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Application of Surface Electromyographic Signals to Control Exoskeleton Robots

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1. Introduction

The electromyographic signals abbreviated as EMG, represent the amount of electrical potential generated by the muscle cells when they contract or when they are at rest. Basically, EMG signals can be classified into two types according to the place where they are extracted. The EMG signals detect from inside of the muscles are called as intramuscular EMG whereas EMG signals detect from skin surface of the muscles are called surface EMG. The extraction procedure of intramuscular EMG signals is invasive. The intramuscular EMG signals are difficult to use practically, since the invasive procedure of extraction. EMG signals of human muscles are important biological signals to understand the motion intention of human. Therefore, the EMG signals can be used as input information to control robotic systems (Farry *et al.*, 1996; Kiguchi *et. al.*, 2001). The surface EMG signal is commonly used for this purpose since it can be extracted easily without applying a non-invasive method (Farry *et al.*, 1996).

The exoskeleton robot is a device which can be worn by the human operator as an orthotic device (Perry & Rosen, 2007). The same system operated in different modes can be used for different fundamental applications: power-assist device, human-amplifier, rehabilitation device, and haptic interface (Perry & Rosen, 2007). The skin surface EMG signals of the muscles can be used as input information of the controllers of exoskeleton robot (Kiguchi *et al.*, 2001). The EMG signals vary from person to person. In addition, it differs for the same motion even with the same person. The physical conditions such as tiredness, sleepiness, *etc.* (Kiguchi *et al.*, 2007). Therefore, characteristics of the EMG signals should be carefully considered when developing a control method for exoskeleton robot using EMG signals as input information. Since the surface EMG signals can directly reflect the human motion intention they can be used as main input information to the controller of exoskeleton robot to realize automatic control for the physically weak persons without manipulating any other equipment. Such kind of control is especially important for the system used by elderly, injured, or physically weak persons.

This chapter presents an experimental study of upper-limb surface EMG signals and two cases of applying surface EMG signals to control an upper-limb exoskeleton robot. The applied method to process surface EMG signals to use as input information to the control method is also explained. At first, surface EMG signal extraction method and processing method are presented in this chapter. Then, the upper-limb muscle activities during daily upper-limb motions have been studied to enable exoskeleton robots to estimate human upper-limb motions based on EMG signals of related muscles. The muscle combinations are identified to separate some motions of upper-limb. Minimum number of muscles to extract signals to control frequent daily upper-limb motions has been identified. In the next step, EMG signal of identified muscles are used to control two upper-limb exoskeleton robots. A three degree of freedom (DOF) exoskeleton robot (W-EXOS) for the forearm pronation/supination, wrist flexion/extension and ulnar/radial deviation are controlled by applying the surface EMG signals of six muscles. Surface EMG signals of upper-limb muscles are applied as input information to control a 6DOF exoskeleton robot (SUEFUL-6). In each case of applying EMG signals experiments have been carried out to evaluate the effectiveness of the EMG based control method.

In the next section, the detection and processing of surface EMG signals are presented. The experimental study of upper-limb surface EMG is explained in section 3. Application of EMG signals to control the W-EXOS is described in section 4. Section 5 explains the EMG based control of the SUEFUL-6. The discussion in section 6 is followed by the conclusion in the section 7.

2. Detection and processing of surface EMG signals

Detection methods of the EMG signals vary according to its type. Since almost all of the EMG-based control methods use surface EMG signals, the surface EMG signal detection and processing procedure is discussed in this subsection.

2.1 Detection of surface EMG signals

Detection procedure of surface EMG signals is illustrated in Fig. 1. First step of the EMG signal detection procedure is attaching the surface electrodes [e.g., NE-101A, Nihon Kohden Co., Japan] on the skin surface of the muscles. The electrode and the skin should be cleaned well before adhering on the skin. Usually, alcoholic liquid is used for the cleaning. In this study, ethanol is used. A conductive ionic paste is applied between the skin and the electrode to get rid of static electric insulation of dry skin. In this study, EEG paste [Z-181JE, Nihon Kohden Co., Japan] is used as the conductive ionic paste. Usually, a pair of surface electrodes is adhered on the skin surface of the muscle with a separation of 1cm (Luca, 2002). Additionally, a reference electrode is attached on electrically unrelated tissue. Detected EMG signals are then passed to an input box. Input box consists of input channels for several electrodes and a reference electrode. The input box [JB-620J, Nihon Kohden Co., Japan] used in this study has eight input channels for eight electrodes and another one for the reference electrode. From the input box EMG signals are passed to multi-channel amplifier. The gain of the multi-channel amplifier [MEG-6108, Nihon Kohden Co., Japan] is set to 50 μV/V in this study. Amplified EMG signals are then passed to a computer via an interface card [e.g., JIF-171-1, JustWare Co., Japan] by converting to digital signals. EMG signals are processed on the computer for feature extraction.

2.2 Feature extraction of raw EMG signals

Since raw EMG data is difficult to be dealt as input information for the controller of exoskeleton robots, the features have to be extracted from the raw EMG data. Several feature extraction methods are available for this purpose (Hudgins, 1993). Some of them are mean

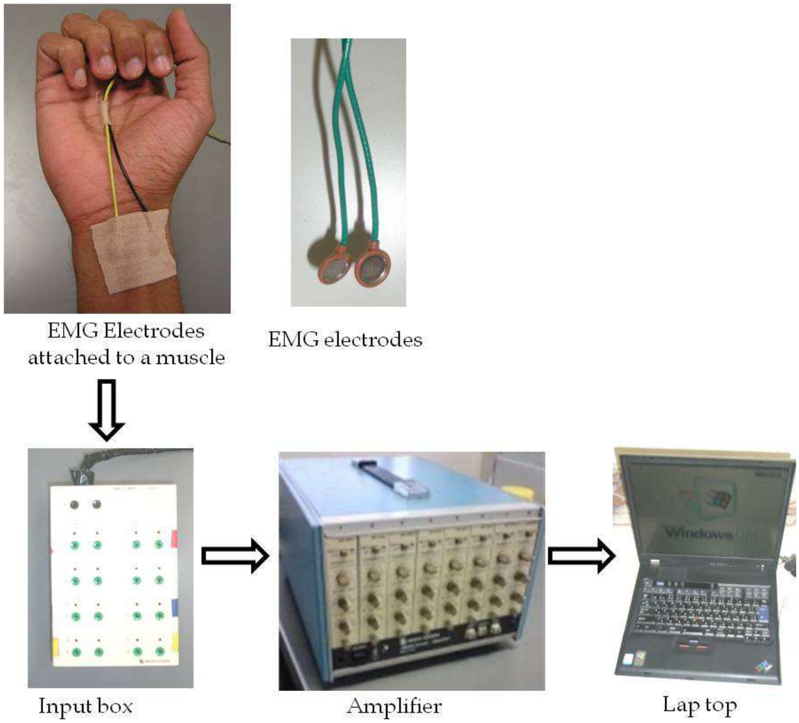


Fig. 1. Detection procedure of surface EMG signals.

absolute value, mean absolute value slope, waveform length, zero crossings, and root mean square value. The features of raw EMG data have to be extracted in real time to use EMG as input information for the controllers of exoskeleton robots. Considering the advantage of ability of real time feature extraction, Root Mean Square (RMS) method is applied to extract features of raw EMG in this study. RMS value can be stated as follows.

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} v_i^2} \tag{1}$$

where, v_i is the voltage value at the ith sampling and N is the number of samples in a segment. The number of sample is set to be 100 and the selected sampling frequency is 2 kHz in this study. Figure 2 shows an example for a raw EMG signal and its RMS value. The RMS value of EMG is used as input information for the exoskeleton robot controller.

3. Experimental study of upper-limb surface EMG signals

Human upper-limb consists of several degrees of freedoms (DOF); basically 3DOF in the shoulder joint, 2DOF in the elbow joint and 2DOF in the wrist joint. The basic motions of upper-limb can be categorized into eight individual motions (Rosen *et al.*, 2005); shoulder vertical flexion/extension, shoulder horizontal flexion/extension, shoulder adduction/ abduction, shoulder internal/external rotation, elbow flexion/extension, forearm

Motion	Activated Muscles
Shoulder vertical flexion (SVF)	Coracobrachialis, Deltoid (anterior), Pectoralis major
Shoulder vertical extension (SVE)	Deltoid (posterior), Teres major, Latissimus dorsi
Shoulder horizontal flexion (SHF)	Pectoralis major (calvicular part)
Shoulder horizontal extension (SHE)	Deltoid (posterior)
Shoulder adduction (SAD)	Coracobrachialis, Latissimus dorsi, Teres major, Pectoralis major
Shoulder abduction (SAB)	Deltoid, Supraspinatus
Shoulder internal rotation (SIR)	Deltoid (anterior), Subscapularis, Latissimus dorsi, Teres major
Shoulder external rotation (SER)	Deltoid (posterior), Infraspinatus, Teres minor
Elbow flexion (EF)	Biceps brachii, Brachioradialis, Brachialis
Elbow extension (EE)	Anconeus, Triceps brachii
Forearm supination (FS)	Supinator, Biceps brachii (long head)
Forearm pronation (FP)	Pronator quadratus, Pronator teres
Wrist flexion (WF)	Flexor carpi radialis, Flexor carpi ulnaris, Palmaris longus
Wrist extension (WE)	Extensor carpi radialis longus, Extensor carpi radialis brevis, Extensor carpi ulnaris
Wrist ulnar deviation (WUD)	Flexor carpi ulnaris, Extensor carpi ulnaris
Wrist radial deviation (WRD)	Extensor carpi radialis longus, Extensor carpi radialis brevis, Flexor carpi radialis

Table 1. Activated muscles for upper-limb motions.

