if error is negative, then TS3 is activated. Consequently, patient can receive both motion information and force (MCL) information through tactile feedback.

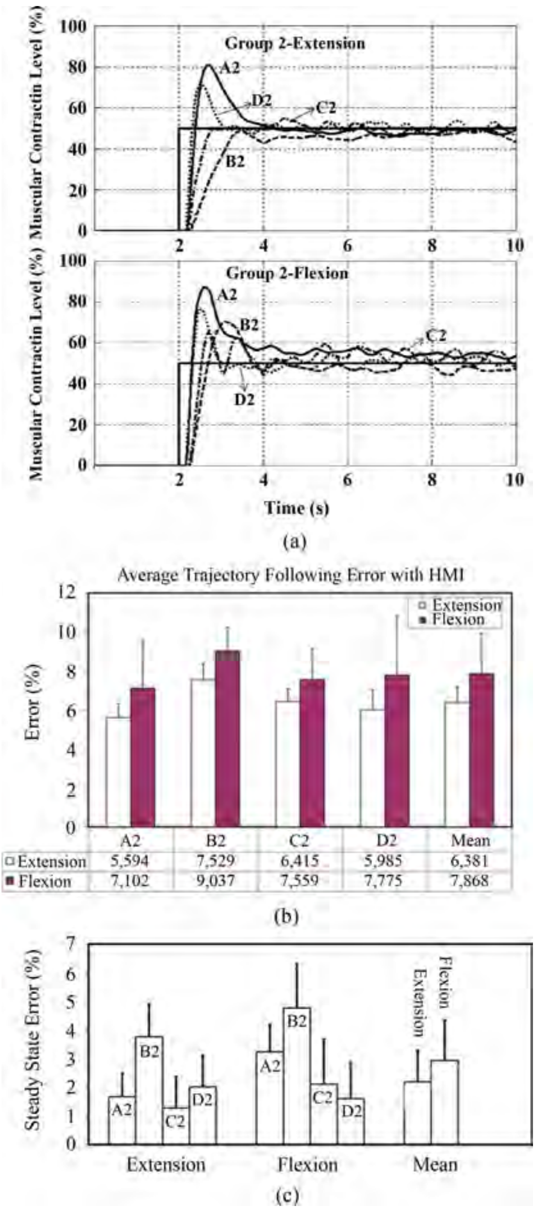

Fig. 8. (a) Step response of test subjects with HMI. (b) Average trajectory-following error. (c) Steady-state error. Mean values and standard deviations of all subjects for extension and flexion are shown in (b) and (c).

patterns, compare the desired muscular contraction levels in terms of system commands and resulting contractions by the patient, and then control the tactile stimulators according to the classification results and the control error of the patient.

3) *HHI Mode:* An example of the experimental results in the human–human communication and related photos are shown in Figs. 10 and 11, respectively. With the HHI, the test subjects were able to follow the desired (therapist's) trajectory with an error of less than 19.3% (A1: mean, SD $= 19.3\%, 1.9\%$; B1: mean, SD $= 16.0\%, 2.4\%$; C1: mean, SD $= 12.8\%, 1.9\%$; D1: mean, SD $= 14.1\%, 1.8\%$). The average correlation constants for trajectory following were between 0.68 and 0.83 $(\mathrm{A1} = 0.68, \mathrm{B1} = 0.70, \mathrm{C1} = 0.83, \mathrm{D1} = 0.79)$. The average error for each muscle activation level was 15.1% $(\mathrm{SD} = 21.0\%)$.

Fig. 12 presents examples of EMG signals obtained from the therapist and the patient during tactile feedback for direct teaching. It shows tactile stimulator signals computed from the therapist's measured EMG signals, which were rectified and normalized using the maximum value. The results of EMG pattern evaluation using the LLGMN before and after tactile teaching for each subject are shown in Fig. 13 and Table I. Overall discrimination rates improved by 24.6% compared with the teaching-by-showing approach.

