Neuro-Fuzzy Control of a Robotic Exoskeleton With EMG Signals

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***Abstract*—We have been developing robotic exoskeletons to assist motion of physically weak persons such as elderly, disabled, and injured persons. The robotic exoskeleton is controlled basically based on the electromyogram (EMG) signals, since the EMG signals of human muscles are important signals to understand how the user intends to move. Even though the EMG signals contain very important information, however, it is not very easy to predict the user's upper-limb motion (elbow and shoulder motion) based on the EMG signals in real-time because of the difficulty in using the EMG signals as the controller input signals. In this paper, we propose a robotic exoskeleton for human upper-limb motion assist, a hierarchical neuro-fuzzy controller for the robotic exoskeleton, and its adaptation method.**

***Index Terms*—Biomedical signal analysis, electromyography, exoskeleton, power amplifiers, robots.**

I. Introduction

DUE TO A decrease in birthrate and progress of aging society, role of robotics technology becomes important in the field of medicine and welfare. We have been developing robotic exoskeletons [1]–[3] to assist motion of physically weak persons such as elderly, disabled, and injured persons. These kinds of robotic systems can be used for power assist of physically weak persons in daily activity and rehabilitation. It is important for the robotic exoskeleton, especially that for medical or welfare use, to move according to the user's intention. The skin surface electromyogram (EMG) is one of the most important biological signals in which the human motion intention is directly reflected. Consequently, it is often used as a control command signal for a robot system [4]–[6]. In this paper, a robotic exoskeleton for human upper-limb motion assist, which is controlled with the EMG signals, and its control system is proposed.

Human body is a typical complex fuzzy system. Therefore, the biological signals such as skin surface EMG signal contains a lot of fuzziness. It is very difficult to obtain the same EMG signals for the same motion even with the same person. Furthermore, each muscle activity for a certain motion is highly nonlinear, because the responsibility of each muscle for the motion varies in accordance with joint angles [7], [8]. One muscle is not only concerned with one motion but also another kinds of motion. Moreover, activity level of each muscle and the way of using each muscle for a certain motion is different between persons. Physiological condition of the user also affects the activity level of muscles [9]. In addition to these problems, the activity level of some muscles such as biarticular muscle is affected by the motion of the other joint, because the load acting on the other joint affects the activity level of them. The relationship between the load acting on the other joint and the change in biarticular muscle activity level is different between persons. Furthermore, the activity level of muscles is affected by the external load acting on the arm. Therefore, flexible and adaptive nonlinear control must be applied to control the robot with the skin surface EMG signals. Moreover, real-time control ability is required to the controller for a power assist robot since motion delay gives a lot of stress to the user.

In this paper, we propose the effective hierarchical neuro-fuzzy controller for the robotic exoskeleton and its adaptation method. It is known that the hierarchical fuzzy controller is more effective than the conventional fuzzy controller [10]–[12]. The proposed hierarchical controller consists of three stages (first stage: input signal selection stage, second stage: posture region selection stage, and third stage: neuro-fuzzy control stage). The control is carried out based on the EMG signals when the robot user is activating his/her muscles. However, when the muscle activity level of the robot user is not so high (i.e., when the robot user is not activating his/her muscles), the control is carried out based on the wrist force sensor signals in the proposed control method. By applying sensor fusion with the skin surface EMG signals and the generated wrist force, error motion caused by little EMG levels and the external force affecting to human arm can be avoided. This process is performed in the first stage of the controller.

Since anatomy and the way of muscle use of each person are basically similar, design of basic initial fuzzy control rules for each shoulder and elbow posture region of the robotic exoskeleton is not too difficult. However, since activity level of each muscle and the way of using each muscle for a certain motion is different between persons, the controller must be adjusted based on physical and physiological condition of each robot user. Therefore, the required structure of the neuro-fuzzy (control rules) is sometimes different between persons. If the patterns of EMG signals for certain motion are completely unknown, control rules extraction is not required, and preparation time is not limited, a well structured adaptive neuro controller [13] or neuro-fuzzy controller [14] might be one of the most suitable controllers for the control of robotic exoskeleton with EMG signasl. However, the patterns of EMG signals for certain motion can be basically known by performing experiment and using anatomical knowledge. Furthermore, we

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are not allowed to take a lot of time for controller preparation for each robot user. Therefore, we propose a flexible neuro-fuzzy controller, which is used in the stage three of the proposed hierarchical controller, for a robotic exoskeleton for any user. The structure of the proposed neuro-fuzzy controller is basically the same as the conventional simplified fuzzy controller. So that the weight of the consequent part of the most control rules is singleton. However, the weight of the consequent part of some control rules is described by equation in order to take into account the subeffect caused by another muscles. In this point, the controller is similar to the Takagi–Sugeno–Kang (TSK) model [15]–[19]. Unlike the traditional TSK model where all the input variables are used in the equation of the consequent part, only the related EMG signals are used in the proposed method. Thus, the main effect of each muscle is taken into account in the antecedent part of the controller and the subeffect of some muscles is taken into account in the consequent part of the controller. If there is no subeffect from the other muscles, the neuro-fuzzy controller is the same as the simplified neuro-fuzzy controller.

This paper is organized as follows. The architecture of the proposed robotic exoskeleton system is explained in Section II. In Section III, features of the EMG signals are described. The hierarchical control method is presented in Section IV. In Section V, the effectiveness of the robotic exoskeleton and its control method are evaluated. Finally, conclusions are summarized in Section VI.