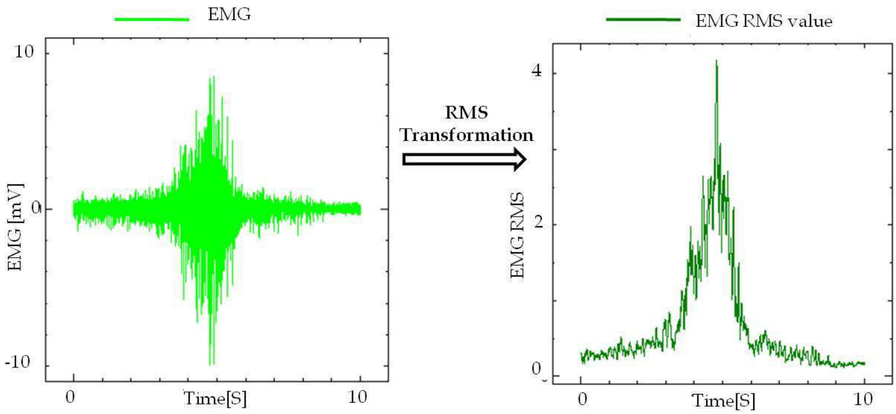


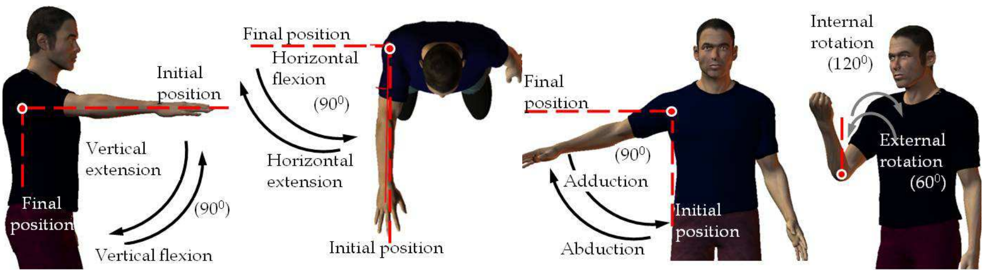
Fig. 2. Example of a raw EMG signal and its RMS value.

supination/pronation, wrist flexion/extension, and wrist ulnar/radial deviation. The daily upper-limb motions are the combination of these basic motions. Additionally fingers also have several DOF.

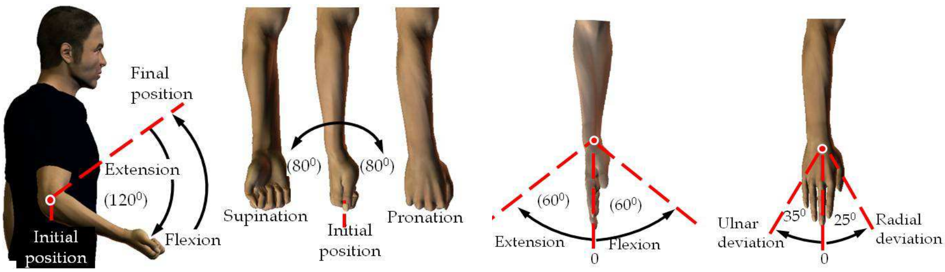
Human upper limb is activated by many kinds of muscles. Some of them are bi-articular muscles and the others are uni-articular muscles. In the upper-limb agonist-antagonist muscles activate shoulder, elbow and wrist. The upper-limb motions and the related muscles for the motions (Martini *et al.*, 1997) are shown in Table 1.

3.1 Procedure of experimental study

In order to obtain the relationships between the human upper-limb motions and activities of related muscles, the experiments were performed with 26 and 28 years old healthy male subjects (subject A and B, respectively). In the experiment, the basic motions and the selected daily activities of upper-limb were performed three times by each subject. Figure 3 shows the initial position and motion range of each basic motion in the experiments. The daily activities were performed in either standing or sitting posture in accordance with the nature of the daily activity. Initial and final postures of the daily activities are shown in Fig. 4. The angles of each joint of the upper-limb during the daily activities were measured by the motion capture system (Vicon MX+, 2009). Reflective markers were attached to subjects at key anatomical locations as shown in Fig. 5. Considering the muscle characteristics, sixteen muscles; Ch.1: Deltoid (anterior), Ch.2: Deltoid (posterior), Ch.3: Pectoralis major (calvicular part), Ch.4: Teres major, Ch.5: Pectoralis major, Ch.6: Infraspinatus, Ch.7: Biceps brachii, Ch.8: Triceps brachii, Ch.9: Brachialis, Ch.10: Supinator, Ch.11: Pronator teres, Ch.12: Pronator quadratus, Ch.13: Extensor carpi radialis brevis, Ch.14: Extensor carpi ulnaris, Ch.15: Flexor carpi radialis and Ch.16: Flexor carpi ulnaris, were selected for analysis in this study. Additionally another EMG electrode is attached on the skin of the abdomen as ground electrode. EMG signals of selected muscles were measured for each activity. The locations of EMG electrode are shown in Fig. 6. Subscapularis, teres minor, and anconeus are neglected in this analysis since they are overlapped with other muscles (Martini *et al.*, 1997). Since the palmaris longus is a weak flexor (Martini *et al.*, 1997), it is not taken into account. Only extensor carpi radialis brevis is taken for analysis from extensor muscle group. The brachialis is selected from the brachialis and brachioradialis since both seem to act for the elbow flexion motion. EMG signals are processed using the procedure given in the previous section.



(a) Shoulder motions



(b) Elbow and forearm motions (c) Wrist motions

Fig. 3. Initial positions and motion ranges of experimental motions.

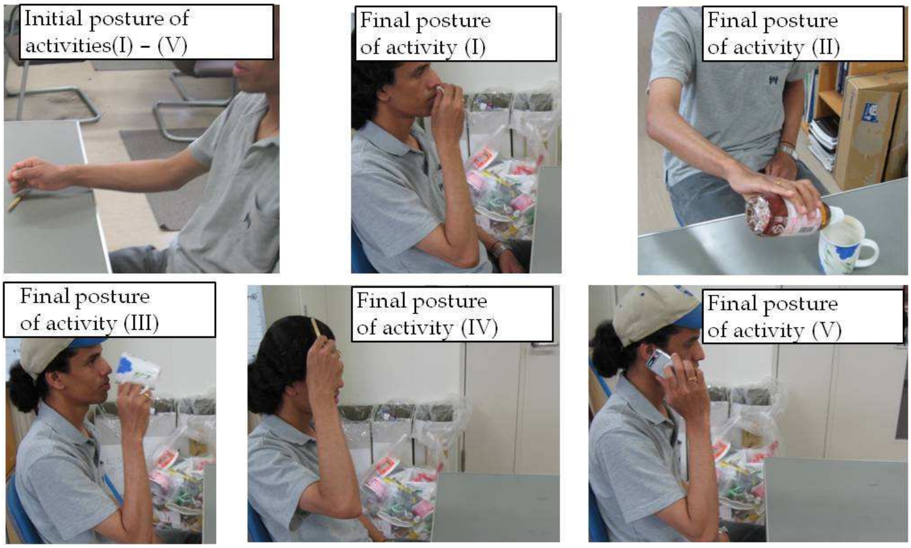
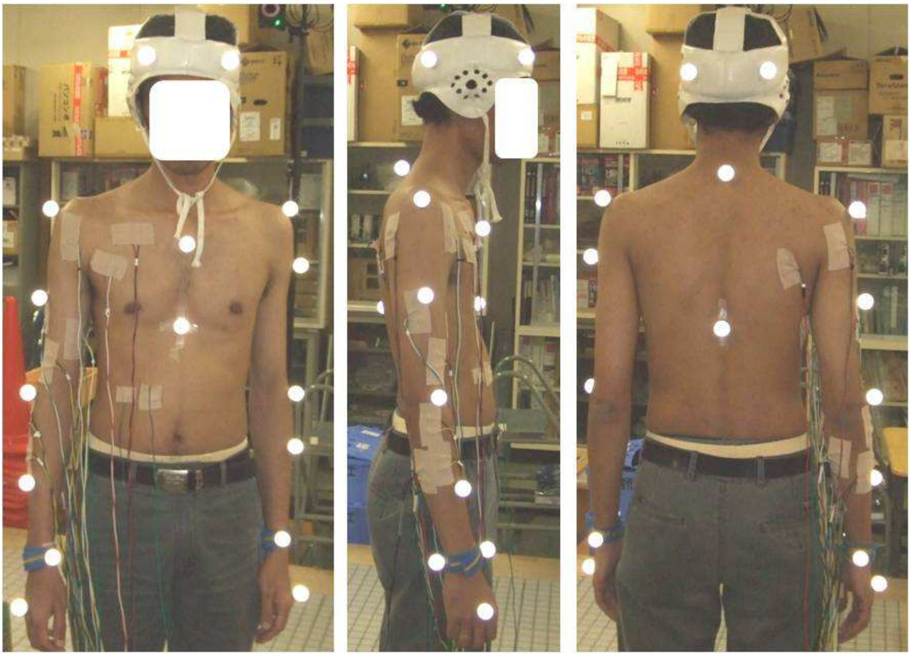


Fig. 4. Initial and final positures of selected daily activities.



(a) (b) (c)

Fig. 5. Locations of markers. (a) Anterior view (b) Lateral view (c) Posterior view.

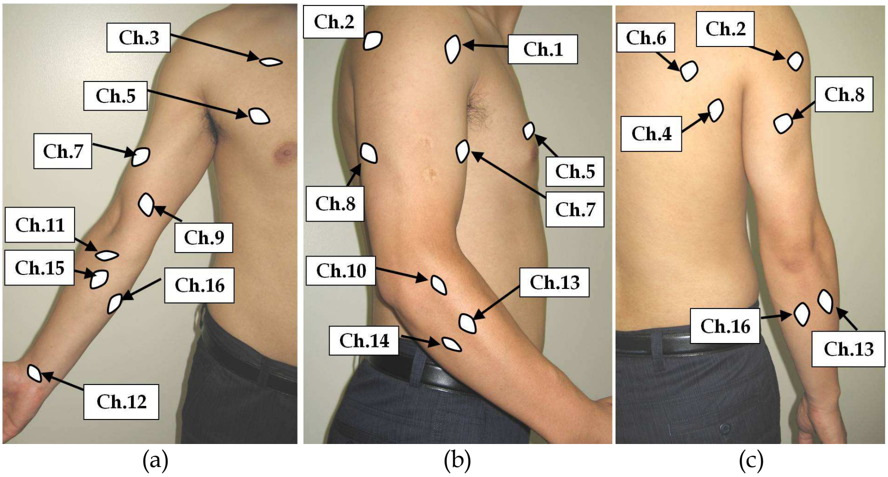


Fig. 6. Locations of EMG electrodes. a) Front view, (b) Side view, (c) Rear view.

