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Full paper

Development of a wearable exoskeleton for daily forearm motion assist

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Abstract—The paper presents a 2-d.o.f. wearable exoskeleton system designed for forearm motion assist in daily activity and rehabilitation. The proposed exoskeleton system is supposed to be directly attached to the lateral side of a patient's upper limb, and assist the forearm motion (elbow flexion–extension motion and forearm supination–pronation motion) of the patient for daily activity and rehabilitation. The proposed exoskeleton is controlled based on the activation patterns of the electromyogram signals of the patient's muscles, which directly reflect the motion intention of the patient, in order to realize natural automatic motion assist. A sophisticated real-time neuro-fuzzy control method, in which the effect of a muscle common to both motions is taken into account, is proposed. The proposed control method enables cooperative motion of the elbow and forearm of the patient by learning the muscle activation patterns of each patient. The effectiveness of the proposed exoskeleton system is evaluated by experiment.

Keywords: Power assist; exoskeleton; robotic suits; bio-robotics; welfare robot.

1. INTRODUCTION

Recent progress in robotics and automation technology has brought a lot of benefit not only in industry, but also in many other fields such as medicine, welfare, amusement, etc. It is important that advanced robotics and automation technology is used to realize sophisticated assist systems for physically weak persons such as the elderly, injured or disabled. We have been developing robotic exoskeletons [1–4] to assist the motion of physically weak persons (patients) for the purpose of rehabilitation and daily use. So far, exoskeletons for elbow motion [1, 2], shoulder motion [3], upper-limb motion (shoulder and elbow motion) [4, 5] and lower-limb

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motion [6, 7] assist have been proposed for daily use and rehabilitation for the patients. Although whole upper-limb motion (shoulder, elbow and wrist motion) is especially important for patients to perform daily activities such as eating and drinking, exoskeletons for whole upper-limb motion assist have not been realized up to the present. This paper proposes a 2-d.o.f. wearable robotic exoskeleton system for forearm motion assist (both elbow flexion–extension and forearm pronation–supination motion) in daily activity and rehabilitation for patients. The patient's forearm motion, which is essential for daily activities, is assisted by the exoskeleton according to the motion intentions of the patient.

Electromyogram (EMG; 10–2000 Hz) signals of human muscles are important signals when trying to understand the motion intentions of a person. Therefore, EMG signals have been used as input information for the control of many robotic systems [8–11]. EMG signals of muscles in the forearm and upper-arm of a patient are also used as the main input information for the control of the robotic exoskeleton in this study. The wrist force (i.e. the force caused by the motion difference between the wrist part of the robotic exoskeleton and that of the patient) is also used as subordinate input information for the controller. By applying EMG signals as main input signals to the controller, natural automatic motion assist can be realized for each patient without manipulating any equipment. This kind of control is especially important for medical systems used by the elderly, injured or disabled. The forearm and upper arm, however, consist of many kinds of muscles, which are involved in many motions [12, 13], in a limited space (inside of the arm). Consequently, the same muscle is sometimes used for different motions. However, it is not easy to distinguish the EMG signal of each muscle, since all of the muscles are allocated only a limited space. Furthermore, the muscle activation level and the muscle activation pattern for a certain motion sometimes differ between individuals. Moreover, physiological conditions, such as fatigue, affect the activity level of EMG signals [14]. EMG signals are also affected by arm posture, since the role of each muscle is changed according to the arm posture [2]. Therefore, it is not easy to apply EMG signals of muscles of the forearm and upper arm as input signals to the controller of the exoskeleton. For this reason, EMG-controlled exoskeletons for forearm motion have not been realized up to the present. In order to cope with these problems, soft computing techniques (i.e. fuzzy control, neural networks and neuro-fuzzy control) have been applied for the control of the robotic exoskeleton in our previous studies [1–4, 15]. Although these techniques are very effective for most of the above-mentioned problems, they do not take into account the effect of a muscle common to multiple motions. Therefore, improper motion assist might occur in the case of cooperative motion of the elbow and forearm (i.e. simultaneous elbow flexion–extension motion and forearm supination–pronation motion).

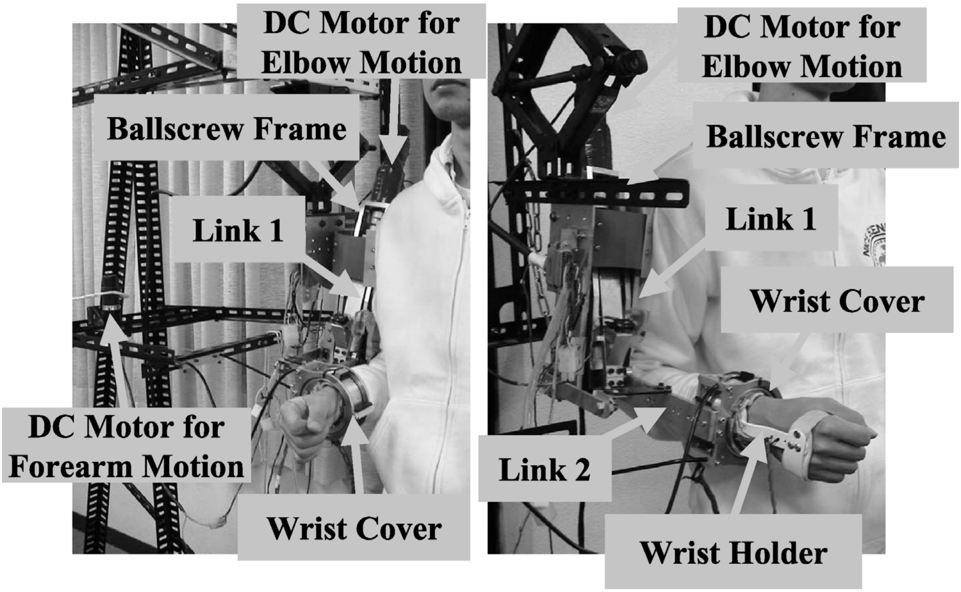
A sophisticated real-time neuro-fuzzy control method, in which the effect of a muscle common to both motions is taken into account, is proposed in this paper. In the proposed neuro-fuzzy control method, the weight of the consequent part of some control rules is described by equations in order to take into account the sub-effect caused by other muscles. Consequently, the effect of a muscle common to multiple motions can be taken into account without changing the structure of the neuro-fuzzy (control rules), although the required structure of the neuro-fuzzy (control rules) sometimes differs between persons. Thus, the proposed control method enables cooperative elbow and forearm motion of the patient by learning the muscle activation patterns of each patient, although some muscles are used for both elbow motion and forearm motion. In order to eliminate the problems caused by changing the arm posture, multiple neuro-fuzzy controllers [2], which are switched in accordance with the elbow angle, are prepared in this study.

Painless attachment of the exoskeleton to the patient's body is an important issue for power assist. It is not easy to assist the forearm supination–pronation motion with exoskeletons, since the cross-section of the human wrist is oval. A new type of wrist holder is designed to realize natural assist of the forearm supination–pronation motion. The effectiveness of the proposed method was evaluated by experimention with several human subjects.