II. Robotic Exoskeleton System

The proposed robotic exoskeleton is supposed to be attached to the lateral side of a user directly. The architecture of the exoskeleton system is shown in Fig. 1. The robotic exoskeleton system consists of four main links (two links for shoulder joint motion and another two links for elbow joint motion), a frame, three dc motors, an upper-arm holder, a wrist force sensor (strain gauges), driving wires, wire tension sensors, and driving motors. An air cushion is attached inside of the upper arm holder. By adjusting the air pressure of the air cushion, the upper arm holder can be properly attached to the upper arm of any user. The generated wrist force (i.e., the force caused from the motion difference between the robotic exoskeleton and the user) is measured by the wrist force sensor in three dimensions. The shoulder vertical and horizontal flexion-extension of the user (see Fig. 2) are assisted by the robotic exoskeleton system by activating the upper arm holder, which is attached on the main link-2 for shoulder joint motion, using driving wires driven by two dc motors. Since the center of rotation of the exoskeleton's shoulder joint is different from that of human shoulder joint, the radius of rotational joint is adjusted in accordance with the joint motion. Assuming that the physically weak persons use a wheel chair, the heavy parts such as the dc motors are supposed to be attached on the frame of the wheel chair. The basic structure of the shoulder joint of the robotic exoskeleton is the same as that in our previous study [2]. The shoulder angle is measured by potentiometers attached to the shoulder link-1 and the shoulder link-2 of the exoskeleton. The wire tension (driving force) is measured by the wire tension sensors. The signals from the sensors are sampled at a rate of 2 kHz and low-pass filtered at 8 Hz.

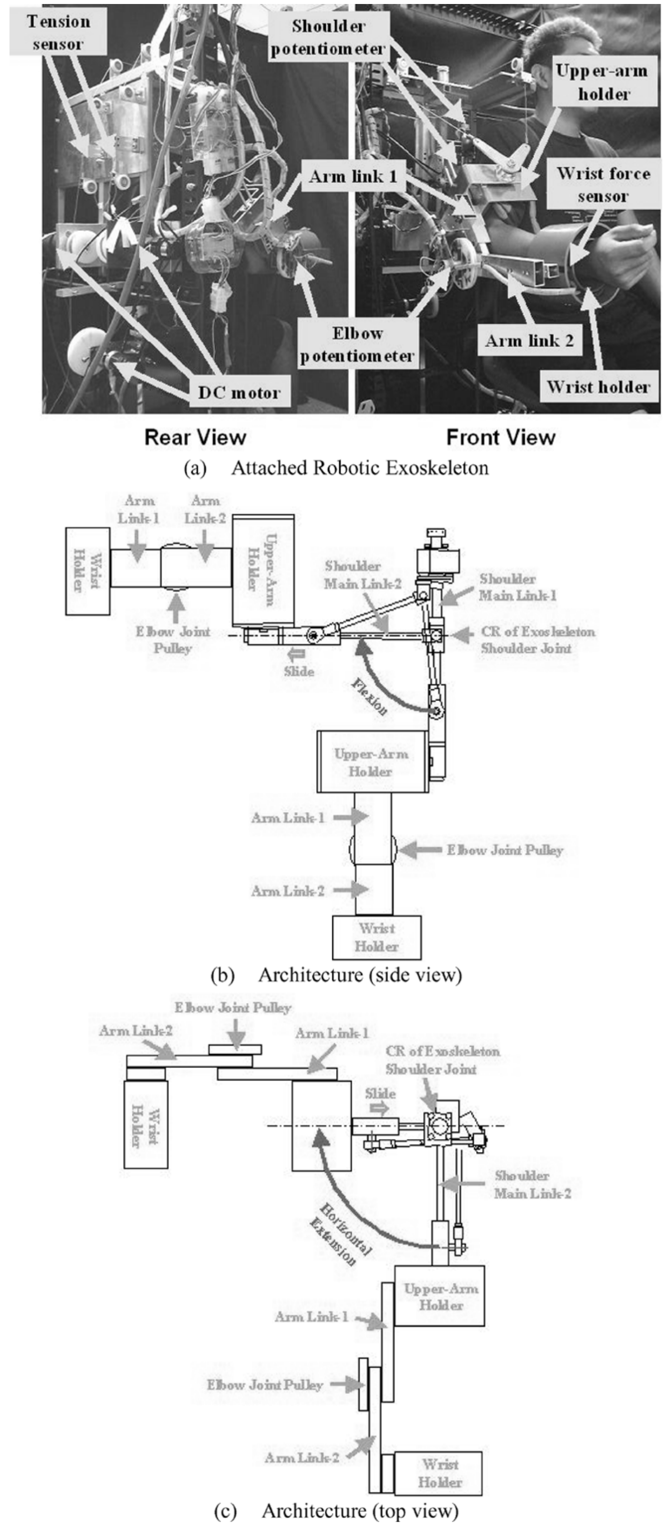


Fig. 1. Architecture of the robotic exoskeleton.

The elbow flexion-extension motion of the user (see Fig. 2) is assisted by the exoskeleton system by activating the elbow joint pulley, which is attached between the arm link-1 and the arm link-2, using the driving wire. The driving wire for the elbow motion is activated by another dc motor. In order to make the movable link light weight, the dc motor is fixed on the frame.