An example of the experimental results in the joint trajectories communication from therapist to patient is also shown in Fig. 14. The subjects were able to follow the target joint trajectories with an average error of 20.5% $(\mathrm{SD} = 16.0\%)$.

IV. Discussion

A. HMI and HCI

The mean values of the trajectory-following errors for four subjects were calculated as 6.3% for extension and 7.86% for flexion with the HMI [Fig. 8(b)], and as 8.36% for extension

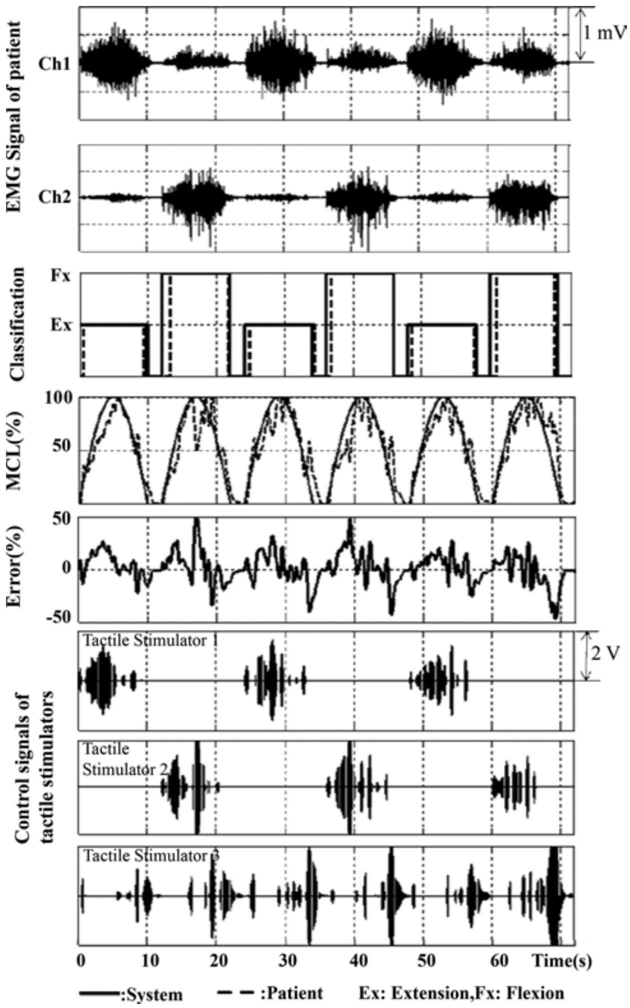

Fig. 9. Example of experimental results for HMI with BIODEX. This figure shows (from top to bottom) EMG signals of patient (test subject), motion classification results, desired and resulting muscular contraction levels ($\mathrm{MCL}_{\mathrm{des}}$ and MCL_{P}), MCL error and control signals for tactile stimulators. Instruction commands are generated by system in this mode. CIP receives and classifies EMG patterns of patient, then compares resulting MCL of patient with MCL command generated by the system. According to error between two MCLs and motion classification result, tactile stimulators are activated by CIP.