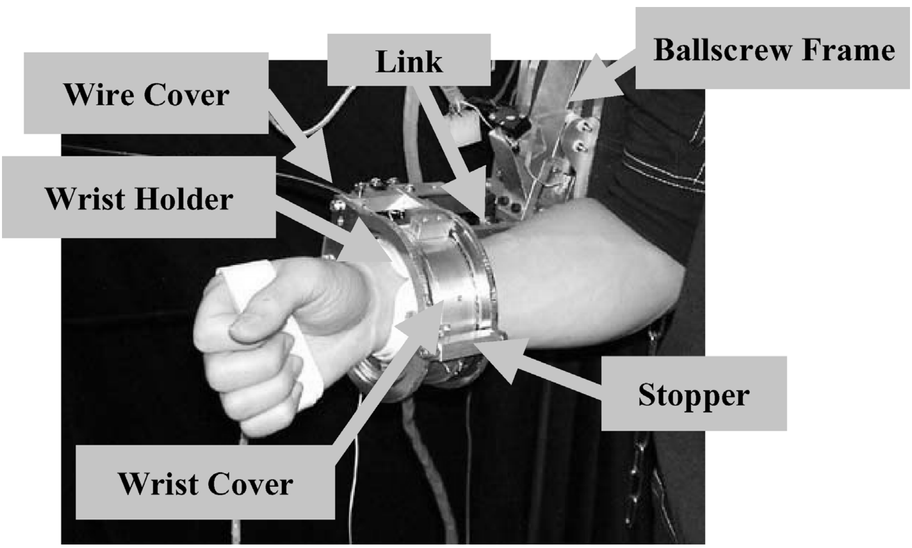
2. EXOSKELETON SYSTEM

The architecture of the proposed 2-d.o.f. wearable robotic exoskeleton system for forearm motion assist is shown in Fig. 1. Some parts of the architecture (i.e. the architecture for the elbow flexion–extension motion assist) are the same as those in our previous study [1, 2]. The exoskeleton consists of two links, two DC motors, a ballscrew drive shaft, a ballscrew support frame, a driving wire, a wrist frame, an inner and an outer wrist holder, a wrist cover, potentiometers and a wrist force sensor. The total weight of the system is about 6.0 kg. The patient is supposed to attach his/her wrist in the wrist holder (the wrist orthosis). Then the wrist holder is attached to the wrist cover as shown in Fig. 2. Ball-bearings are used between the wrist cover and the wrist frame. Link-1 is supposed to be directly attached to the lateral side of the patient's upper arm [1], although it is attached to the frame in the experiment, since it is a little heavy to wear for a long time. The proposed wearable robotic exoskeleton system can be installed in a wheelchair to make the system mobile since many physically weak persons may need to use it. When the exoskeleton is attached to the patient, the axis of the exoskeleton's elbow joint is set to be the same as the patient's elbow joint axis passing through the centers of the arcs formed by the capitellum and the trochlear sulcus. The strain-gauge-based wrist force sensor is installed in the wrist holder (between the inner and outer wrist holder) in order to measure the force caused by the motion difference between the patient's wrist and the exoskeleton's wrist. The rotation angle of the wrist cover with respect to the wrist frame (i.e. the forearm pronation–supination angle) and that of link-2 with respect to link-1 (i.e. the elbow flexion–extension angle) are measured by the potentiometers.

In order to generate the elbow flexion (or extension) motion, link-2 is flexed (or extended) by contracting (or expanding) the prismatic joint along the ballscrew drive



(a)



(b)

Figure 1. Architecture of the exoskeleton. (a) View from the lateral side. (b) View from the medial side.

shaft in the ballscrew support frame, which is attached to link-1, using the DC motor on the top of the ballscrew support frame [1, 2]. The forearm pronation–supination

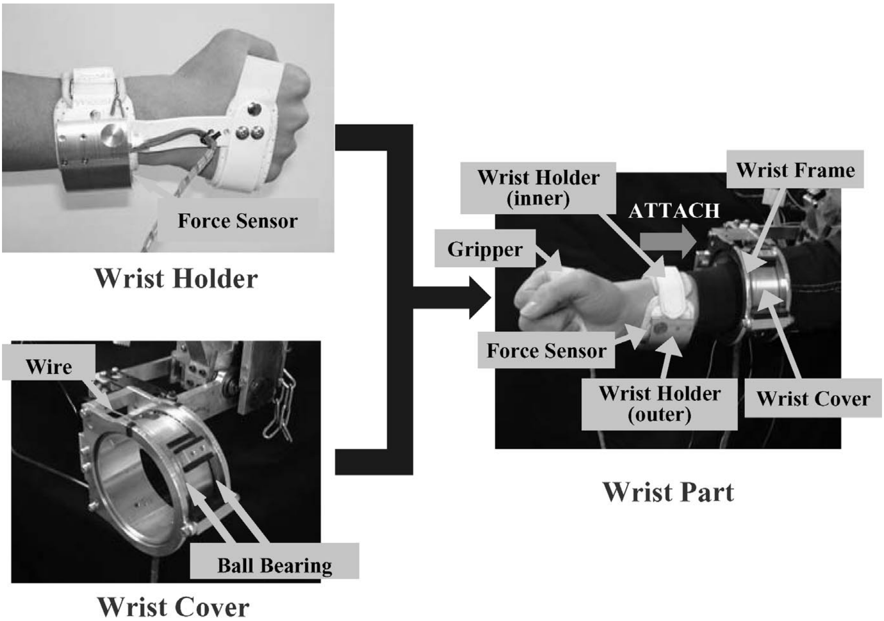


Figure 2. Wrist part of the exoskeleton.

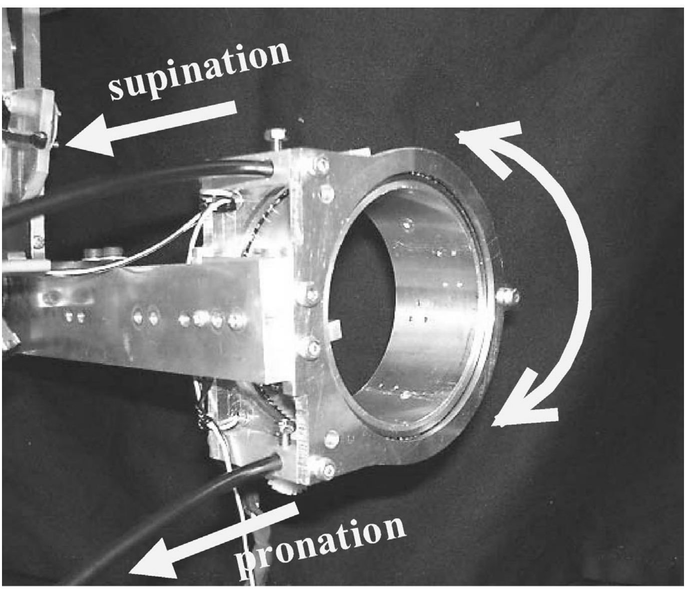


Figure 3. Generation of the forearm supination–pronation motion.

motion (the rotational motion of the wrist cover with respect to the wrist frame) is generated by a wire that is driven by the other DC motor as shown in Fig. 3.

Usually, the limit of the movable range of the forearm pronation–supination motion is 50–80° in pronation and 80–90° in supination, and that of the elbow flexion–extension motion is 145° in flexion and −5° in extension. Considering the safety of the patient, the limit of the exoskeleton's forearm motion is decided to be 50° in pronation and 80° in supination, and that of the exoskeleton's elbow motion is decided to be 120° in flexion and 0° in extension. Stoppers are attached on the exoskeleton to physically prevent the forearm motion from exceeding the movable range.

3. CONTROLLER

The robotic exoskeleton is controlled based on EMG signals (eight channels) and the wrist force of the patient. Here, the motion assist is essentially carried out based on EMG signals. However, the motion assist is carried out based on the wrist force when the amount of EMG activity levels is low in order to avoid misoperation. For the wrist-force-based control, a PD controller has been applied to make the wrist force caused by the elbow and forearm motion difference between the exoskeleton and the patient to be zero. The details of this switching algorithm and its effectiveness are given in our previous paper [1]. The whole structure of the controller is described in Fig. 4. The output of the controller ($\tau : [\tau_f \tau_e]^T$) is the torque command vector required for the forearm motion (forearm pronation–supination and elbow flexion–extension) assist.