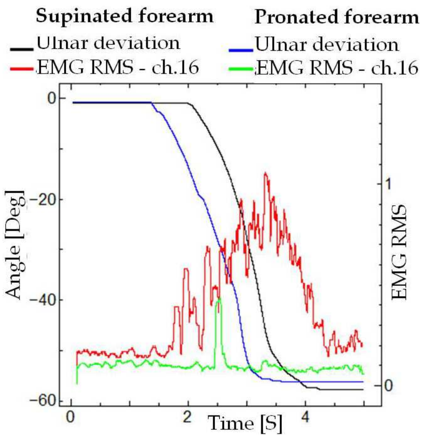


Fig. 7. EMG RMS for Ulnar deviation.

3.2 Analysis of results

It can be identified that the EMG activity levels related to the basic upper-limb motions (see Fig. 3) depend on the joint angles and the upper-limb posture (Gil Coury *et al.*, 1998). As an example, the experimental result of the full range ulnar deviation shown in Fig. 7 indicated that EMG RMS values for ulnar deviation are different in the supinated forearm posture and pronated forearm posture. Figure 8 shows the relationship of activity level of extensor carpi radialis brevis for wrist extension and radial deviation. Although some muscles are not bi-articular muscles, they act for a few motions (see Fig. 8). From Fig. 8, it can be seen that extensor carpi radialis brevis is activated for both wrist extension and radial deviation. Figure 9 shows the relationship between EMG RMS values of muscles and wrist motions. The extensor carpi ulnaris is activated for both wrist extension and ulnar deviation (see Fig. 9). Flexor carpi radialis is activated for both wrist flexion and radial deviation.

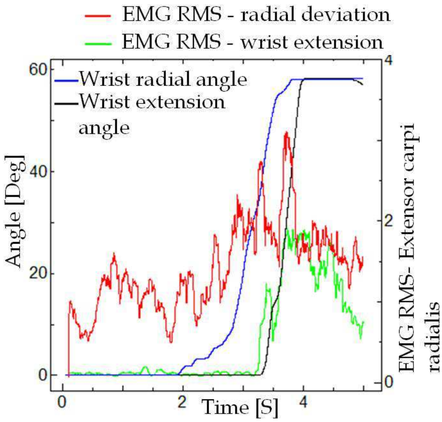


Fig. 8. EMG RMS- extensor carpi radialis brevis.

Although the flexor carpi ulnaris is not bi-articular muscle, it is activated for both wrist flexion and ulnar deviation. By analyzing results of the experiments, it can be seen that some basic upper-limb motions within the motion ranges used in the experiments can be separated by using the combinations of related muscles. Although many muscles are involved in wrist motions, each basic wrist motion can be uniquely identify in any forearm posture by considering simultaneous activation of two of muscles. Although the extensor carpi radialis longus, extensor carpi radialis brevis and extensor carpi ulnaris generate the wrist extension, the extensor carpi radialis brevis and extensor carpi ulnaris can be used to separately identify the wrist extension [see Fig. 9(b)]. Simultaneous activation of both muscles generates wrist extension in any forearm posture even though extensor carpi radialis brevis also activates the wrist radial deviation and extensor carpi ulnaris also activates the wrist ulnar deviation. Similarly, simultaneous activation of flexor carpi radialis and flexor carpi ulnaris generates wrist flexion even though they generate wrist radial and ulnar deviations, respectively [see Fig. 9(a)]. Therefore, wrist flexion motion can be separated by considering simultaneous activation of the flexor carpi radialis and flexor carpi ulnaris. Similarly, simultaneous activation of extensor carpi radialis and flexor carpi radialis generates wrist radial deviation [Fig. 9(c)]. Thus, those muscles can be used to separate wrist radial deviation. Simultaneous activation of extensor carpi ulnaris and flexor carpi ulnaris separates the wrist ulnar deviation from the other wrist motions [see Fig. 9(d)]. Even though supinator and biceps brachii activate the forearm supination motion, biceps brachii works only if elbow flexion angle is about 90 degrees. Activation of only supinator can estimate forearm supination (Gopura *et al.*, 2010). The activation of pronator teres or pronator qudratus can be used to identify forearm pronation motion although both activate the motion (Martini *et al.,* 1997). Figure 10 depicts the relationship of EMG RMS values of activated muscles and elbow and shoulder motions. When performing the basic elbow motions shown in Fig. 10, the shoulder angles was maintained about 0 degrees.

The elbow flexion is generated by the biceps brachii, brachialis, and brachioradialis. However, from the analysis, it was found that even only the brachialis can be used to identify the motion [see Fig. 10(a)]. Although several muscles activates for shoulder motions, activation of one/two muscles can be used to identify each shoulder motion. As shown in Fig. 10(e), activation of infraspinatus and/or deltoid-posterior can be used to

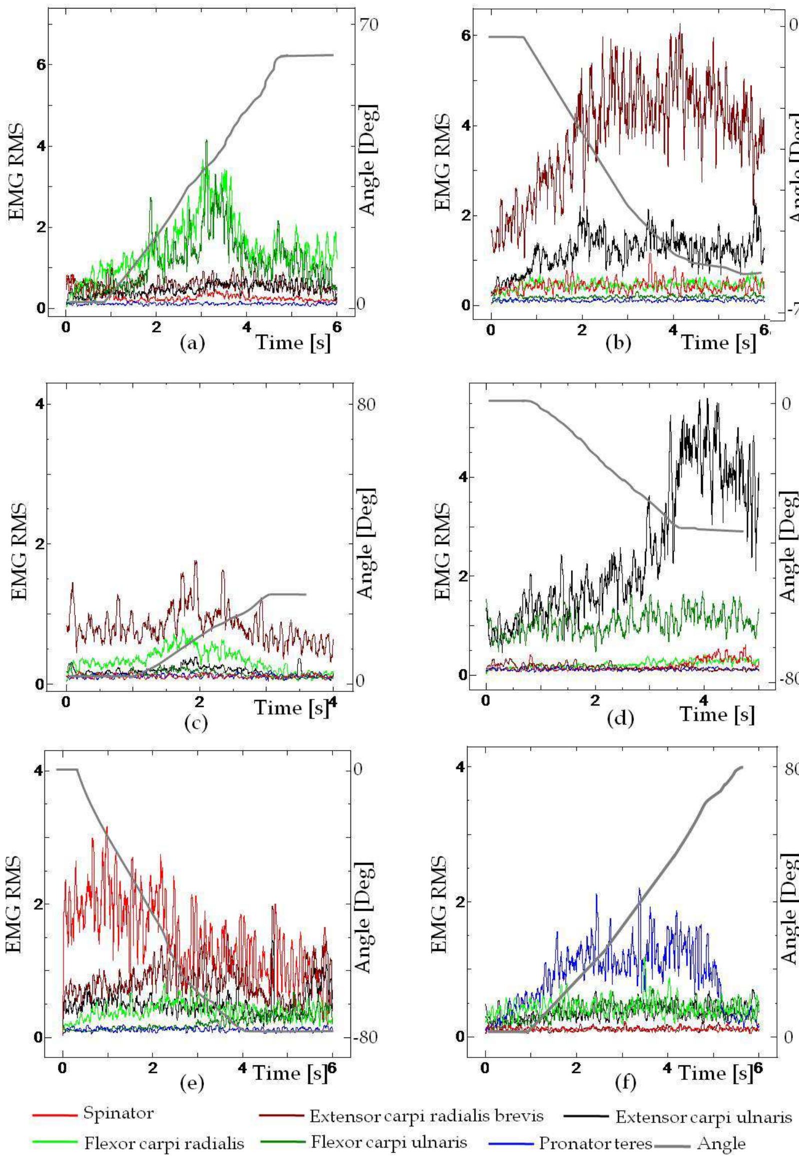


Fig. 9. Relationship of EMG RMS and basic wrist motions. (a) Wrist flexion. (b) Wrist extension. (c) Radial deviation. (d) Ulnar deviation.

identify external rotation within the experimental motion ranges. Activation of the whole deltoid muscle (*i.e.*, anterior and posterior) can be used to recognize the shoulder abduction [see Fig. 10(b)] within the experimental motion range. When the shoulder internal rotation is not activated, teres major and pectoralis major simultaneously generate shoulder adduction

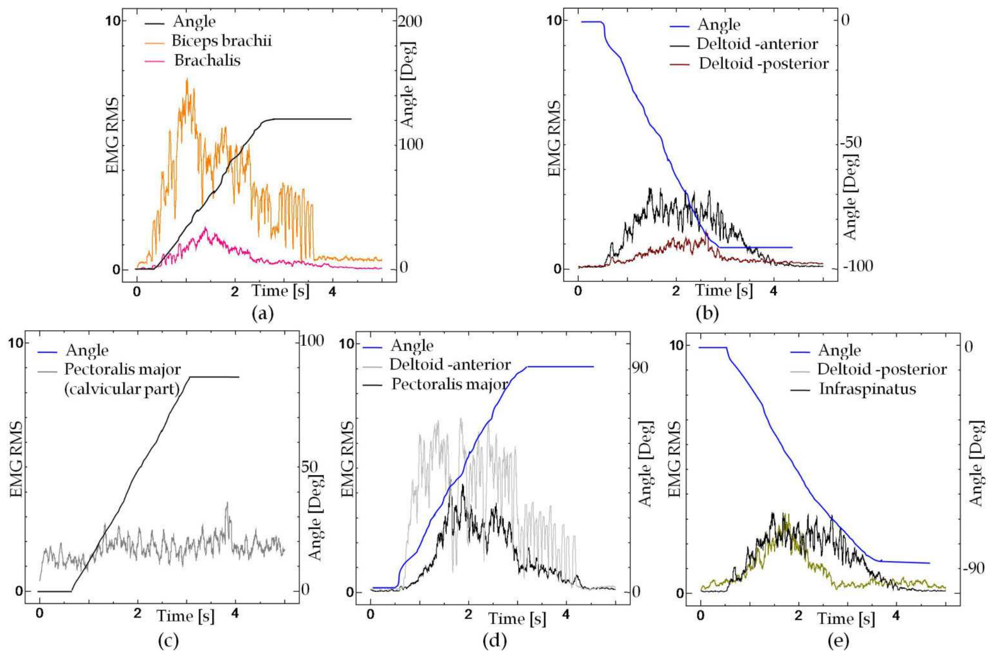


Fig. 10. Relationship of EMG RMS and basic elbow and shoulder motions. (a) Elbow flexion. (b) Shoulder abduction. (c). Shoulder horizontal flexion. (d) Shoulder vertical flexion. (e) Shoulder external rotation.