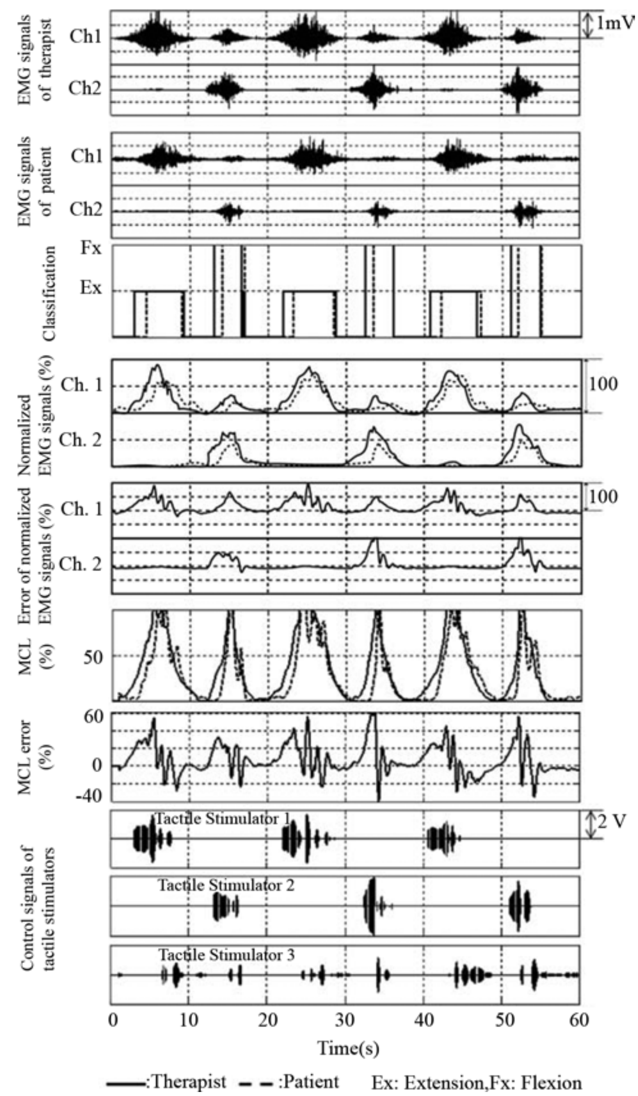

Fig. 10. Example of experimental results with HHI. Figure shows (from top to bottom) EMG signals measured from therapist and patient (test subject), motion classification results, normalized EMG signals of therapist and patient, error between normalized EMG signals of therapist and patient, desired and resulting muscular contraction levels ($\mathrm{MCL}_{\mathrm{des}}$ and MCL_{P}), MCL error and control signal for tactile stimulators. Each tactile stimulator is activated in turn by CIP according to MCL error signal in the same way as with HCI and HMI.

and 8.43% for flexion with the HCI [Fig. 6(b)]. According to the t-test results, there was no significant difference between the values at the 0.05 level ($t_{\mathrm{stat}} = 2.16$, $p = 0.1$ for extension and $t_{\mathrm{stat}} = 0.55$, $p = 0.65$ for flexion).

The experiments indicated that human responses reach a stable level after 10 s. Accordingly, the steady-state error was calculated for the period between 10 and 15 s. The mean steady-state errors for the HCI were 4.4% for extension and 4.9% for flexion. For the HMI, the corresponding values were 2.2% for extension and 2.9% for flexion. According to a t-test, there was again no significant difference between the two groups at the 0.05 level ($t_{\mathrm{stat}} = 1.675$, $p = 0.144$ for extension, and $t_{\mathrm{stat}} = 1.17$, $p = 0.284$ for flexion).

Consequently, it can be judged that integrating the Biodex into the system did not precipitate any negative effect. Additionally, the rehabilitative task capacity of the system increased with the diversity of the Biodex exercise modes. The CIP is able to monitor not only muscle activation in patients but also related mechanical parameters during rehabilitation. This can be considered very useful for evaluation and teaching of motor skills in patients.

B. HCI and HHI

The HHI experiments performed with six repetitions per session using therapist commands and the HCI experiments performed with six repetitions per session using sinusoidal system commands were compared using the average correlation coefficients and the mean values of the trajectory-following error. With the HCI (Fig. 9), the subjects were able to follow the desired trajectory better than with the HHI (Fig. 10). According to a t-test, there was a significant difference at the 0.05 level between the average correlation coefficients ($t_{\mathrm{stat}} = 3.79$, $p = 0.008$) and the mean values of the trajectory-following error ($t_{\mathrm{stat}} = 3.39$, $p = 0.01$). This demonstrates that the tracking