3.1. Neuro-fuzzy controller

The forearm motion (especially the forearm pronation–supination motion) is generated by many muscles, such as the pronator teres, pronator quadratus, brachioradialis, anconeus, flexer carpi radialis, biceps, supinator, brachioradialis, extensor carpi radialis longus and extensor carpi radialis brevis. In this study, eight kinds of EMG signals (ch.1: pronator teres, ch.2: flexer carpi radialis, ch.3: anconeus, ch.4: extensor carpi radialis longus, ch.5: proximal part of biceps, ch.6: lateral part of biceps, ch.7: proximal part of triceps and ch.8: lateral part of triceps) are measured for control of the forearm pronation–supination motion and elbow flexion–extension motion. The location of each electrode is shown in Fig. 5. Three of them (ch.1: pronator teres, ch.2: flexer carpi radialis and ch.3: anconeus) are used to determine the pronation motion and another three (ch.4: extensor carpi radialis longus, ch.5: proximal part of biceps and ch.6: lateral part of biceps) are used to determine the supination motion. Furthermore, three of them (ch.1: pronator teres, ch.5: proximal part of biceps and ch.6: lateral part of biceps) are used for the elbow flexion motion and another two (ch.7: proximal part of triceps and ch.8: lateral part of triceps) are used for the elbow extension motion [1]. Thus, the biceps is used for both the forearm supination motion and elbow flexion motion. Consequently, it is very difficult to properly assist the cooperative motion of elbow flexion and forearm supination of the patient based on EMG signals of these muscles.

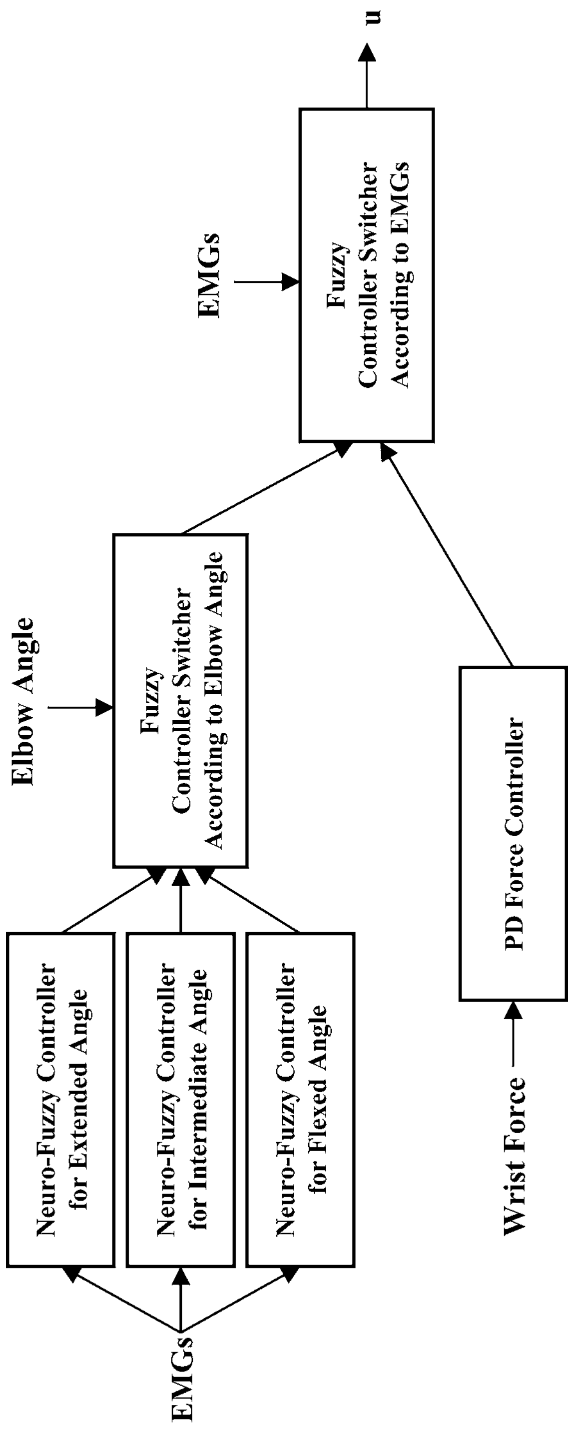
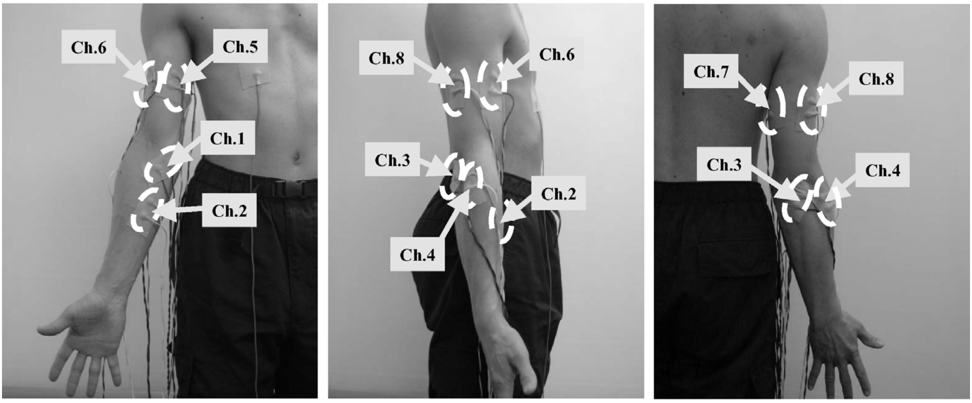


Figure 4. Controller structure.

Ch.1: Pronator teres
Ch.2: Flexor carpi radialis
Ch.3: Anconeus
Ch.4: Extensor carpi radialis longus
Ch.5: Biceps (short head)
Ch.6: Biceps (long head)
Ch.7: Triceps (long head)
Ch.8: Triceps (lateral head)



Front view **Side view** **Rear view**

Figure 5. Location of the electrodes.

In this study, the mean absolute value (MAV) is calculated to extract the features of the EMG signals and then used as an input signal for the fuzzy-neuro controllers. MAV is determined using the following equation:

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

where x_k is the voltage value at the kth sampling and 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 0.5 ms in this study.

The initial fuzzy IF–THEN control rules are designed based on the analyzed human forearm motion patterns in a pre-experiment and then transferred to the neural network form to be a neuro-fuzzy controller. The designed control rules are listed in Table 1. In the proposed neuro-fuzzy control method, the weight of the consequent part of some control rules is described by an equation in order to take into account the sub-effect caused by other muscles. The structure the fuzzy control rules is similar to the Takagi–Sugeno–Kang (TSK) model [15, 16] with regard to this point. Consequently, the effect of a muscle common to both elbow flexion–extension and forearm pronation–supination motions can be taken into account without changing the structure of the neuro-fuzzy, although the required structure of the neuro-fuzzy sometimes differs between persons if there are some muscles common to multiple motions. Thus, the proposed control method enables the cooperative motion of the elbow and forearm of the patient by learning the muscle activation patterns of each patient precisely.