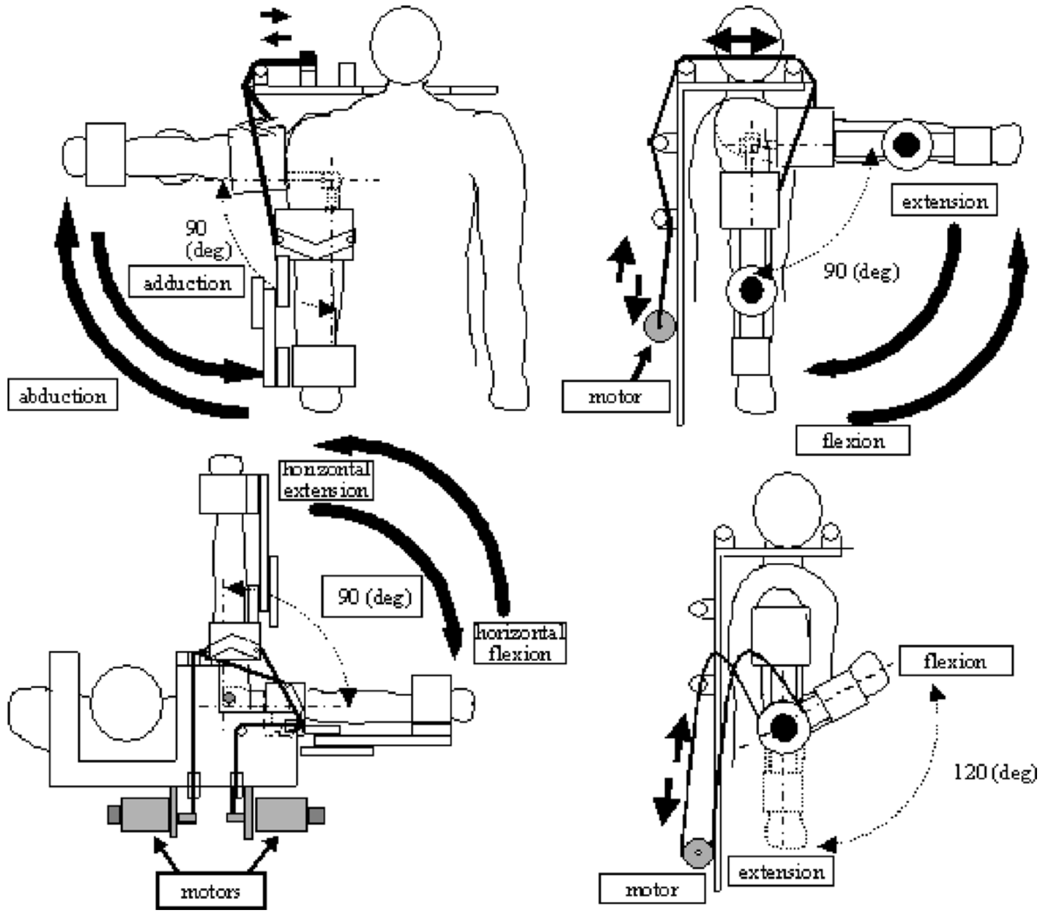


Fig. 2. Movement of robotic exoskeleton.

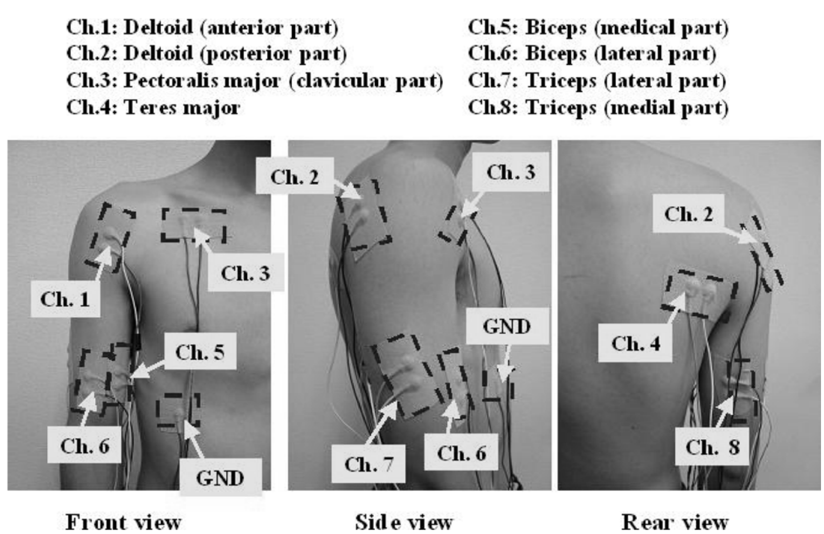


Fig. 3. Location of electrode.

Human elbow joint is mainly activated by biceps and triceps, and moves in 1 degree-of-freedom (DOF). Human shoulder joint is activated by many muscles such as deltoid, pectoralis major, teres major, and trapezius, and moves in 3 DOF. In this study, user's skin surface EMG signals of biceps (lateral and medial parts), triceps (lateral and medial parts), deltoid (anterior and posterior parts), pectoralis major (clavicular part), and teres major are measured and used for control of the proposed robotic exoskeleton system. A pair of electrode is attached on each measuring muscle to measure the EMG signal. The location of each electrode is shown in Fig. 3. The measured EMG signals are amplified by an EMG amplifier and sampled at a rate of 2 kHz.