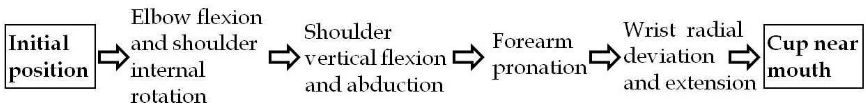


Fig. 11. Sequence of joint motion activation by the subject-A for moving the upper-limb for drinking from cup.

in the experimental motion range. When shoulder vertical motion angle is within 0 to 90 degrees, pectoralis major-calvicular part can be used [see Fig. 10(c)] to identify shoulder horizontal flexion. As identified from Fig. 10(d), deltoild-anterior and pectoralis major can be used to identify shoulder vertical flexion.

Every daily activity of upper-limb is a combination of basic upper-limb motions. Therefore, the relationship between each basic motion angle and related muscle activities are analyzed. A daily activity is explained in detail here as an example. In the activity of moving the upper-limb for drinking from a cup, initially the hand was kept near the cup on the table as shown in Fig. 11. The final position of the hand was near the mouth. In the activity, each upper-limb joint motion of subject-A were generated as follows. At first elbow flexion and the shoulder internal rotation were carried out at the same time. Then, shoulder was vertically flexed and adducted. When the cup came near the mouth, forearm pronation was carried out. Finally, wrist flexion and radial deviation were carried out. However, forearm

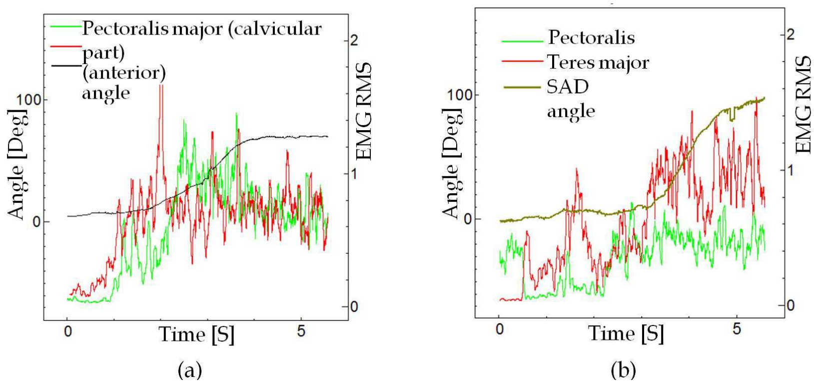


Fig. 12. Relationships between muscle activities and motion angles for moving upper-limb for drinking from cup. (a) Shoulder vertical flexion (SV) angle. (b) Shoulder adduction (SAD) angle.

Motion	Identified Muscles for Motion
SVF	Deltoid -anterior, Pectoralis major-calvicular part
SVE	Deltoid -posterior, Teres major
SHF	Pectoralis major-calvicular part
SHE	Deltoid-posterior
SAD	Teres major, Pectoralis major
SAB	Deltoid -anterior, Deltoid -posterior
SIR	Deltoid-anterior, Teres major
SER	Infraspinatus,
EF	Biceps brachii, Brachialis
EE	Triceps brachii
FS	Supinator
FP	Pronator teres
WF	Flexor carpi radialis, Flexor carpi ulnaris
WE	Extensor carpi radialis brevis, Extensor carpi ulnaris
WUD	Flexor carpi ulnaris, Extensor carpi ulnaris
WRD	Extensor carpi radialis brevis, Flexor carpi radialis

Table 2. Identified muscles to generate upper-limb motions.

and wrist motions were minimal. The relationship between the shoulder vertical flexion angle and EMG RMS levels of the related muscle are shown in Fig. 12(a). As shown in Fig. 12(a), the shoulder vertical flexion motion of this activity can be identified considering the simultaneous activation of pectoralis major-calvicular part and deltoid-anterior. The shoulder adduction of the activity can be identified from the activation of pectoralis major and teres major [see Fig. 12(b)]. Some other experimental results and details of this study can be found in (Gopura *et al.*, 2010).

By analysing the experimental results following conclusions are derived. Although several muscles activate to generate upper-limb motions, sixteen upper-limb muscles can be used to estimate the upper-limb motions. Simultaneous activation of two muscles involved in wrist motions can uniquely identify the basic wrist motions. The identified muscles to generate basic upper-limb motions (only in the experimental motion range) are listed in Table 2. The combinations of the EMG signals of identified muscles can be used as input information to the controllers of upper-limb exoskeleton robot.

4. Application of EMG signal to control 3DOF exoskeleton robot

A 3DOF exoskeleton robot, W-EXOS is shown in Fig. 13. It has been developed to assist forearm pronation/supination, wrist flexion/extension and ulnar/radial deviation (Gopura & Kiguchi, 2008a). The original feature of the design is the axes offset of wrist joint, which was not considered in any other design. Therefore, undesired pain of the user's wrist joint can be avoided. In addition, the hand-robot interface has been designed so as not to disturb the finger motions. The axes offset of wrist joint is important for a wrist exoskeleton robot, since the wrist joint is sensitive to change in position and torque (Perry & Rosen, 2007). The W-EXOS mainly consists of forearm motion support part and wrist motion support part. The forearm motion support part consists of two links (upper-arm link and forearm link), a direct current (DC) motor, a drive and driven spur gear pair (gear ratio 1:3), a wrist holder, a forearm cover and torque sensors. The wrist motion support part consists of a link attachment, two DC motors, two drive and driven bevel gear pairs (gear ratio-1:2), a palm holder, a three axis force sensor and a link (wrist link) which connects the

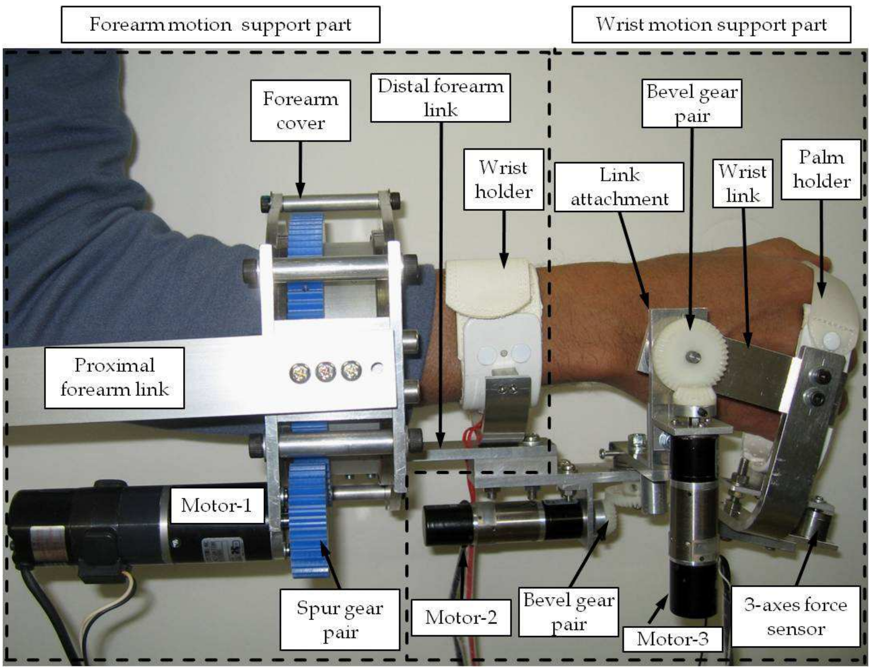


Fig. 13. 3DOF upper-limb exoskeleton robot (W-EXOS).

palm holder and link attachment as shown in Fig. 13. Proximal end of the Link-1of the W-EXOS can be attached to the upper-limb exoskeleton robot which is installed on a mobile wheel chair that can be used by many physically weak persons. Therefore, the user does not feel the weight of the exoskeleton robot at all. The details about the design and the mechanism of the W-EXOS can be referred in (Gopura & Kiguchi, 2008a). Since the W-EXOS is directly in contact with the human user, safety is essential. Mechanical stoppers are attached for each motion to prevent the exceeding of the movable range. The robot does not include any sharp edges in its mechanical construction and mechanical stoppers. Furthermore, each motor has an individual switch and there is an emergency stop switch beside the exoskeleton robot.

4.1 EMG-based control of the W-EXOS

The W-EXOS is controlled based on EMG signals as main input information to its controller. Additionally, the force/torque sensor signals of the W-EXOS are used as secondary input information. Hand force is the measured force from the three axes force sensor when the robot user performs wrist flexion/extension and/or radial/ulnar deviation. Forearm torque is measured with the torque sensor when the robot user performs the forearm supination/pronation. In the control method, the power assist is carried out based on the EMG activity levels and/or the hand force/forearm torque according to the fuzzy rules of the controller. EMG signals of six muscles are measured to control the motions of the W-EXOS. The muscles are selected according to the experimental results explained in the previous section. Monitored muscles are Ch.10: supinator (SP), Ch.11: pronator teres (PT) Ch.13: extensor carpi radialis brevis (ECRB), Ch.14: extensor carpi ulnaris (ECU), Ch.15: flexor carpi radialis (FCR) and Ch.16: flexor carpi ulnaris (FCU). In the control method, movable ranges of forearm supination/pronation and wrist flexion/extension are divided into three sections each and expressed by membership functions (Gopura & Kiguchi, 2008c). Therefore nine movable range combinations are available for forearm supination/pronation and wrist flexion/extension. By expressing the range of each section with membership functions, the controller can be gradually switched to membership functions of each section according to angles of the motions. The movable range of wrist radial/ulnar deviation is not divided into sections, since its range is comparatively narrow. In each movable range combination, a fuzzy-neuro controller has been designed. Therefore, nine fuzzy-neuro controllers are designed altogether for forearm supination/pronation and wrist flexion/extension. Another fuzzy-neuro controller is designed for wrist radial/ulnar deviation.