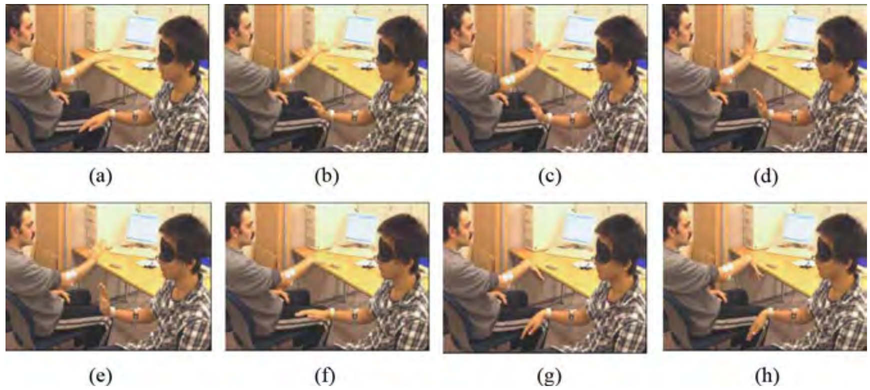

Fig. 11. Photos of experiments in HHI mode for wrist flexion and extension. Virtual therapist is on left, and test subject (A1) wearing an eye mask is on right. (a) $t = 0$ s, (b) $t = 2$ s, (c) $t = 4$ s, (d) $t = 6$ s, (e) $t = 8$ s, (f) $t = 10$ s, (g) $t = 12$ s, and (h) $t = 14$ s.

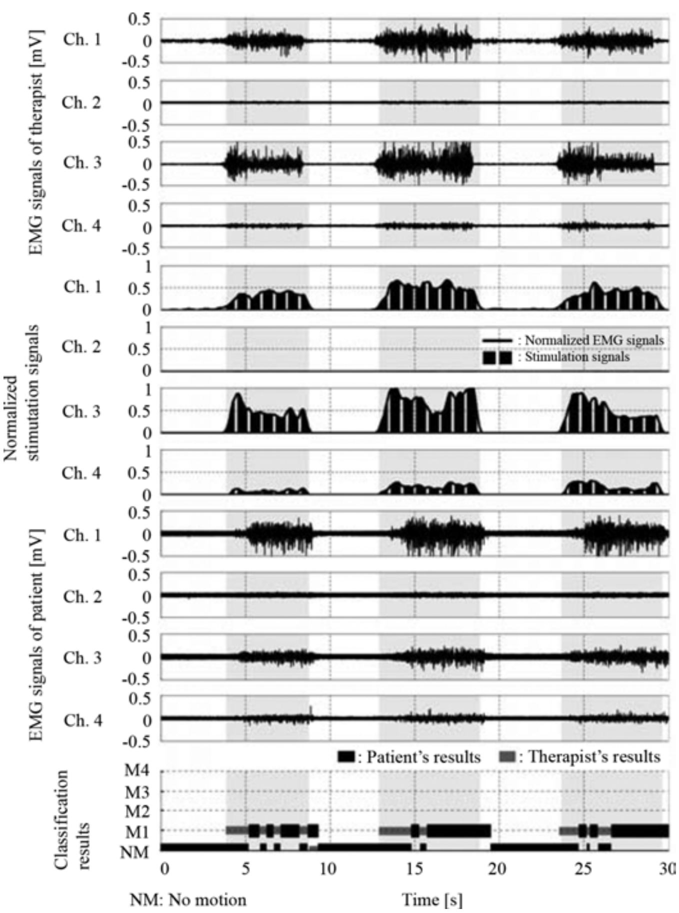

Fig. 12. Sample EMG signals of EMG patterns from virtual therapist and virtual patient during tactile feedback. Figure shows (from top to bottom) EMG signals measured from therapist, control signal for tactile stimulators as computed from muscular contraction levels ($\mathrm{MCL}_{\mathrm{des}}$ and MCL_P) of therapist, test subject's EMG signals, and motion classification results. Gray areas show periods during which the motions of virtual therapist were generated and tactile stimulation was presented in line with (2).

performance of the test subjects with the HCI is better than that with the HHI because the therapist is not able to constantly generate identical patterns (see Fig. 10). A key point for future confirmation is how smoother and more stable motion patterns can be obtained from the therapist. The ability to produce and save appropriate patterns on a computer will allow the rehabilitation