Usually, the limitation of the movable range of human elbow is between -5 and 145° and that of human shoulder are 180° in flexion, 60° in extension, 180° in abduction, and 75° in adduc-

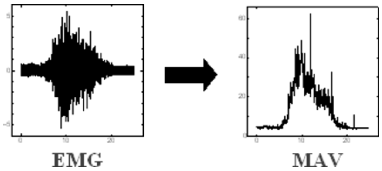


Fig. 4. Example of EMG and MAV.

tion. Considering the minimally required motion in everyday life and the safety of the user, the elbow joint motion of the proposed exoskeleton system is limited between 0° and 120°, and the limitation of the shoulder joint motion of the proposed exoskeleton system are decided to be 0 degrees in extension and adduction, 90° in flexion, and 90° in abduction.

III. EMG Signal

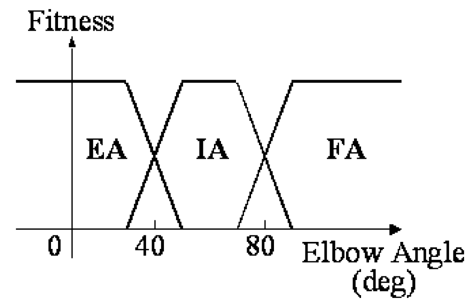
The EMG signal (0.01–10 mV, 10–2,000 Hz) is one of the most important biological signals which directly reflect human muscle activities since it is generated when the muscles contract. The EMG is a measure of an integration of electrical potentials from many muscle fibers [20]. Therefore, the generating motion of the robot user can be directly predicted by monitoring the user's skin surface EMG signals. Since the EMG signal consists of wide range of frequency, it is very difficult to reduce noise by filtering. Furthermore, it is difficult to use raw EMG data as input information of the controller. Therefore, features have to be extracted from the noisy raw EMG data. We have used mean absolute value (MAV) considering its effectiveness for real-time control, although there are many other feature extraction methods, e.g., mean absolute value slope, zero crossings, slope sign changes, or waveform length [21]. The equation of MAV is written as

$$MAV = \frac{1}{N}\sum_{k=1}^{1}|x_k| \tag{1}$$

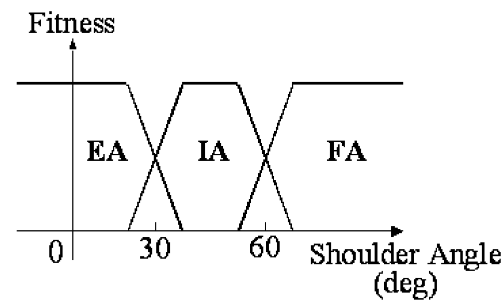
where x_k is the voltage value at k^{th} sampling, N is the number of samples in a segment. The number of samples is set to be 100 and the sampling time is set to be 1 ms in this study. Fig. 4 shows an example of raw EMG signal and its MAV.

Eight kinds of EMG signals (lateral and proximal parts of biceps, lateral and proximal parts of triceps, anterior and posterior parts of deltoid, clavicular part of pectoralis major, and teres major) are used to predict the user's generating upper-limb motion (shoulder vertical and horizontal flexion-extension motion and elbow flexion-extension motion) in this study. The location of each electrode is shown in Fig. 3. Deltoid, pectoralis major, and teres major are mainly involved in shoulder motion. Biceps and triceps are mainly involved in elbow motion.

It is not easy to obtain the same EMG signals for the same motion even with the same person. The EMG signals contain a lot of noise. Furthermore, each muscle activity for a certain motion is highly nonlinear, because the responsibility of each muscle for the motion varies in accordance with joint angles, especially in a complex joint like the shoulder joint. One muscle is not only concerned with one motion but also another kinds of motion. Moreover, activity level of each muscle and the way of



(a) Elbow angle



(b) Shoulder vertical and horizontal angle

Fig. 5. Membership functions.

using each muscle for a certain motion is different between persons. Physiological condition of the user also affects the activity level of muscles. In addition to these problems, the activity level of some muscles such as biceps (biarticular muscle) is affected by the motion of the shoulder joint, because the load acting on the shoulder joint affects the activity level of biceps. The relationship between the load acting on the shoulder joint and the change in muscle activity level of biceps is different between persons. Furthermore, the activity level of muscles is affected by the external load acting on the arm.

IV. Neuro-Fuzzy Controller

The proposed hierarchical controller consists of three stages (first stage: input signal selection stage, second stage: posture region selection stage, and third stage: neuro-fuzzy control stage). In the first stage of the proposed hierarchical controller, the EMG based control or the wrist sensor based control is applied in accordance with the muscle activity levels of the robot user. In the second stage of the proposed hierarchical controller, a proper neuro-fuzzy controller is selected according to the shoulder and the elbow angle region. In the third stage of the proposed hierarchical controller, the desired torque command for each joint is calculated with the neuro-fuzzy controllers to realize the effective motion assist for the robot user.