The structure of the control method of the W-EXOS is shown in Fig. 14. It consists of nine fuzzy-neuro controllers for the forearm motion and the wrist flexion/extension. Another fuzzy-neuro controller is deployed for wrist radial/ulnar deviation. Input information for the nine fuzzy-neuro controllers is the RMS values of six muscles (Ch.10, Ch.11, Ch.13-Ch.16), the force sensor signal, and the torque sensor signal. In addition to the RMS values of EMG signals and force/torque sensor signals, angles of forearm motion and wrist flexion/extension are given as additional input information to the nine controllers for switching the required controller according to the angles of forearm and wrist flexion/extension. Input information for the wrist radial/ulnar fuzzy-neuro controller is the RMS value of EMG signals obtained at four muscles (Ch.11, Ch.13-Ch.15), the force sensor signal and the torque sensor signal. In the controller, generated hand force/forearm torque is considered to be more reliable when the user of the exoskeleton robot slightly activates the muscles (*i.e.*, the EMG activity levels of the user are low), and the EMG signals are

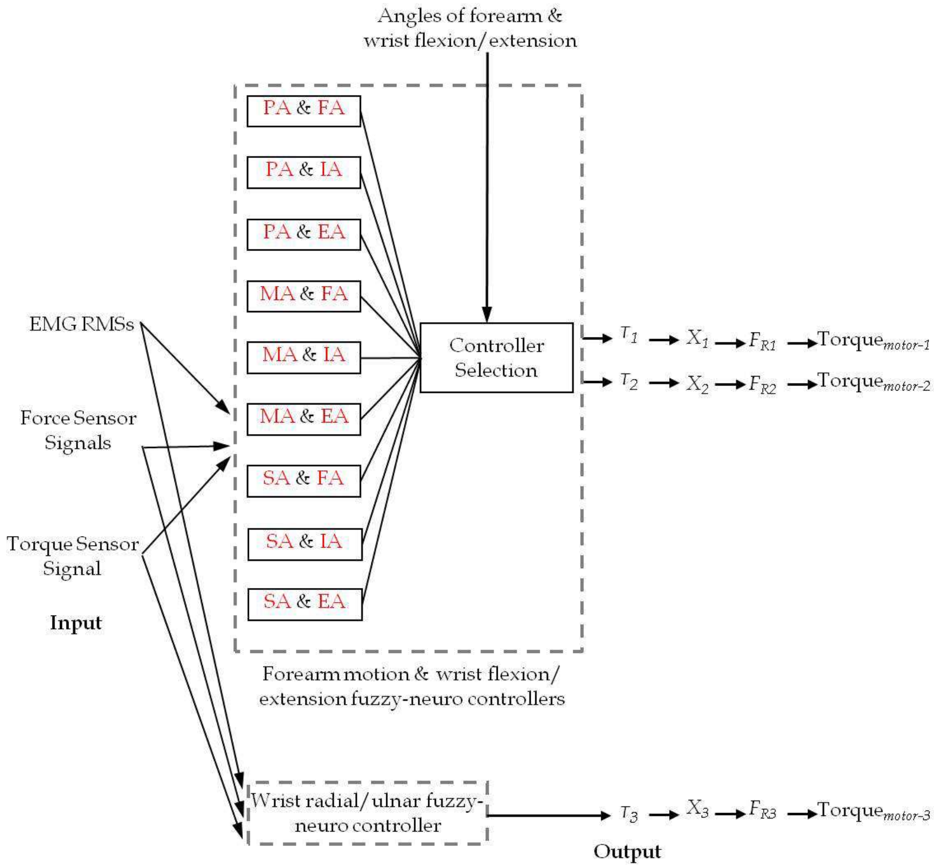


Fig. 14. Structure of the controller of the W-EXOS. PA & FA is the controller which is defined for the forearm pronated region and wrist flexed region. Other controllers are also defined for the relevant regions indicated by their names (Gopura & Kiguchi, 2008c).

more reliable when the user considerably activates the muscles (*i.e.*, the EMG activity levels of the user are high). Therefore, the exoskeleton robot is controlled based on the generated hand force/forearm torque when the EMG activity levels of the user are low, and the exoskeleton robot is controlled based on the EMG signals when the EMG activity levels of the user are high. Consequently, the exoskeleton robot can be controlled in accordance with the user intention.

The initial fuzzy if-then control rules have been designed based on preliminary experiment (Gopura & Kiguchi, 2008a) which was performed to find out the activity patterns of EMG signals of the muscles used for the forearm and wrist motions. In the experiment, EMG patterns have been identified for different motions and different torques of wrist and forearm. Fuzzy rules are designed to provide torque commands according to the EMG RMSs of six muscles and force/torque sensor signals. Defined fuzzy rules are listed in Table 3 and Table 4 (Gopura & Kiguchi, 2008a). Then the defined fuzzy rules are transferred to a neural network to implement in a fuzzy-neuro controller. Therefore, nine fuzzy rule

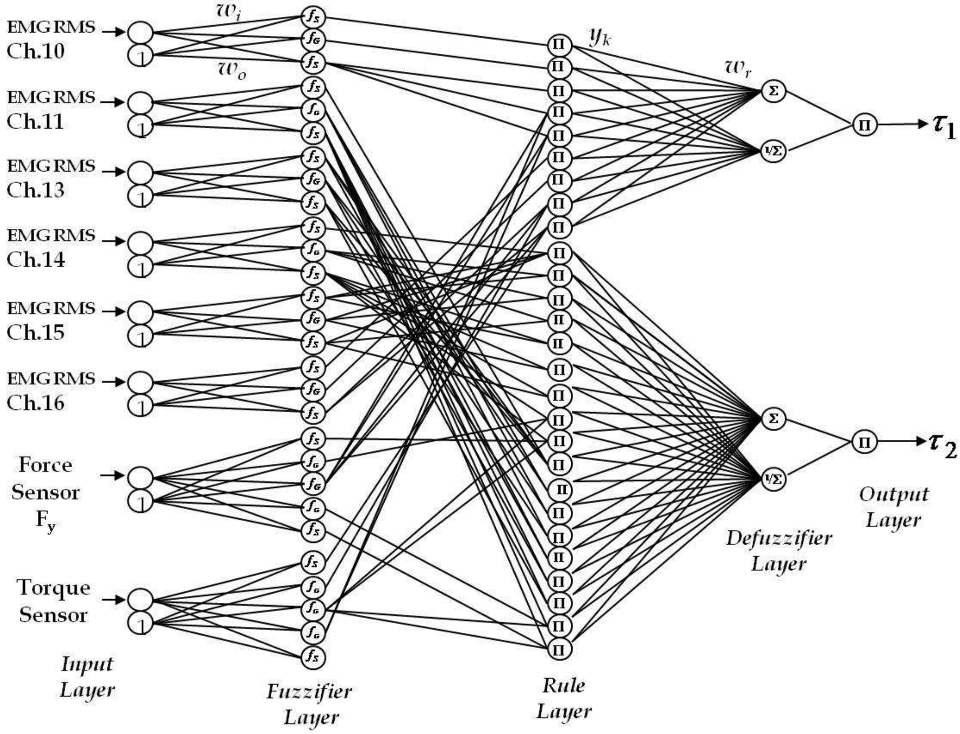


Fig. 15. Architecture of fuzzy-neuro controller.

structured neural network (fuzzy-neuro) controllers are designed in total for the forearm motion and wrist flexion/extension. For wrist radial/ulnar deviation, another fuzzy-neuro controller is designed considering movable range of wrist radial/ulnar deviation as one section. The architecture of one fuzzy-neuro controller is shown in Fig. 15 as an example. The architectures of the other controllers are also similar to the shown controller except the changes in the connection between the fuzzifier and rule layers, since the fuzzy rules are different. Each fuzzy-neuro controller consists of five layers: input layer, fuzzifier layer, rule layer, defuzzifier layer, and output layer.

4.1.1 Input layer

EMG RMS values and force/torque sensor signals are input to the input layer (see Fig. 14) of each fuzzy-neuro controller. Six EMG RMS values, a force sensor signal [Fx], and a torque sensor signal are applied to each forearm motion and wrist flexion/extension fuzzy-neuro controller. Four EMG RMS values, a force sensor signal [Fz], and a torque sensor signal are applied to wrist radial/ulnar deviation fuzzy-neuro controller. Fx and Fz are the force sensor signals for x and z axis, respectively.

4.1.2 Fuzzifier layer

Input information is then fuzzified in the fuzzifier layer. Three fuzzy linguistic variables (ZO: Zero, PS: Positive Small and PB: Positive Big) are prepared for each EMG RMS and five variables (NB: Negative Big, NS: Negative Small, ZO: Zero, PS: Positive Small and PB: Positive Big) are prepared for each sensor signal and torque command. The nonlinear functions f_G and f_S are applied to express the membership of the fuzzy linguistic variables. f_G is the Gaussian function and f_S is the Sigmoid function which are expressed in the following equations.

$$f_S(u_S) = \frac{1}{1+e^{-U_S}} \tag{2}$$

$$u_S(x) = w_o + w_i x \tag{3}$$

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

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

where w_o is the threshold value, w_i is the weight value, and x is the input value. w_o and w_i is calculated using membership functions of fuzzy linguistic variables.