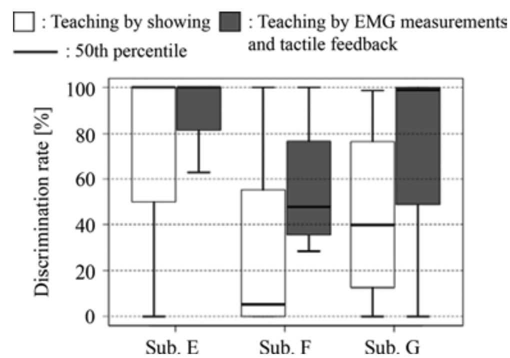

Fig. 13. Results of evaluating EMG patterns discriminated using LLGMN before and after tactile teaching for each subject. Vertical axis shows motion discrimination rate, and horizontal axis the subject. White bars show discrimination rates of subjects' EMG patterns before tactile teaching (i.e., those produced exclusively through teaching by showing), and gray bars show corresponding patterns after tactile teaching based on EMG measurement.

TABLE I
EMG Pattern Discrimination Rates Before and After Tactile Teaching

Subject	Discrimination rate for teaching by showing [%]	Discrimination rate for after tactile teaching [%]
E	75.0 ± 43.3	90.7 ± 16.0
F	27.7 ± 42.0	56.0 ± 26.9
G	44.5 ± 36.7	74.4 ± 43.0

of patients using computerized commands obtained from the therapist.

Fig. 12 clearly shows that muscle contractions in the patient were observed in response to the tactile stimulation triggered and determined in real time exclusively from the measured EMG signals of the therapist. It can be seen from Fig. 13 and Table I that the motion discrimination rates were improved after tactile teaching, although individual variations for each subject were observed. These results lead us to conclude that the proposed teaching method has the potential to be used for direct teaching during rehabilitation.

In the joint trajectories communication, the subjects were able to follow the target joint trajectories with an average error of 20.5% $(\mathrm{SD} = 16.0\%)$, which showed similar finding to EMG communication. It was thus confirmed that joint trajectories set

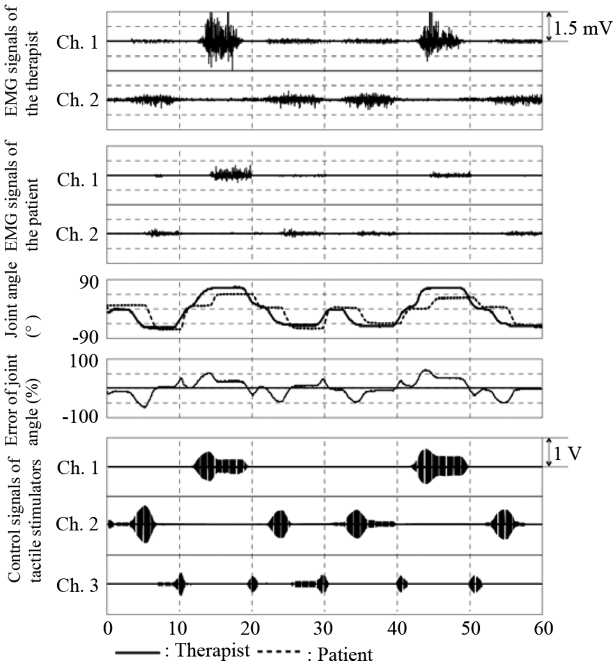

Fig. 14. Example of experimental results in joint-angle communication. Figure shows (from top to bottom) EMG signals measured from therapist and patient (test subject), joint angles measured using goniometers, angle error and control signal for tactile stimulators. Joint trajectories seen during the motions of therapist were transferred to patients in place of EMG signals used in the experiment shown in Fig. 10. That is, each tactile stimulator was activated in turn according to joint trajectory error.

by the therapist can be used as control signals to ensure that the desired movement is actually achieved, although the resulting EMG signals of the patients were smaller than those of the therapist. These results indicate that the CIP can be used for direct communication based on joint kinematics, and that the use of joint kinematics in combination with muscle activation as a control variable could enhance system performance.