A. Input Signal Selection Stage

In the first stage of the controller, proper input information for the controller is selected in accordance with the user's muscle activation levels. The control is carried out based on the EMG signals when the robot user is activating his/her shoulder and/or upper-arm muscles. However, when the muscle activity level of the robot user is not so high (i.e., when the robot user is not activating his/her shoulder and/or upper-arm muscles), the control

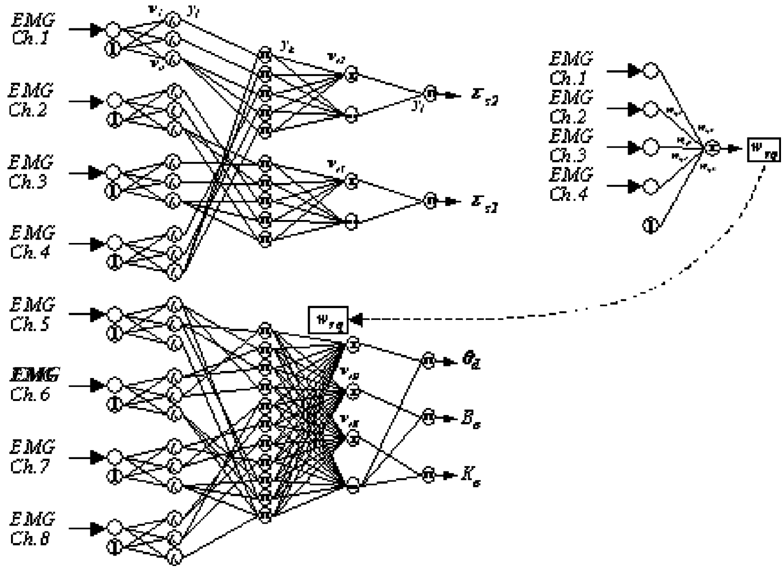


Fig. 6. Neuro-fuzzy controller.

is carried out based on the wrist force sensor signals in the proposed control method. Consequently, both elbow and shoulder motion is controlled based on the generated wrist force when the activity level of all muscle is low, and only elbow motion is controlled based on the generated wrist force when the activity level of only the upper-arm muscle is low. When the activity level of the muscle is medium, both the skin surface EMG signals and the generated wrist force are used simultaneously for the control. In the case of control based on the generated wrist force, force control is carried out to make the generated wrist force become zero. By applying sensor fusion with the skin surface EMG signals and the generated wrist force, error motion caused by little EMG levels and the external force affecting to human arm can be avoided.

The membership function (PB: positive big) of each muscle is used to switch the controller input information. By applying the membership function of each muscle for switching, the input information for the controller is gradually switched in this stage.

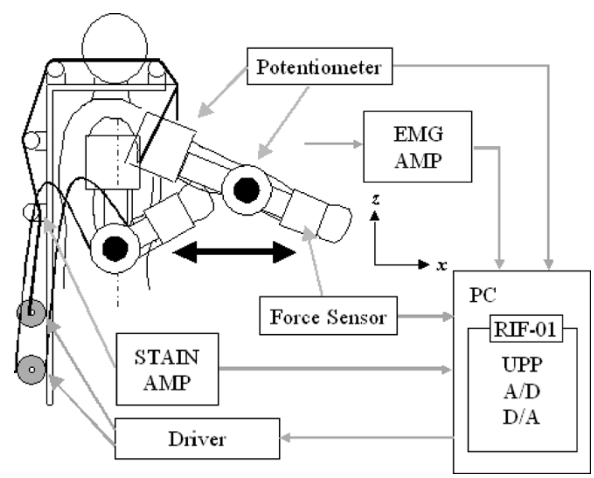


Fig. 7. Experimental setup.

B. Posture Region Selection Stage

In the second stage of the controller, proper neuro-fuzzy controller is selected in accordance with the user's arm posture. The EMG-based control rules are sometimes completely different when the arm posture is changed since role of each muscle is changed according to the arm posture. In order to cope with this problem, multiple neuro-fuzzy controllers have been designed and applied under the certain arm posture. Consequently, the proper neuro-fuzzy controller is selected according to the shoulder and elbow posture region in this stage. The details of each neuro-fuzzy controller are presented in the next sub-section.

The movable range of elbow flexion/extension angle, shoulder vertical flexion/extension angle, and shoulder horizontal flexion/extension angle are divided into three regions (FA: flexed angle, IA: intermediate angle, and EA: extended angle), respectively. Therefore, the movable range of the elbow motion is divided into three regions and that of the shoulder motion is divided into nine regions. The membership functions of the elbow and shoulder region are depicted in Fig. 5. By applying these membership functions, the appropriate controllers are moderately selected in accordance with the arm posture of the robot user. Thus, four kinds of neuro-fuzzy controller might be used at the same time in maximum for shoulder motion and two kinds of neuro-fuzzy controller might be used at the same time in maximum for elbow motion.

C. Neuro-Fuzzy Control Stage

The desired torque command for each joint is derived by the neuro-fuzzy control in the third stage of the controller. One neuro-fuzzy controller is prepared for each posture region. The structure of the neuro-fuzzy controller is basically the same as the conventional simplified fuzzy controller since it can be easily designed based on our anatomical knowledge and the