4.1.3 Rule layer

In the rule layer, defined fuzzy if-then rules are applied. For the wrist radial/ulnar fuzzy-neuro controller, eighteen fuzzy rules are applied (see Table 3). Number of applied fuzzy

Rule	If	Then
01	Ch.11 = ZO and Ch.14 = ZO or Ch.14=PS or Ch.14=PB	T3= ZO
02	Ch.11 = PS and Ch.14 = ZO	T3= ZO
03	Ch.11 = PS and Ch.14 = PS	T3= PS
04	Ch.11 = PS and Ch.14 = PB	T3= PS
05	Ch.11 = PB and Ch.14 = ZO	T3= ZO
06	Ch.11 = PB and Ch.14 = PS	T3= PS
07	Ch.11 = PB and Ch.14 = PB	T3= PB
08	Ch.11! = PB and T=ZO and Fz=NS	T3=PS
09	Ch.11! = PB and T=ZO and Fz=NB	T3=PS
10	Ch.13 = ZO and Ch.15 = ZO or Ch.15=PS or Ch.15=PB	T3= ZO
11	Ch.13 = PS and Ch.15 = PS	T3= NS
12	Ch.13 = PS and Ch.15 = ZO	T3= ZO
13	Ch.13 = PS and Ch.15 = PB	T3= NS
14	Ch.13 = PB and Ch.15 = ZO	T3= ZO
15	Ch.13 = PB and Ch.15 = PS	T3= NS
16	Ch.13 = PB and Ch.15 = PB	T3= NB
17	Ch.13! = PB and T = ZO and Fz=PS	T3=NS
18	Ch.13! = PB and T = ZO and Fz=PB	T3=NS

Table 3. Fuzzy if-then control rules for wrist radial/ulnar deviation. NB, NS, ZO, PS and PB are fuzzy linguistic variables. In Table 3; Chi- Channel i, i =11, 13,14, 15; Fz=Force sensor signal for Z-axis; T=Torque sensor signal; T3 =Torque command for wrist radial/ulnar motor.

Rule	If	Then
01	Ch.10 = ZO	T1= ZO
02	Ch.10= PS	T1= PS
03	Ch.10 = PB	T1= PB
04	Ch.10! = PB and Fx! = ZO and T = PS	T1= PS
05	Ch.10! = PB and Fx! = ZO and T = PB	T1= PB
06	Ch.16 = ZO	T1= ZO
07	Ch.16 = PS	T1= NS
08	Ch.16! = PB and Fx! = ZO and T = NS	T1= NS
09	Ch.16! = PB and Fx! = ZO and T = NB	T1= NB
10	Ch.14 = ZO and Ch.15 = ZO or Ch.15=PS or Ch.15=PB	T2= ZO
11	Ch.14 = PS and Ch.15 = ZO	T2= ZO
12	Ch.14 = PS and Ch.15 = PS	T2= NS
13	Ch.14 = PS and Ch.15 = PB	T2= NS
14	Ch.14 = PB and Ch.15 = ZO	T2= ZO
15	Ch.14 = PB and Ch.15 = PS	T2= NS
16	Ch.14 = PB and Ch.15 = PB	T2= NB
17	Ch.14! = PB and T = ZO and Fx=NS	T2= NS
18	Ch.14! = PB and T = ZO and Fx=NB	T2= NS
19	Ch.11 = ZO and Ch.13 = ZO or Ch.13=PS or Ch.13=PB	T2= ZO
20	Ch.11 = PS and Ch.13 = ZO	T2= ZO
21	Ch.11 = PS and Ch.13 = PS	T2= PS
22	Ch.11 = PS and Ch.13 = PB	T2= PS
23	Ch.11 = PB and Ch.13 = ZO	T2= ZO
24	Ch.11 = PB and Ch.13 = PS	T2= PS
25	Ch.11 = PB and Ch.13 = PB	T2= PB
26	Ch.11! = PB and T = ZO and Fx=PS	T2= PS
27	Ch.11! = PB and T = ZO and Fx=PB	T2= PS

Table 4. Fuzzy if-then control rules for one of the forearm motion and wrist flexion/extension fuzzy-neuro controllers (PA & FA controller). In Table 4; Chi- Channel i, i =10, 11, 13, 14, 15, 16; Fx=Force sensor signal for X-axis; T=Torque sensor signal; Tk =Torque command for motor k, k=1, 2; '!=' represents "not equal".

control rules is different in each of the forearm motion and wrist flexion/extension fuzzy-neuro controller. Fuzzy if-then rules for one of forearm motion and wrist flexion/extension fuzzy-neuro controllers, PA & FA controller are shown in Table 4 as an example. In rule layer, π is the multiplicand of the fuzzified inputs.

4.1.4 Defuzzifier layer and output layer

The defuzzification is carried out in the defuzzifier layer. Σ is summation of inputs of defuzzifier layer. The following equation is used to calculate the outputs of the fuzzy-neuro controllers, since the process of the fuzzy-neuro controller is same as that of an ordinal fuzzy controller.

$$\text{Output} = \frac{\sum_{i=1}^{N} w_{ri} y_{ki}}{\sum_{i=1}^{N} y_{ki}} \tag{6}$$

$$\text{Torque}_{motor\ j} = (\text{Output}) \times X_j + F_{Rj} \tag{7}$$

where, y_{ki} is the degree of fitness of ith rule, w_{ri} is the weight for ith rule, N is number of rules for the particular motion, X is the assist rate, F_R is the friction compensation, and j = 1, 2, 3. The outputs of the forearm motion and wrist flexion/extension fuzzy neuro controllers are the torques of forearm supination/pronation and wrist flexion/extension. They are represented as τ_1 and τ_2 in the output layer of the fuzzy-neuro controller respectively [see Fig. 13]. The output, τ_3 of wrist radial/ulnar fuzzy-neuro controller is the torque of the wrist radial/ulnar deviation motor. Controller outputs are multiplied by the power-assist rate and the friction compensation value is added to obtain the torque commands of three motors as in equation (7).

4.2 Controller adaptation

The adaptation of the controllers to the conditions of the robot user is important (Kiguchi *et al.*, 2001), since the EMG signal is a biological signal that varies according to the person and also to the physical and psychological conditions of the same person even for the same motion. The adaptation of fuzzy-neuro controllers is carried out by adjusting each weight values of the fuzzy-neuro controller to minimize an evaluation function. In this study, error back-propagation learning algorithm has been applied to minimize the squared error function given below.

$$\mathrm{E} = \frac{1}{2}\left((\theta_d - \theta)^2 + a \sum \left(RMS_d - RMS \right)^2 \right) \tag{8}$$

where θ_d is desired joint angle indicated by a motion indicator (*i.e.*, a teaching device), θ is the joint angle of the robot, a is the rate of EMG adaptation, and RMS_d is the desired EMG RMS level. Certain percentage of the maximum value of each related EMG RMS are modeled as sinusoidal function at the beginning and the ending of the motions and taken as RMS_d. This modeling eliminates the undesired errors of the RMS_d at the beginning and the ending of the motions. In the middle of the motions, the same percentage of the maximum value of EMG RMS is taken as RMS_d. More details of controller adaptation can be referred in (Kiguchi *et al.*, 2004).

4.3 Evaluation of EMG-based control method

The experiments have been performed with three young healthy male subjects (subject A, B, and C) to evaluate the effectiveness of the EMG-based control method. The experimental set-up is shown in Fig. 16. In the first experiment, subject-A performed individual and cooperative motions of wrist and forearm with and without power-assist of the W-EXOS. Forearm and wrist motions have been performed with assist of the W-EXOS for three different power-assist rates: lower rate, medium rate, and higher rate. If the exoskeleton robot properly assists the motions the muscle activation levels should be reduced with the

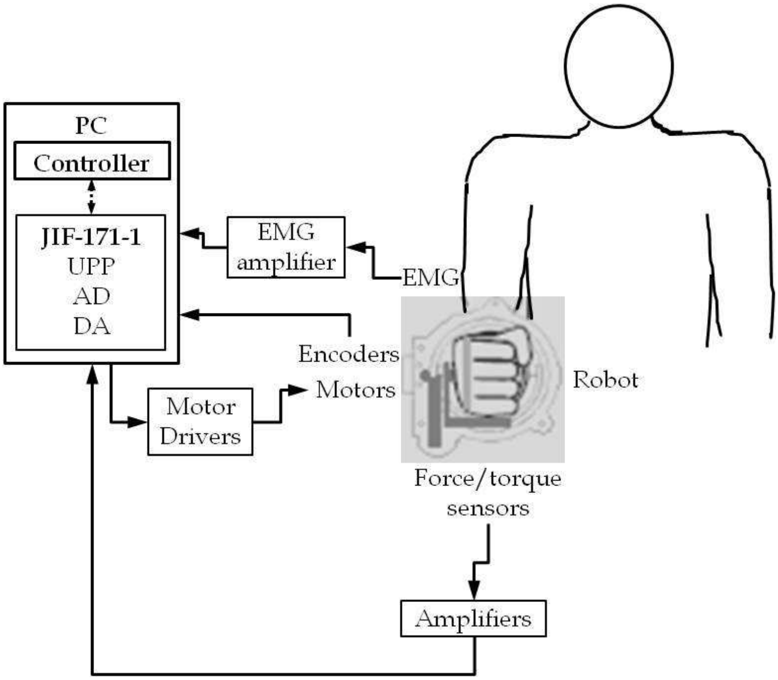


Fig. 16. Experimental set-up.

power-assist. In the second experiment, subject-B and C performed wrist and forearm motions with and without power-assist of the exoskeleton robot.

EMG RMS levels of extensor carpi ulnaris and extensor carpi radialis brevis of subjects-A for combined wrist radial deviation and wrist extension are shown in Fig. 17. 20% power-assist ratio was applied when the motion was carried with power-assist. The power-assist ratio indicates percentage of power supplied from the robot and required power for the motion. Figure 17 shows that the average value of EMG RMS of extensor carpi radialis brevis has reduced from 3.17 to 2.58 when applied the power-assist of the W-EXOS with the EMG-based control method. The EMG RMS value reduction is by 18.61%. The reduction of average value of EMG RMS of extensor carpi ulnaris is by 18.68% for the same motion. Therefore, with the EMG-based control method the W-EXOS has assisted the motion approximately equal assist rate that has been set in the program (20%). Figure 18 shows the experimental result for wrist flexion/extension. From Fig. 18, it can be seen that the activation level of ECRB and FCR is reduced with power-assist (assist rate-20%) of the W-EXOS when applied the EMG-based controller. The activation level the flexor carpi ulnaris for wrist flexion is shown in Fig. 19. The result shows that the raw EMG level of FCU is reduced with the power-assist. From the results it is concluded that EMG can effectively be applied to control the exoskeleton robot. Further, the results show that the EMG-based control method can be used to effectively assist human wrist and forearm motions.