Table 1.
Initial control rules

Forearm control algorithm
Rule01 : IF EMG ch.1 is PB and EMG ch.2 is PB and EMG ch.3 is PB and EMGch.5 is ZO and EMG ch.6 is ZO THEN Motor is 4.0 [N m]
Rule02 : IF EMG ch.1 is PB and EMG ch.3 is PS and EMG ch.5 is ZO and EMG ch.6 is ZO THEN Motor is 2.0 [N m]
Rule03 : IF EMG ch.1 is PS and EMG ch.3 is PS and EMG ch.4 is PB and EMG ch.5 is ZO and EMG ch.6 is ZO THEN Motor is 2.0 [N m]
Rule04 : IF EMG ch.1 is PS and EMG ch.3 is PS and EMG ch.5 is ZO and EMG ch.6 is ZO THEN Motor is 2.0 [N m]
Rule05 : IF EMG ch.1 is PS and EMG ch.3 is PB and EMG ch.5 is ZO and EMG ch.6 is ZO THEN Motor is 2.0 [N m]
Rule06 : IF EMG ch.1 is ZO and EMG ch.2 is ZO and EMG ch.4 is PB and EMG ch.5 is PB and EMG ch.6 is PB THEN Motor is −4.0 [N m]
Rule07 : IF EMG ch.1 is ZO and EMG ch.2 is ZO and EMG ch.5 is PS THEN Motor is −2.0 [N m]
Rule08 : IF EMG ch.1 is ZO and EMG ch.2 is ZO and EMG ch.4 is ZO and EMG ch.5 is PB and EMG ch.6 is PB THEN Motor is −2.0 [N m]
Rule09 : IF EMG ch.1 is ZO and EMG ch.2 is ZO and EMG ch.5 is PB and EMG ch.6 is PS THEN Motor is −2.0 [N m]
Rule10 : IF EMG ch.1 is ZO and EMG ch.2 is ZO and EMG ch.5 is PS and EMG ch.6 is PB THEN Motor is −2.0 [N m]
Rule11 : IF EMG ch.1 is ZO and EMG ch.2 is ZO and EMG ch.5 is ZO and EMG ch.6 is ZO THEN Motor is 0.0 [N m]
Rule12 : IF EMG ch.1 is PS and EMG ch.5 is ZO and EMG ch.6 is ZO THEN Motor is 2.0 [N m]
Rule13 : IF EMG ch.1 is PB and EMG ch.3 is PB and EMG ch.5 is ZO and EMG ch.6 is ZO THEN Motor is 3.0 [N m]
Rule14 : IF EMG ch.1 is PS and EMG ch.3 is PS and EMG ch.4 is PS and EMG ch.5 is ZO and EMG ch.6 is ZO THEN Motor is 2.0 [N m]
Rule15 : IF EMG ch.1 is ZO and EMG ch.2 is ZO and EMG ch.4 is PS and EMG ch.5 is PB and EMG ch.6 is PB THEN Motor is −3.0 [N m]

Figure 6 shows the architecture of the proposed neuro-fuzzy controller. Here, Σ means the summation of the inputs and Π means the multiplication of the inputs. Two kinds of non-linear functions (f_{G} and f_{S}) are used to express the membership function of the neuro-fuzzy controller:

$$f_{\mathrm{S}}(u_{\mathrm{S}}) = \frac{1}{1+\mathrm{e}^{-u_{\mathrm{S}}}}, \tag{2}$$

$$u_{\mathrm{S}}(x) = w_0 + w_i x, \tag{3}$$

$$f_{\mathrm{G}}(u_{\mathrm{G}}) = \mathrm{e}^{-u_{\mathrm{G}}^2}, \tag{4}$$

$$u_{\mathrm{G}}(x) = \frac{w_0 + x}{w_i}, \tag{5}$$

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

The input variables for the neuro-fuzzy controller are eight kinds of MAVs of the EMG. Three kinds of fuzzy linguistic variables (ZO, PS and PB) are prepared

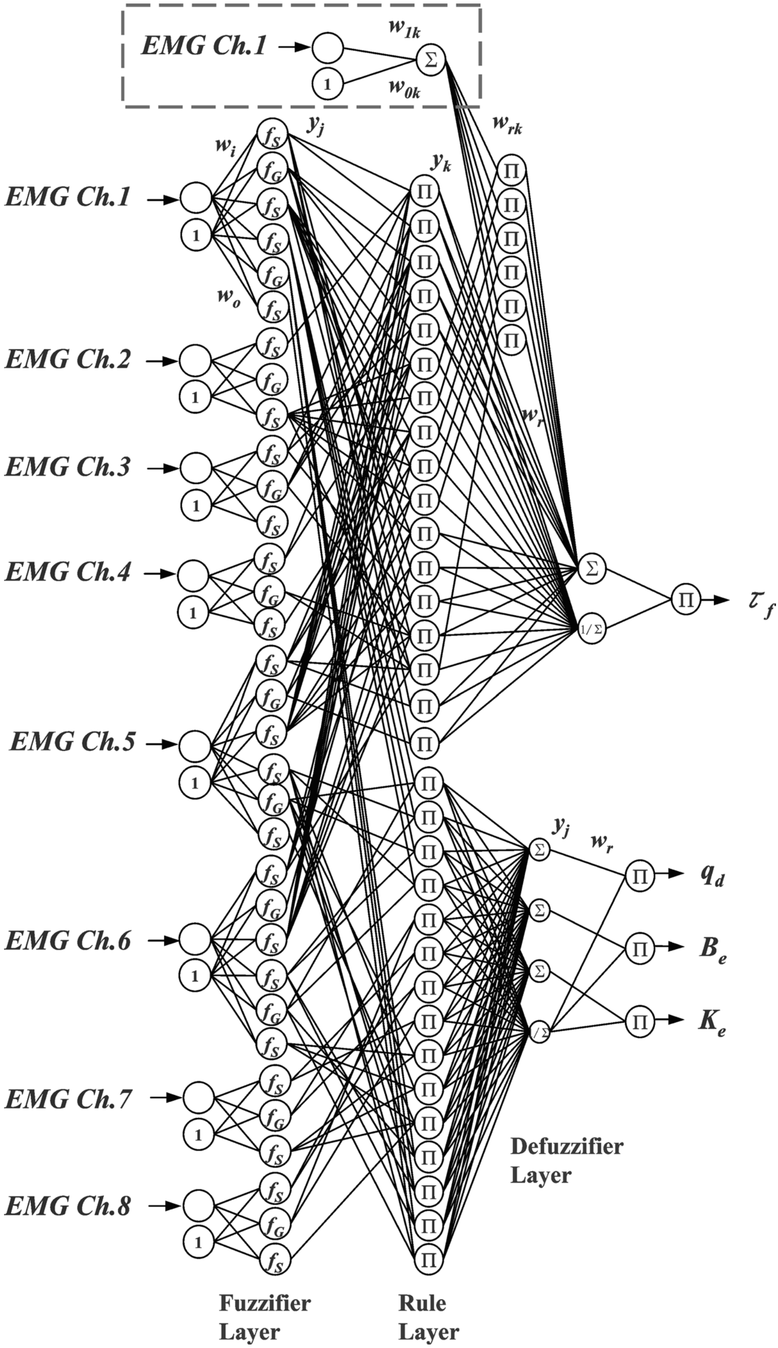


Figure 6. The neuro-fuzzy controller.

for each input variable. The MAV of the pronator teres (ch.1), which is a muscle common to both elbow flexion–extension and forearm pronation–supination motions, is used as an input variable as shown inside the dotted rectangle in Fig. 6 to adjust the weight in the consequent part of the fuzzy control rules for the supination motion assist. The activity level of the biceps (ch.5 and ch.6) used for elbow flexion motion can be predicted by monitoring this muscle during the simultaneous motion of elbow flexion and forearm supination, since this muscle is used for both the pronation and elbow flexion motion. Consequently, the activity of the biceps (ch.5 and ch.6) used for elbow flexion motion can be canceled out by adjusting the weight of the consequent part of control rules for forearm supination based on the amount of the muscle of pronator teres (ch.1). This process cancels out the force generated for the elbow flexion motion by the biceps in the fuzzy control rules for the supination motion assist.