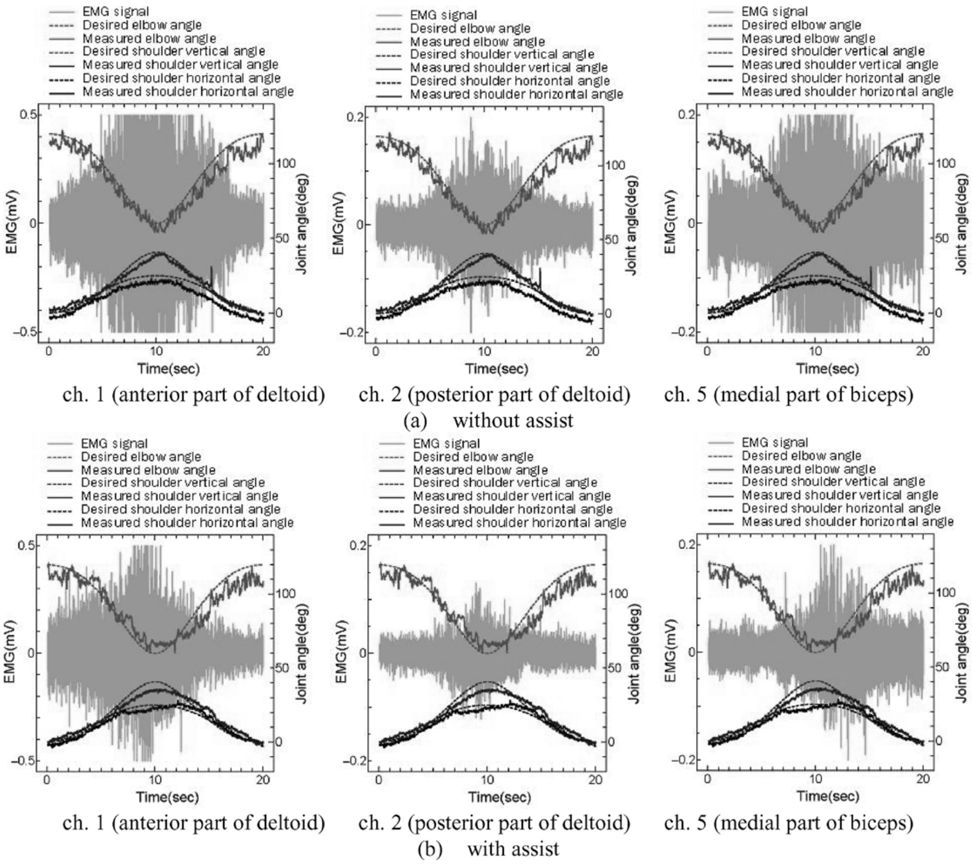


Fig. 8. Experimental results (Subject A).

results of previously performed experiment. However, the weight of the consequent part of control rules for the elbow motion assist is described by equation in order to take into account the subeffect caused by shoulder motion. Therefore, the main-effect of each muscle is taken into account in the antecedent part and the subeffect of some muscles is taken into account in the consequent part in this neuro-fuzzy control method. Even though there exists difference in anatomy and the way of muscle use between persons, the neuro-fuzzy controllers are able to adapt themselves to any robot user by adjusting both the antecedent part and the consequent part of the controllers using the backpropagation learning algorithm. The architecture of the neuro-fuzzy controller is shown in Fig. 6. Here, Σ means the summation of the inputs and Π means the multiplication of the inputs. Two kinds of nonlinear functions (f_G and f_S) are applied to express the membership function of the neuro-fuzzy controller

$$f_s(u_s) = \frac{1}{1+e^{-u_s}} \tag{2}$$

$$u_s(x) = w_0 + w_i x \tag{3}$$

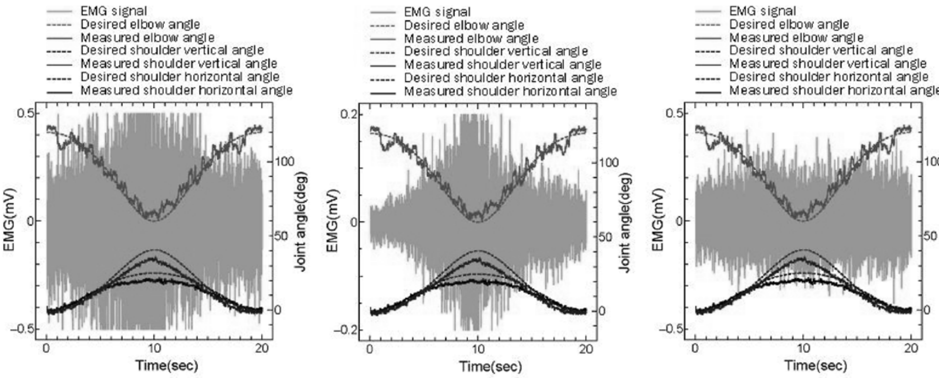
$$f_G(u_G) = e^{-u_G^2} \tag{4}$$

$$u_G(x) = \frac{w_0 + x}{w_i} \tag{5}$$

where w_0 is a threshold value and w_i is a weight.

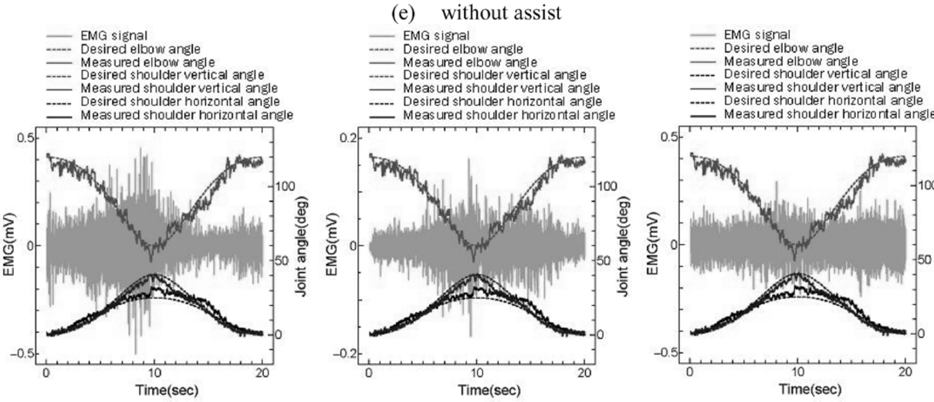
The initial fuzzy IF–THEN control rules are designed based on the analyzed human elbow and shoulder motion patterns in the pre-experiment, and then transferred to the neural network form. The EMG characteristics of human elbow and shoulder muscles studied in another research [22]–[25] are also taken into account. The input variables for the neuro-fuzzy controller are 8 kinds of MAVs of EMG. Three kinds of fuzzy linguistic variables (ZO, PS, and PB) are prepared for the MAVs of EMG. There are 21 rules (ten rules for shoulder and eleven rules for elbow) in each neuro-fuzzy controller. Four kinds of MAVs of EMG (ch.1: Deltoid – anterior part, ch.2: Deltoid – posterior part, ch.3: Pectoralis, and ch.4: Teres major) are used as input variables for the weights in the consequent part of the control rules generating the desired elbow joint angle. Consequently, the weights in the consequent part of the control rules generating the desired elbow joint angle are the function of four kinds of MAVs of EMG (chs.1–4). Note that four input variables mentioned above for the weights in the consequent part are different from the input variables in the antecedent part of the control rules for elbow motion. Thus, the subeffect of the shoulder muscles (the subeffect of torque generated by the shoulder muscles) is taken into account in the consequent part of the control rules for elbow motion.