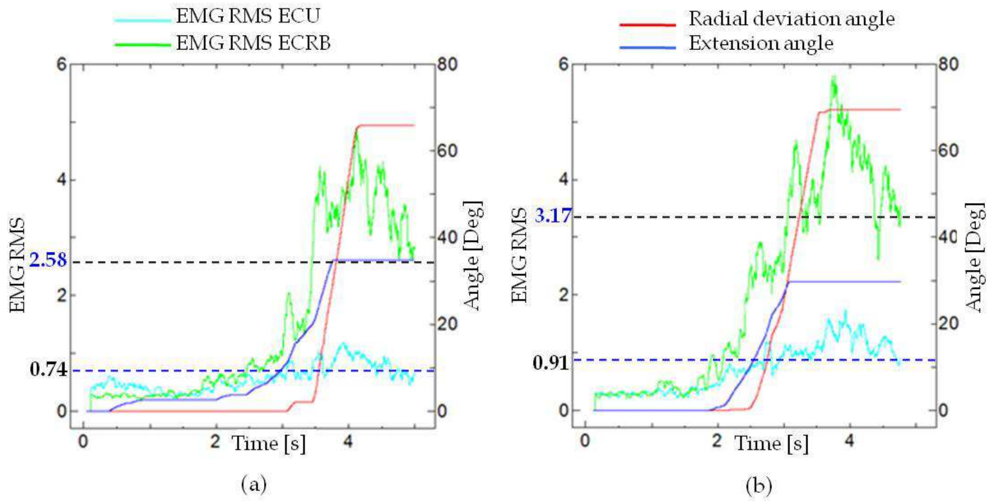


Fig. 17. Experimental results of subject-A for wrist extension and radial deviation. (a) With 20% power-assist. (b) Without power-assist.

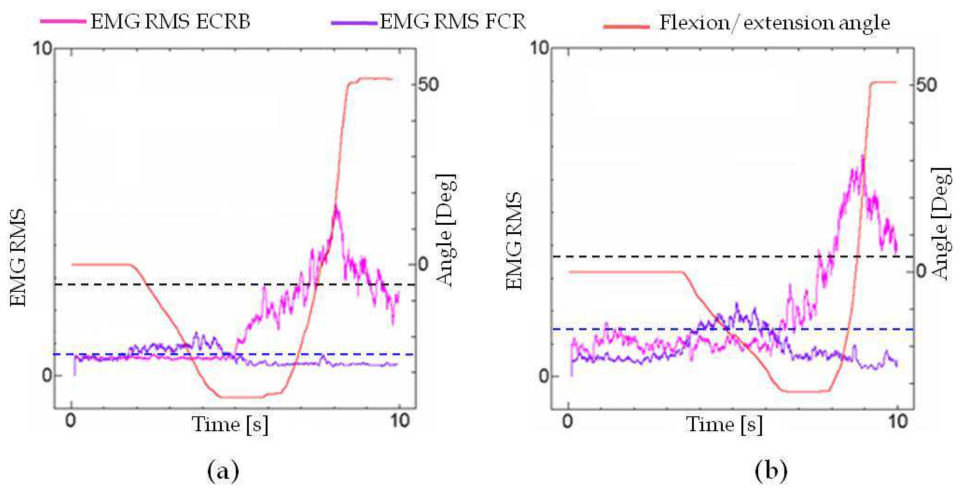


Fig. 18. Experimental results of subject-B for wrist flexion/extension. (a) With 20% power-assist. (b) Without power-assist.

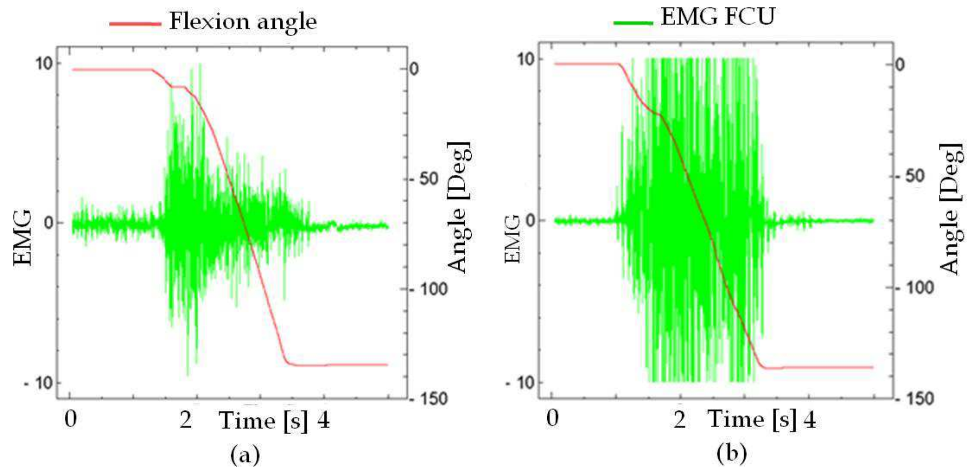


Fig. 19. Experimental results of subject-C for wrist flexion. (a) With 20% power-assist. (b) Without power-assist.

5. EMG-based control of a 6DOF exoskeleton robot

The 6DOF exoskeleton robot, SUEFUL-6 (Gopura & Kiguchi, 2008b) has been designed to be worn by a right upper-limb as shown in Fig. 20. Considering that most physically weak persons use wheel chairs, the SUEFUL-6 is designed to be installed on a wheel chair of physically weak persons. Therefore, the user does not feel the weight of the robot. The SUEFUL-6 mainly consists of a shoulder motion support part, an elbow motion support part, a forearm motion support part and a wrist motion support part. Figure 21 depicts the six axes of the SUEFUL-6. The shoulder motion support part of the SUEFUL-6 consists of an upper-arm link, driven pulleys for shoulder horizontal flexion/extension motion and shoulder vertical flexion/extension motion, potentiometers, an arm holder, a slider and the mechanism for moving center of rotation (CR). The rotational motions generated in the motors are transferred to the shoulder driven pulleys of the SUEFUL-6 through cable drives. The arm holder is attached to upper-arm link as shown in Fig. 20. The arm holder is made of thin flexible plastic with magic tape ribbon to hold the user's upper-arm. The distance between the arm holder and the CR of the shoulder joint of the exoskeleton is moderately adjusted automatically in accordance with the shoulder motion, in order to cancel out the ill effects caused by the position difference between the CR of the robot shoulder and the human shoulder (Kiguchi *et al.*, 2008). The distal end of the upper-arm link is attached to the elbow joint. The 1DOF elbow motion assist part of the exoskeleton robot consists of the proximal forearm link, a pulley, and a potentiometer. The motor pulley acts as driven pulley to generate elbow flexion/extension motion. The motor for the elbow flexion/extension motion have been fixed in the separate location of the frame of the robot. The rotational motion generated in the motor is transferred to the elbow driven pulleys of the SUEFUL-6 through a cable drive. The forearm motion support part and wrist motion support part are same as the W-EXOS. Only different is the attachment of forearm force sensor between proximal forearm link and distal forearm link as shown in the Fig. 20. The motor for supination/pronation (motor-D) is attached in the outer housing of the forearm cover. The distal forearm link is attached to the inner frame of the

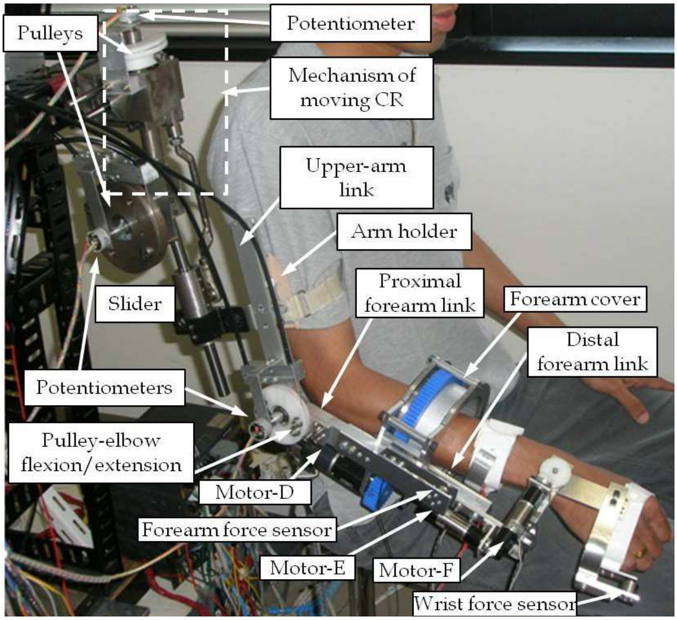


Fig. 20. 6DOF upper-limb motion power-assist exoskeleton robot (SUEFUL-6).