V. Conclusion

This paper proposes a novel rehabilitation system that functions as an HHI, an HCI and an HMI not only to monitor the motor skills of patients but also to directly teach them such skills using biological signals. The related experiments demonstrated that the CRA system can work with all three modes and can be proper for direct teaching during rehabilitation. The structure of the CRA system is also perfectly suited for use as a human–machine–human interface.

In this study, our aim was to convey the desired muscle activity and motion to the patient. To this end, we used two parameters for rehabilitation—muscular activation level and discriminated motion. This situation is encountered in a variety of cases such as rehabilitation training for artificial limbs, in which well-coordinated muscle activity is extremely important for the control of such prostheses. In other cases, however, it might be better to control movement trajectories and let the patient choose any combination of muscle activity that can produce the desired movement. Even in such cases, the voluntarily obtained muscle activity of the patient must be evaluated; if it is found to be inefficient (from an energy point of view, for example), it can be retrained using the proposed CRA system to induce activity that results in less energy-consuming motion.

In future work, we plan to apply the proposed CRA to rehabilitation training for EMG-controlled artificial limbs. In this area, the number of therapists is steadily increasing but remains insufficient, and cooperative muscle activity is extremely important in discriminating the motions intended by a patient from his or her EMG signals. In addition to providing muscle coordination training, the CRA also allows a one-to-many rehabilitation environment, meaning that it can solve the above-mentioned problems in rehabilitation training with EMG-controlled devices. In order to apply the CRA to practical rehabilitation training, more complex and general cases involving multiple muscles and joints must be treated within its framework. For such complex motions, joint kinematics should be considered in addition to muscle activation to improve the proposed method for use in more general and effective rehabilitation scenarios. We would like to showcase the performance of the CRA system with real therapists and patients to allow additional performance parameters and different extremities to be considered depending on patient conditions and to enable a more user-friendly graphical user interface to be integrated. We also plan to consider the joint kinematics as well as muscle activation in order to improve the proposed method efficiency for more general rehabilitation scenarios.

Acknowledgment

The authors would like to thank T. Günday and the students of Biological Systems Engineering Lab at Hiroshima University Graduate School of Engineering for their participation in these experiments.

References

[1] Y. Morita, K. Akagawa, E. Yamamoto, H. Ukai, and N. Matsui, "Basic study on rehabilitation support system for upper limb motor function," in *Proc. 7th Int. Workshop Advanced Motion Control*, 2002, pp. 127–132.

[2] H. Lee *et al.*, "Basic experiments of upper limb rehabilitation using haptic device system," in *Proc. IEEE 9th Int. Conf. Rehab. Robot.*, 2005, pp. 444–447.

[3] J. Lieberman and C. Breazeal, "TIKL: Development of a wearable vibrotactile feedback suit for improved human motor learning," *IEEE Trans. Robot.*, vol. 23, no. 5, pp. 919–926, May 2007.

[4] E. Akdogan, E. Tacgin, and M. A. Adli, "Knee rehabilitation using an intelligent robotic system," *J. Intell. Manuf.*, vol. 20, no. 2, pp. 195–202, 2009.

[5] E. Akdogan, K. Shima, H. Kataoka, M. Hasegawa, A. Otsuka, and T. Tsuji, "The cybernetic rehabilitation aid: A novel concept for direct rehabilitation," in *Proc. IEEE ROBIO 2008—Int. Conf. Robot. Biomimet.*, Thailand, 2009, pp. 852–858.

[6] H. Kataoka, E. Akdogan, K. Shima, T. Tsuji, M. Hasegawa, and A. Otsuka, "Direct rehabilitation using EMG signal and tactile feedback," in *Proc. SOBIM 2008 Conf.* (in Japanese), 2008, pp. 269–272.

[7] T. Tsuji, O. Fukuda, H. Ichinobe, and M. Kaneko, "A log-linearized Gaussian mixture network and its application to EEG pattern classification," *IEEE Trans. Syst., Man, Cybern. Part C*, vol. 29, no. 1, pp. 60–72, Jan. 1999.