The outputs of the neuro-fuzzy controller are the torque command for the forearm pronation–supination motion (τ_f), the desired impedance parameters (B_e is the damping coefficient and K_e is the spring constant) and the desired angle (q_d) for the elbow flexion–extension motion of the robotic exoskeleton. The torque command for the forearm pronation–supination motion is then transferred to the force command for the driving wire. Impedance control is performed with the derived impedance parameters and the derived desired angle for the elbow joint control of the exoskeleton [1]. The equation is written as:

$$\tau_e = M_e \ddot{q}_d + B_e(\dot{q}_d - \dot{q}) + K_e(q_d - q), \tag{6}$$

where M_e is the inertia moment of the human forearm and link-2, and q is the measured elbow angle.

3.2. Multiple controllers

In order to eliminate problems caused by a change the arm posture, three kinds of neuro-fuzzy controllers, which are (moderately) switched in accordance with the elbow angle, are prepared in this study. The movable range of the elbow motion is divided into three regions. A membership function is defined for each region (FA: flexed angle, IA: intermediate angle and EA: extended angle) to switch the neuro-fuzzy controller smoothly. By applying these membership functions (Fig. 7),

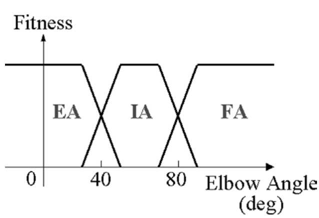


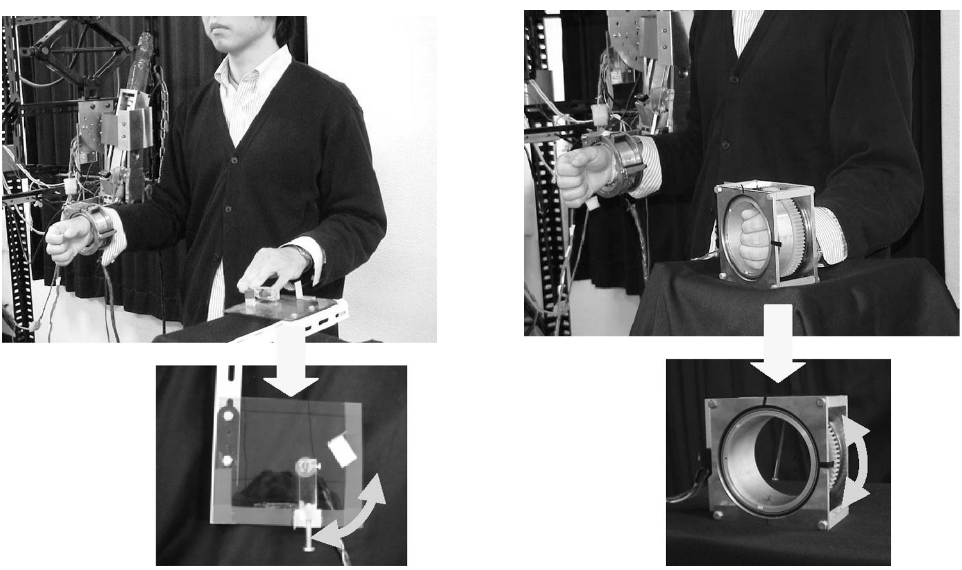
Figure 7. Membership function.

the appropriate neuro-fuzzy controllers are switched in accordance with the arm posture of the patient.

3.3. Controller adaptation

Cooperative motion of the elbow and forearm of the patient is realized by precisely learning the muscle activation patterns of each patient in all of antecedent parts and some of consequent parts of the fuzzy IF–THEN control rules. In the controller adaptation process, the controller adapts itself to the physical and physiological conditions, and the method of muscle use of a patient. In this study, adjustment of the controller is performed using the back-propagation learning algorithm. The desired motion required for the adaptation of the controller is given using the motion indicators by the patient. Figure 8(a and b) shows the motion indicators for the elbow and forearm motion, respectively. The motion intention of the patient (i.e. the desired motion required for controller adaptation) is directly indicated by the wrist motion of the patient as shown in Fig. 8.

In the controller adaptation process, the patient is supposed to give the desired forearm pronation–supination motion or the desired elbow flex–extension motion using the motion indicator and try to generate the same motion (the desired motion) in the assisted arm at the same time. The elbow flexion–extension motion is given in each elbow region (flexed, intermediate and extended region) for the adjustment of the elbow flexion–extension control rules and the forearm pronation–supination motion is given for the adjustment of the forearm pronation–supination control rules. The control rules are adjusted if the motion indicated by the patient



(a) (b)

Figure 8. Motion indicator. (A) Elbow flexion–extension. (b) Forearm pronation–supination.

(the desired motion) and the assisted motion by the robotic exoskeleton differ. The controller adaptation is carried out for about 2–3 min for each patient. The evaluation function for the controller adaptation is written as:

$$E = \frac{1}{2}\left((\theta_{\mathrm{d}} - \theta)^2 + \alpha \sum_{i=1}^{n} (\mathrm{MAV}_{i\_\mathrm{d}} - \mathrm{MAV}_i)^2\right), \tag{7}$$

where θ_{d} is the desired angle indicated by the patient, θ is the measured angle of the exoskeleton, α is a coefficient which changes the degree of consideration of the muscle activity minimization, $\mathrm{MAV}_{i\_\mathrm{d}}$ is the desired muscle activity level in ch.i for each motion and MAV_i is the measured muscle activity level in ch.i. Minimizing the evaluation function using the back-propagation learning algorithm results in precise power assist with the desired assist level [4].

4. EXPERIMENT

In order to evaluate the effectiveness of the proposed method, an experiment was carried out with three healthy human male subjects. The experimental setup is shown in Fig. 9. In order to examine the effectiveness of the proposed method in motion assist in daily living and rehabilitation, cooperative motion of the elbow and forearm was performed in the experiment. In this experiment, the human subjects were supposed to perform cooperative motion of the elbow and forearm (i.e. a combination of elbow flexion–extension motion and forearm pronation–supination motion) under an external load. In practice, having something like a cup, food,

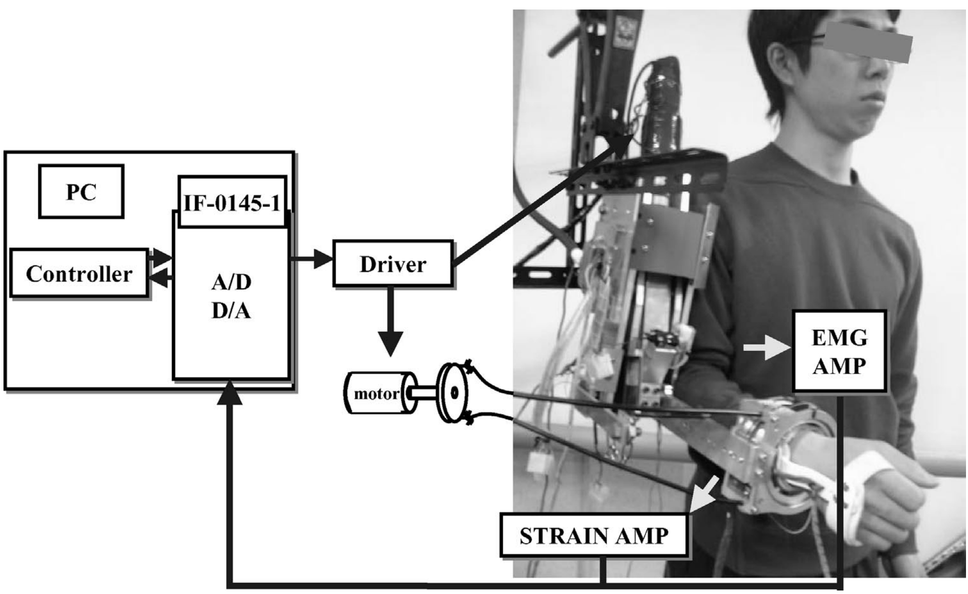


Figure 9. Experimental setup.

a hairdryer, a kettle, etc., was the external load. The external load was given by a rubber tube (one end was attached to the floor below the attachment point of the exoskeleton to the frame, and the other end was attached to the subject's, hand) to prevent cooperative motion in order to verify the effect of the EMG-based control clearly, although the effective power assist can be also performed as well. Each experiment was carried out with and without robotic exoskeleton assist for comparison. The sampling time was set to be 0.5 ms for every experiment.