The outputs of the neuro-fuzzy controller are the torque command for shoulder motion, and the desired impedance parameters and the desired angle for elbow motion of the exoskeleton system. The torque command for the shoulder joint of the exoskeleton system is then transferred to the force command for each driving wire. The relation between the torque command



ch. 1 (anterior part of deltoid) ch. 2 (posterior part of deltoid) ch. 5 (medial part of biceps)

(e) without assist



ch. 1 (anterior part of deltoid) ch. 2 (posterior part of deltoid) ch. 5 (medial part of biceps)

(f) with assist

Fig. 9. Experimental results (Subject B).

for the shoulder joint of the exoskeleton system and the force command for driving wires is written as the following equation:

$$\tau_s = J_s^T f_{sd} \tag{6}$$

where τ_s is the torque command vector for the shoulder joint of the exoskeleton system, f_{xd} is the force command vector for the driving wires, and J_s is the Jacobian which relates the exoskeleton's joint velocity to the driving wire velocity. Force control is carried out to realize the desired force (f_{sd}) in driving wires by the driving motors for shoulder motion of the exoskeleton system.

Impedance control is performed with the derived impedance parameters and the derived desired angle for the elbow joint control of the exoskeleton system. The equation of impedance control is written as

$$\tau_e = M_e(\ddot{\theta}_d - \ddot{\theta}_e) + B_e(\dot{\theta}_d - \dot{\theta}_e) + K_e(\theta_d - \theta_e) \tag{7}$$

where τ_e denotes torque command for the elbow joint of the exoskeleton system, M_e is the moment of inertia of the arm link-2 and human subject's forearm, B_e is the viscous coefficient generated by the neuro-fuzzy controller, K_e is the spring coefficient generated by the neuro-fuzzy controller, θ_d is the desired joint angle generated by the neuro-fuzzy controller, and θ_e is the measured elbow joint angle of the exoskeleton system. The torque command for the elbow joint of the exoskeleton system is then transferred to the torque command for the driving motor for the elbow motion of the exoskeleton system.

D. Controller Adaptation

The controller adaptation must be performed to realize the desired motion assist for anybody. Consequently, the controller should be able to adapt itself to physical and physiological condition of any robot user. Furthermore, the assist level by the robotic exoskeleton should be adjusted according to the user's condition until the amount of the EMG signals of the user's muscles becomes the desired level. In this study, adjustment of the controller is performed using the backpropagation learning algorithm. All of antecedent part and some of consequence part (the weights in consequence part of rules generating the required shoulder torque and the weights in consequence part of rules generating the desired elbow joint angle) of the fuzzy IF–THEN control rules are adjusted during the controller adaptation process which is carried out for several minutes before operation. The equations of the evaluation function are written as

$$E_s = \frac{1}{2}\left((\theta_{s\_d} - \theta_s)^2 + \alpha \sum_{i=1}^{4} (MAV_{i\_d} - MAV_i)^2\right) \tag{8}$$

$$E_e = \frac{1}{2}\left((\theta_{e\_d} - \theta_e)^2 + \alpha \sum_{i=4}^{8} (MAV_{i\_d} - MAV_i)^2\right) \tag{9}$$

where θ_{s_d} and θ_{e_d} are the desired shoulder and elbow angle calculated from the desired wrist trajectory, θ_s and θ_e are the measured shoulder and elbow angle, α is a coefficient which changes the degree of consideration of the muscle activity minimization, MAV_{i_d} is the desired muscle activity level in ch.i,