[8] A. Y. J. Szeto and F. A. Saunders, "Electrocutaneous stimulation for sensory communication in rehabilitation engineering," *IEEE Trans. Biomed. Eng.*, vol. 29, no. 4, pp. 300–308, Apr. 1982.

[9] K. A. Kaczmarek, G. John, P. Webster, P. Bach-y-Rita, and W. J. Tompkins, "Electrotactile and vibrotactile displays for sensory substitution systems," *IEEE Trans. Biomed. Eng.*, vol. 38, no. 1, pp. 1–16, Jan. 1991.

[10] J. P. Warren, L. R. Bobich, M. Santello, J. D. Sweeney, and S. I. H. Tillery, “Receptive field characteristics under electrotactile stimulation of the fingertip,” *IEEE Trans. Neural Syst. Rehab. Eng.*, vol. 16, no. 4, pp. 410–415, Apr. 2008.
[11] Biodex System 2 User’s Manual, Biodex System Medical.
[12] T. Tsuji, D. Mori, and T. Ito, “Motion discrimination method from EMG signal using statistically structured neural networks,” *Trans. Inst. Elect. Eng. Jpn.*, vol. 112-C, no. 8, pp. 465–473, 1992.
[13] O. Fukuda, T. Tsuji, A. Otsuka, and M. Kaneko, “EMG-based human-robot interface for rehabilitation aid,” in *Proc. IEEE Int. Conf. Robot. Automat.*, 1998, pp. 3492–3497.
[14] O. Fukuda, T. Tsuji, M. Kaneko, and A. Otsuka, “A human-assisting manipulator teleoperated by EMG signals and arm motions,” *IEEE Trans. Robot. Automat.*, vol. 19, no. 2, pp. 210–222, Apr. 2003.

Erhan Akdogan (M’08) received the B.S. degree in electronics and communication engineering from Yildiz Technical University, in 1999, and the M.S. and Ph.D. degrees from Marmara University, Turkey, in 2001 and 2007, respectively.

From 2008 to 2009, he was a Visiting Researcher at Hiroshima University Graduate School of Engineering’s Biological Systems Engineering Laboratory. He is currently an Assistant Professor at the Mechatronics Engineering Department, Yildiz Technical University, Istanbul, Turkey.

Keisuke Shima (M’08) received the B.E. degree in industrial engineering and M.E. and Doctorate of Engineering degrees in systems engineering from Hiroshima University in 2005, 2007, and 2009, respectively.

From 2007 to 2009, he was a Research Fellow of the Japan Society for the Promotion of Science (JSPS). He is currently a Research Fellow of the JSPS at Graduate School of Biomedical & Health Sciences, Hiroshima University, Hiroshima, Japan.

Hitoshi Kataoka received the B.E. and M.E. degrees in industrial engineering from Hiroshima University, Hiroshima, Japan, in 2008 and 2010, respectively.

Masaki Hasegawa received the certificate in physical therapy, in 1999, the B.A. degree in physical therapy, in 2001, from Hiroshima University, Hiroshima, Japan, and the Doctor of Health Sciences degree, in 2010, from Kobe University, Hyogo, Japan.

He is currently an Associate Professor in the Department of Physical Therapy, Prefectural University of Hiroshima, Mihara, Japan.

Akira Otsuka received the certificate in physical therapy in 1972, the B.A. degree in social welfare, in 1983, from Bukkyo University, Kyoto, Japan, and the Doctor of Engineering degree in systems engineering, in 2002, from Hiroshima, University, Japan.

He is currently a Professor in the Department of Physical Therapy, Prefectural University of Hiroshima, Mihara, Japan.

Toshio Tsuji (A’88–M’99) received the B.E., M.E., and Dr. Eng. degrees in 1982, 1985, and 1989, respectively, all from Hiroshima University, Higashi-Hiroshima, Japan.

Since 1985, he has been with the Faculty of Engineering, Hiroshima University, Higashi-Hiroshima, Japan, initially as a Research Associate, then as an Associate Professor, and, currently, as a Professor with the Department of Artificial Complex Systems Engineering.