First, we performed the elbow flexion motion assist experiment under the pronated forearm position with exoskeleton assist in order to show the advantage of the proposed neuro-fuzzy control method over the conventional neuro-fuzzy control method. Here, the conventional neuro-fuzzy controller means the neuro-fuzzy controller in which the weights of the consequent part of the control rules are not functions of the pronator teres muscle (ch.1). Experimental results with the proposed and the conventional method are shown in Fig. 10a and 10b, respectively. In Fig. 10, the black line shows the forearm pronation–supination angle, the dark-gray line shows the elbow flexion–extension angle and the light-gray line depicts the muscle activity level. One can see that inappropriate forearm motion (the forearm pronation–supination angle should not change) is generated in the results with the conventional method only for the elbow flexion motion, since the extensor carpi radialis longus (ch.4) is activated a little in the flexed elbow angle. These results show the advantage of the proposed method.

Figures 11–13 show the experimental results of cooperative motion 1 (i.e. simultaneous elbow flexion and forearm supination) with Subjects A, B and C, respectively. The results without exoskeleton assist are shown in parts (a) and those with exoskeleton assist are shown in parts (b). Here, only the results of ch.5

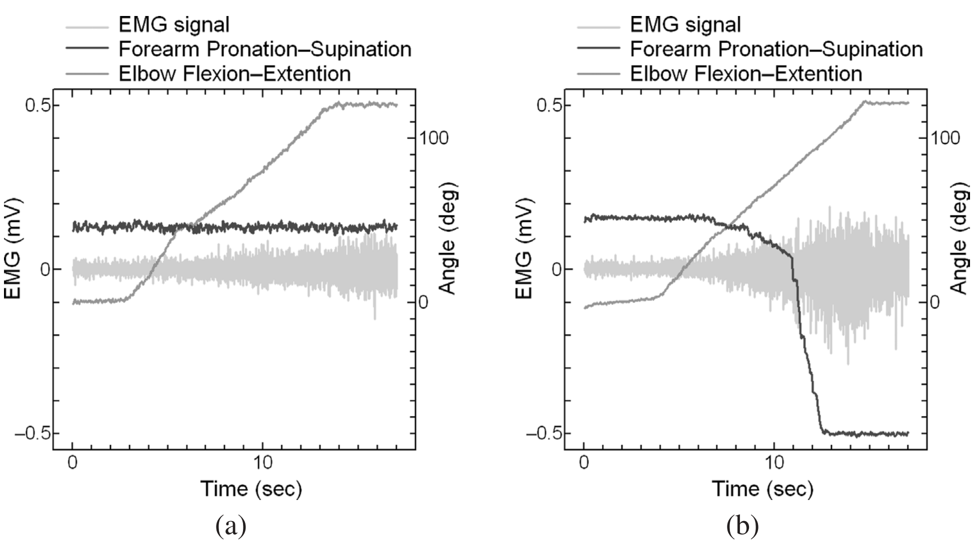


Figure 10. Experimental results (ch.5) for elbow flexion motion with Subject A. (a) Proposed controller. (b) Conventional controller.

(proximal part of biceps) are shown as examples. In these experiments, the subjects were supposed to supinate the forearm from the fully pronated position to the fully supinated position and flex the elbow from the fully extended position to the fully flexed position simultaneously. If the motion assist was effectively performed, the muscle activity level for the motion was supposed to be reduced. One can see from the experimental results that the activity level of ch.5 was reduced for the same motion with the robotic exoskeleton assist. In these experiments, 80.1, 49.1 and 70.2% of the EMG signal was reduced with respect to that without the exoskeleton

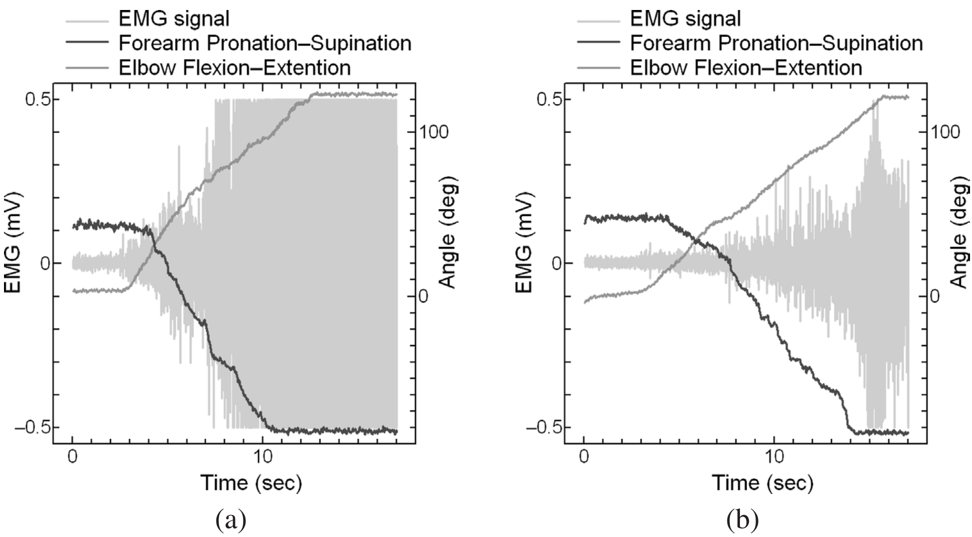


Figure 11. Experimental results (ch.5) motion 1 with Subject A. (a) Without assist. (b) With assist.

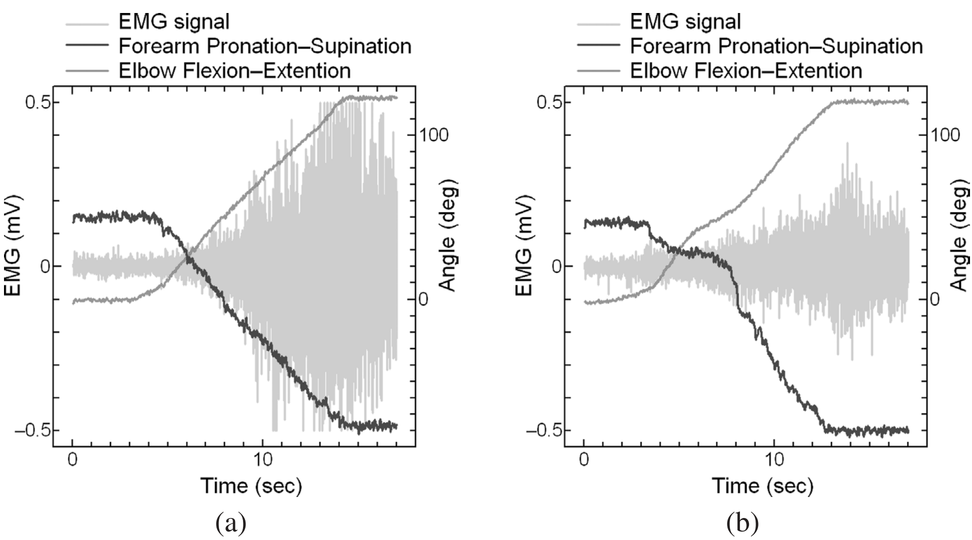


Figure 12. Experimental results (ch.5) motion 1 with Subject B. (a) Without assist. (b) With assist.

assist for the same motion in the case of the Subjects A, B and C, respectively. The average reduction rate was 66.5%.