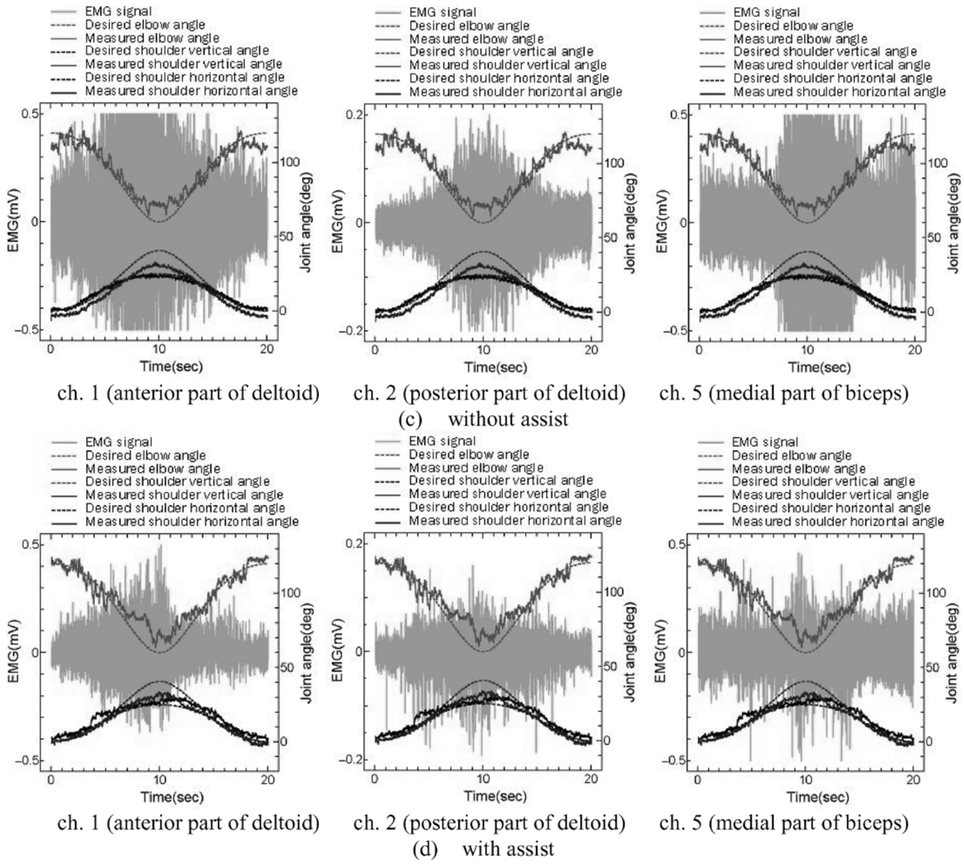


Fig. 10. Experimental results (Subject C).

and MAV_i is the measured muscle activity level in ch.i. The desired muscle activity levels are decided for each user based on the user's physical condition. By evaluating the amount of user's EMG signals as well as the motion error in the evaluation function of the back-propagation learning algorithm during the upper-limb motion for the controller adaptation, the assist level of the robotic exoskeleton system can be adjusted until the amount of user's EMG signals becomes the desired level.

The desired wrist trajectory, which results in cooperative motion of the elbow and shoulder joints, is indicated to the user by the desired trajectory indicator during the controller adaptation process. The controller is adjusted to reduce the trajectory error (the position error between the desired trajectory and the measured trajectory) during the controller adaptation process. This controller adaptation method enables the easy whole controller adaptation to each user.

V. Experiment

In order to evaluate the effectiveness of the proposed control method, upper-limb motion assist (power assist) experiment has been carried out with three healthy human subjects (Subjects A and B are 22 year-old males, Subject C is a 23–year-old male). The experimental setup is shown in Fig. 7 (the detailed architecture of the robotic exoskeleton was described in Section II). In order to examine the effectiveness of the proposed exoskeleton system in motion assist for both the elbow and shoulder joint of the human subject, cooperative motion of the elbow and shoulder joints is performed in the experiment. In this experiment, human subjects are supposed to move their wrist forward horizontally from the initial position and backward again to the initial position following the target trajectory with a 2 kg weight in their hand. The initial position of the upper-limb is set to be 0 [deg] in both horizontal and vertical flexion angle of the shoulder joint, and 120 [deg] in flexion angle of the elbow joint. The desired trajectory of the wrist on the horizontal plane is described as

$$\begin{aligned}(x, y) = (&340[\mathrm{mm}]^* \sin(30[\mathrm{deg}])^* \sin(0.05t)\\ &340[\mathrm{mm}]^* \cos(30[\mathrm{deg}])^* \sin(0.05t)).\end{aligned} \quad (10)$$

The controller adaptation is carried out for about 5 min before every experiment. All experiment is performed with and without the assist of the exoskeleton system for comparison. If the proposed exoskeleton system effectively assists the upper-limb motion, the activity levels of the EMG signals of the activated muscles are supposed to be reduced.

The experimental results of the Subject A without and with assist of the proposed exoskeleton system are shown in Fig. 8(a) and (b), respectively. Only the results the EMG signals of ch. 1 (anterior part of deltoid), ch. 2 (posterior part of deltoid), and ch. 5 (medial part of biceps), which represent the shoulder and elbow muscles, are depicted here. The experimental results of the Subject B and C are shown in Figs. 9 and 10, respectively. From these experimental results, one can see that the activation levels of the EMG signals of the elbow and shoulder muscles were reduced when the human subjects' motions were assisted by the exoskeleton. These results show the effectiveness of the proposed exoskeleton system and its control method in human upper-limb motion assist.

VI. Conclusion

In this paper, we proposed a robotic exoskeleton for human upper-limb motion assist, a hierarchical neuro-fuzzy controller for the robotic exoskeleton, and its adaptation method in order to assist the motion of physically weak persons such as elderly, disabled, and injured persons. The proposed hierarchical controller consists of three stages (first stage: input signal selection stage, second stage: posture region selection stage, and third stage: neuro-fuzzy control stage. The skin surface EMG signals, which directly reflect the human motion intention, are mainly used as controller input signals. In the proposed neuro-fuzzy control method, the main-effect of each muscle is taken into account in the antecedent part and the subeffect of some muscles is taken into account in the consequent part. The effectiveness of the proposed system was evaluated by experiment.

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