The same experiment was performed without the external load with Subject A in order to obtain additional information. The experimental results are shown in Fig. 14. These results also show the effectiveness of the proposed robotic exoskeleton, although the visual difference is not very significant. In these

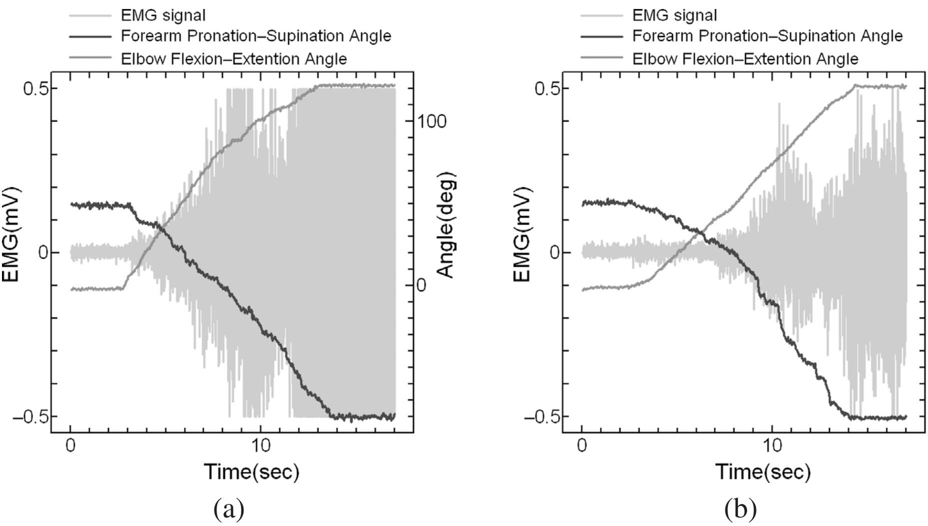


Figure 13. Experimental results (ch.5) for motion 1 with Subject C. (a) Without assist. (b) With assist.

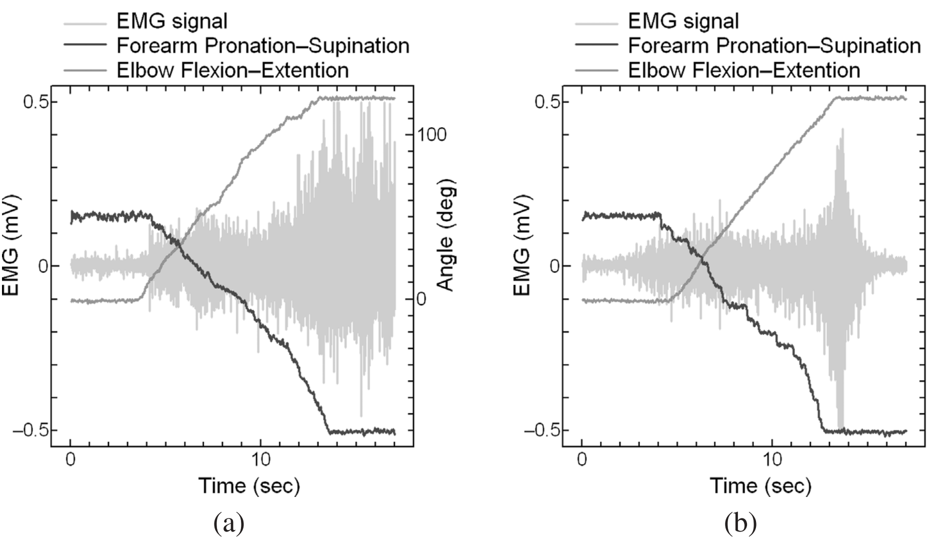


Figure 14. Experimental results (ch.5) for motion 1 without external load. (a) Without assist. (b) With assist.

experiments, 35.9% of the EMG signal was reduced with respect to that without the exoskeleton assist for the same motion.

Figures 15–17 show the experimental results of cooperative motion 2 (i.e. simultaneous elbow flexion and forearm pronation) with Subjects A, B and C, respectively. As mentioned above, the results without exoskeleton assist are shown in parts (a) and those with exoskeleton assist are shown in parts (b). Here, only the

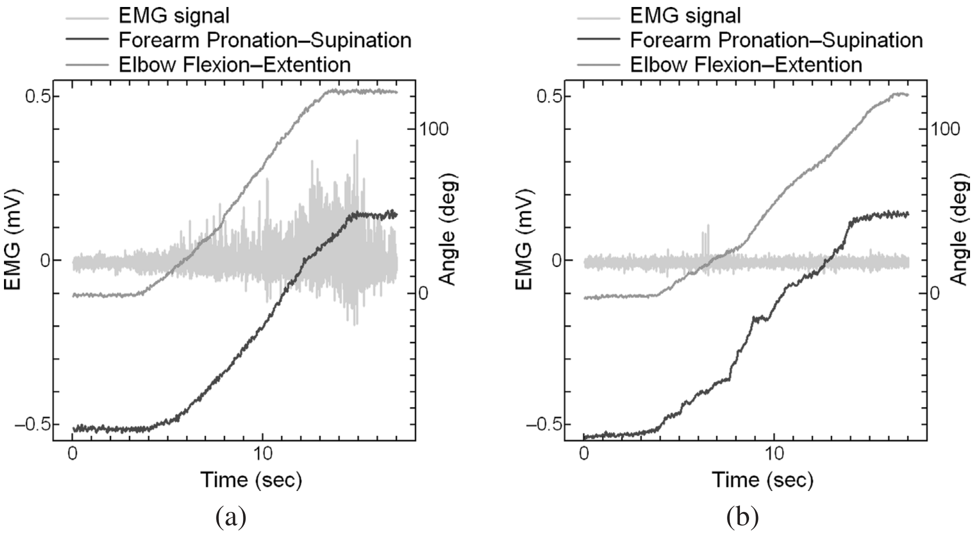


Figure 15. Experimental results (ch.1) for motion 2 with Subject A. (a) Without assist. (b) With assist.

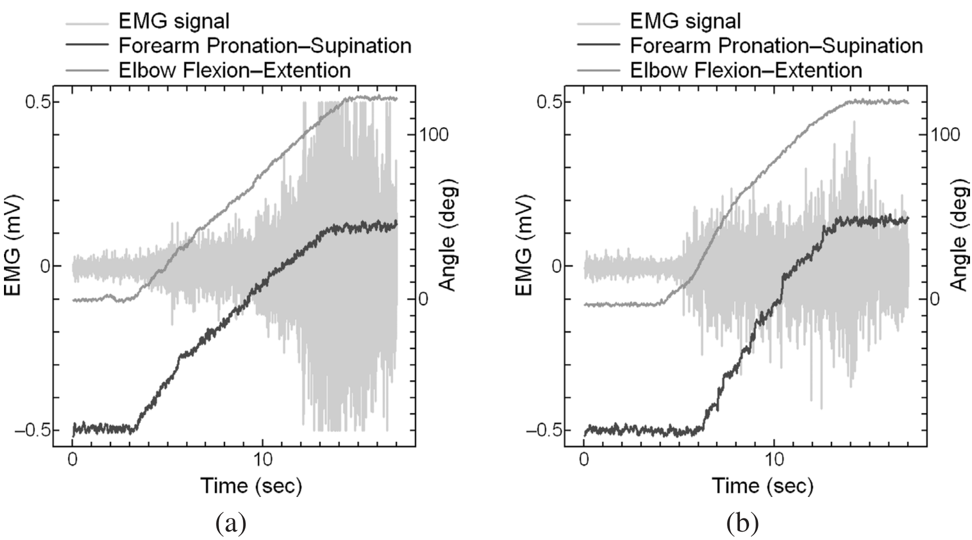
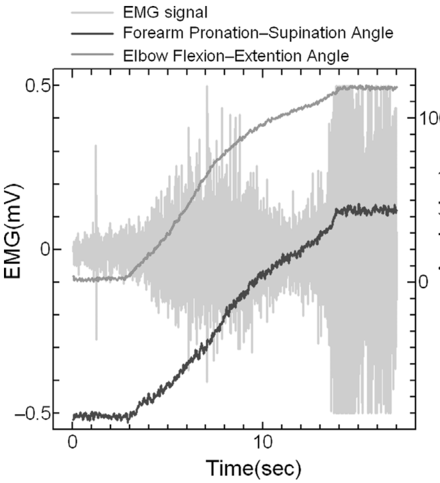
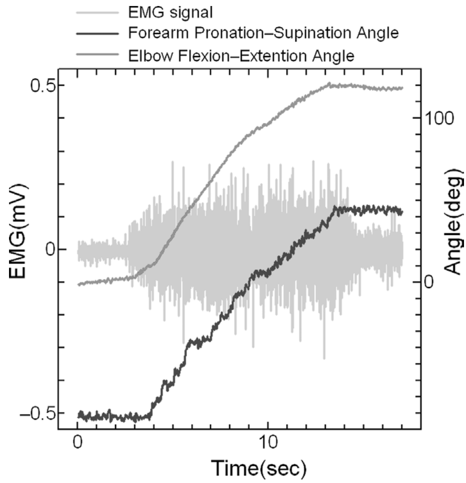


Figure 16. Experimental results (ch.1) for motion 2 with Subject B. (a) Without assist. (b) With assist.



(a)



(b)

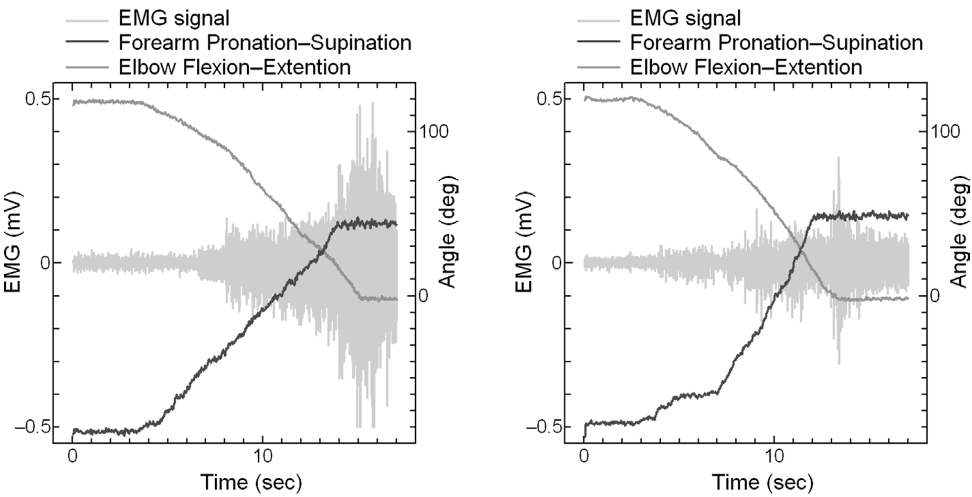
Figure 17. Experimental results (ch.1) for motion 2 with Subject C. (a) Without assist. (b) With assist.

results of ch.1 (pronator teres) are shown as examples. As the results indicate, it is clear that the activity level of ch.1 was reduced for the same motion with the robotic exoskeleton assist. In these experiments, 62.3, 39.4 and 49.7% of the EMG signal was reduced with respect to that without the exoskeleton assist for the same motion in the case of Subjects A, B and C, respectively. The average reduction rate was 50.5%. These results prove the effectiveness of the proposed robotic exoskeleton.

Similar results were obtained in cooperative motion 3 (i.e. simultaneous elbow extension and forearm pronation) and cooperative motion 4 (i.e. simultaneous elbow extension and forearm supination) with all subjects. The experimental results of motions 3 and 4 with Subject A are depicted as examples in Figs 18 and 19, respectively. The results without exoskeleton assist are shown in parts (a) and those with exoskeleton assist are shown in parts (b). Only the results of ch.8 (lateral part of triceps) are depicted. In these experiments, 45.4 and 63.6% of the EMG signal was reduced with respect to that without exoskeleton assist for the same motion in the case of motions 3 and 4, respectively. These results also prove that the cooperative motion is effectively assisted by the robotic exoskeleton.

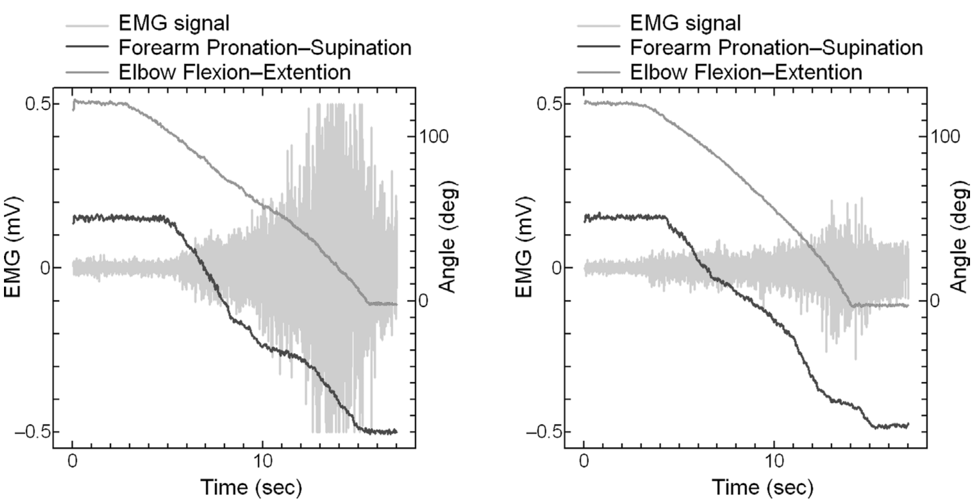
5. CONCLUSIONS

In this paper, a 2-d.o.f. wearable robotic exoskeleton system is proposed to assist the forearm motion (elbow flexion–extension and forearm pronation–supination) of physically weak persons in daily activity and rehabilitation. A neuro-fuzzy control method, in which the effect of a muscle common to some motions is taken into account, is proposed to realize the sophisticated forearm motion assist with the



(a) (b)

Figure 18. Experimental results (ch.8) for motion 3 with Subject A. (a) Without assist. (b) With assist.



(a) (b)

Figure 19. Experimental results (ch.8) for motion 4 with Subject A. (a) Without assist. (b) With assist.

exoskeleton for the purpose of rehabilitation and daily use. In order to eliminate problems caused by a change in the arm posture, multiple neuro-fuzzy controllers, which are moderately switched in accordance with the elbow angle, are applied. Experiments with several human subjects showed the effectiveness of the proposed method.

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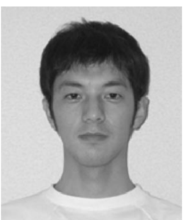

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