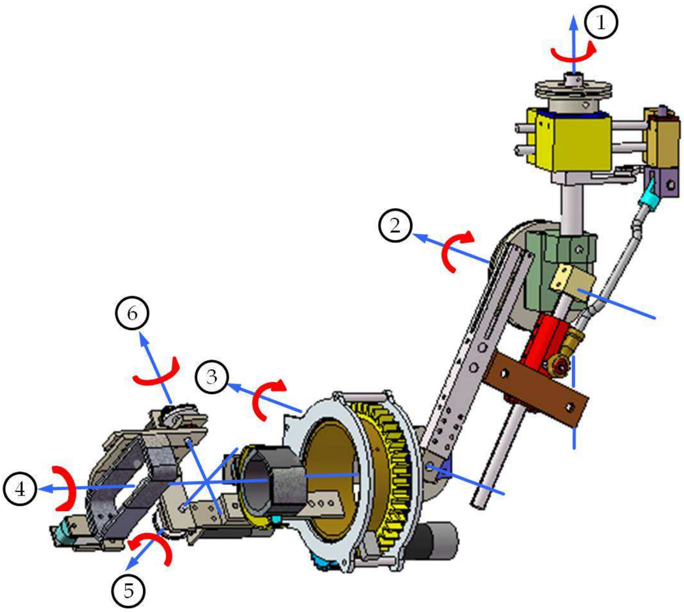


Fig. 21. CAD model of the SUEFUL-6 with axes of rotation. Number 1 to 6 indicates the axis for shoulder horizontal and vertical flexion/extension, elbow flexion/extension, forearm supination/pronation, wrist flexion/extension and radial ulnar deviation, respectively.

forearm cover. The wrist holder can be worn to the forearm of the user. The motor for wrist flexion/extension (motor-E) is fixed on the distal forearm link. The link attachment holds the motor (motor-F) for the wrist radial/ulnar deviation. More details of SUEFUL-6 can be referred in (Gopura & Kiguchi., 2008b).

5.1 EMG-based control method

EMG signals are used as main input information to control the SUEFUL-6 according to the user's motion intention. As in the EMG-based control method of the W-EXOS, the force/torque sensor signals of the sensors of the SUEFUL-6 are used as subordinate input information. The forearm force/torque and hand force are used as input information for the controller. When the user activates the muscles little (*i.e.*, EMG signal level is low) the forearm force/torque and hand force are used to control the SUEFUL-6. When the user activates the muscle a lot (*i.e.*, EMG signal level is high) EMG signals are used to control the SUEFUL-6. When the users muscle activation level is medium EMG signal, forearm force/torque and hand force are used to control the robot. By using input information as above, the error motions cause by the little EMG signal levels and the unexpected motion cause by the external forces affecting the user's upper-limb can be avoided. In order to identify the 6DOF upper-limb motions, the EMG signals of fourteen locations: (see Fig. 6 for locations of muscles) deltoid-anterior part, deltoid-posterior part, pectoralis major-clavicular part, teres major, biceps-short head, biceps-long head, triceps-long head, triceps-lateral head, pronator teres, supinator, extensor carpi radialis brevis, extensor carpi ulnaris, flexor carpi radialis and flexor carpi ulnaris are monitored.
Applying the monitored muscle signals fuzzy if-then control rules were designed. Basically the fuzzy-rules designed for the W-EXOS (Gopura & Kiguchi, 2008a) and 3DOF exoskeleton robots (Kiguchi *et al.,* 2008) were used with the modifications. Ten fuzzy if-then control rules were designed for the shoulder motions (Kiguchi *et al.,* 2008). An additional eleven fuzzy if-then control rules were designed for the elbow motion (Kiguchi *et al.,* 2008). For the forearm and wrist motions the control rules designed for the EMG-based controller of the W-EXOS is basically used (explained in section 4) with the modification to eliminate the effect of shoulder and elbow motion muscles. As an example, the modified fuzzy if-then rules for supination are shown in the Table 5. The fuzzy rules related to the shoulder and elbow motions are transferred to the fuzzy-neuro controller as explained in (Kiguchi *et al.,* 2008). The fuzzy rules related to the forearm and wrist motions are transferred to the fuzzy-neuro controller as explain in section 4. To eliminate the improper motion assist that might occur in the case of cooperative motion of the elbow and forearm (*i.e.*, simultaneous elbow flexion/extension and forearm supination/pronation) the RMS of the pronator teres

Rule	If	Then
01	Ch.10 = ZO and Ch.7=ZO	T1= ZO
02	Ch.10 = PB and Ch.7!=ZO	T1= PB
03	Ch.10! = PB and Ch.7!=ZO and Fx! = ZO and T = PS	T1= PS
04	Ch.10! = PB and Ch.7!=ZO Fx! = ZO and T = PB	T1= PB

Table 5. Some modified fuzzy if-then control rules. In Table 4; Fx=Force sensor signal for X-axis; T=Torque sensor signal; T1 =Torque command for forearm motor; '!=' represents "not equal".

(*i.e.*, a muscle common to both elbow flexion/extension and forearm pronation/supination) was used as an input variable to adjust the weight in the consequent part of the fuzzy control rules for the supination (Kiguchi *et al.*, 2005).

5.1.1 Training of the controller

The training (adaptation) of fuzzy-neuro controllers is carried out by adjusting each weight values of the fuzzy-neuro controller to minimize evaluation functions. In this study, error back-propagation learning algorithm has been applied to minimize the squared error functions. The error function is the same in (8). The adaptation of the controllers to the conditions of the robot user is important, since the EMG signal is a biological signal that varies according to the person and also to the physical and psychological conditions of the same person even with the same motion. The desired joint angle is indicated by a motion indicator (*i.e.*, a teaching device).

5.2 Evaluation of EMG-based controller SUEFUL-6

The experiments are performed with healthy male subjects (subject A-29 years, subject B-27 years) to evaluate the effectiveness of power-assist of the EMG-based control method. Human subjects performed daily activities of upper-limb without and with power-assist of the SUEFUL-6. The experimental set-up is basically similar to the set-up shown in Fig. 16.

The EMG levels of the related muscles were measured for both cases. When the motions are performed without power-assist, sensor signal based control was applied to the exoskeleton robot to perform natural upper-limb motions without any disturbance. If the SUEFUL-6 assists the motions properly from the EMG-based control method, the EMG levels of related muscles should be reduced when the robot assist the motions. The experimental results of subject-A for drinking motion (bringing a cup from table to near the mouth) is shown in Fig. 22. When the drinking motion was carried out with power-assist of 20% the maximum EMG

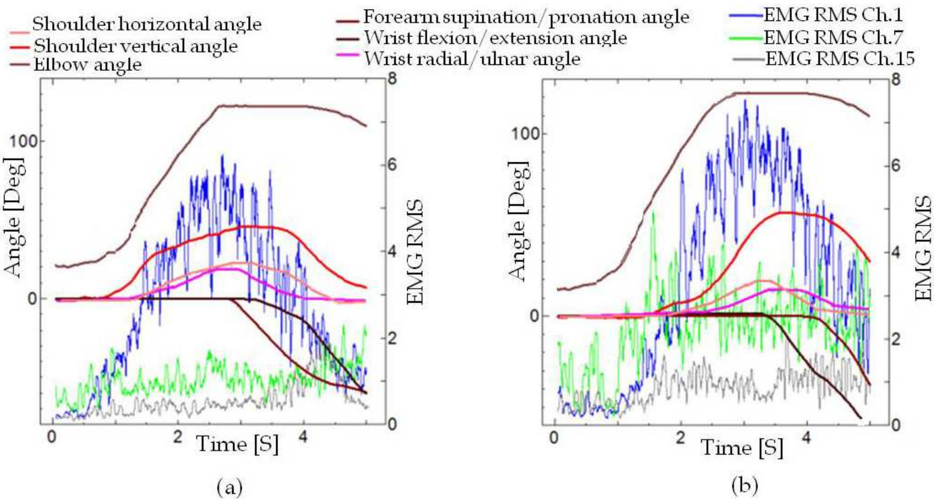


Fig. 22. Experimental result of subject-A for drinking motion. (a) With power-assist (power-assist rate=20%). (b) Without power-assist.

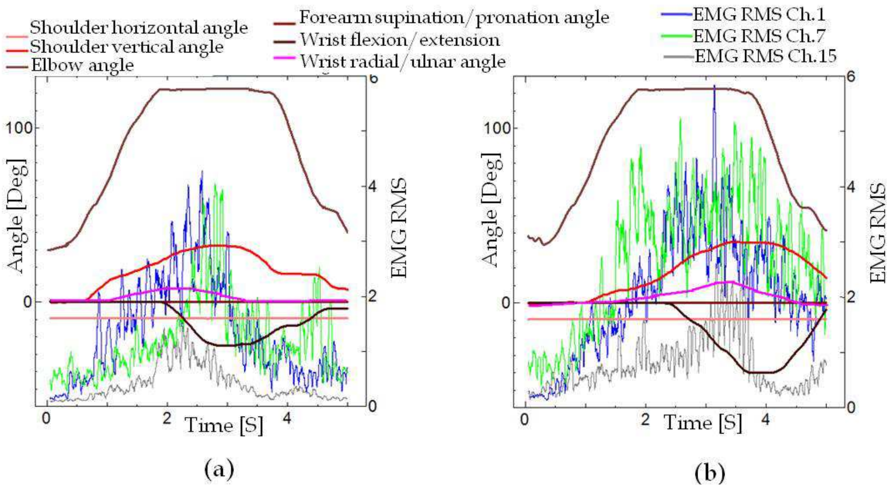


Fig. 23. Experimental result of subject-B for cooperative motions of upper-limb. (a) With power-assist (power-assist rate=45%). (b) Without power-assist.

RMS level of deltoid-anterior part (Ch.1) has reduced, where as it was higher without power-assist. The experimental result of subject-B for the cooperative motions of upper-limb is depicted in Fig. 23. In the experiment, when the motion was carried out with power-assist 45% power-assist is applied. Figure 23 shows that EMG RMS levels of related muscles have been reduced for the with power-assist motion. From the results it can be concluded that EMG can effectively be applied to control the SUEFUL-6. Further, the results show that the EMG-based control method can be used to effectively assist human upper-limb motions.

6. Conclusion

This chapter presents the application of surface EMG signals to control exoskeleton robots. At first the applied method to detect and process the surface EMG signals is explained. Then, the upper-limb muscle activities during daily upper-limb motions have been experimentally studied to enable exoskeleton robots to estimate human upper-limb motions based on EMG signals of related muscles. In the experimental study, minimum number of muscles to extract signals to control daily upper-limb motions has been identified. Then two case studies of application of EMG signals to control exoskeleton robots were presented. In the case studies EMG-based control methods and their evaluation is explained. From the evaluation results it is identified EMG signals can be used to control upper-limb exoskeleton robot. Further, the evaluation results verified that presented EMG-based control methods can be used to effectively assist human upper-limb motions.

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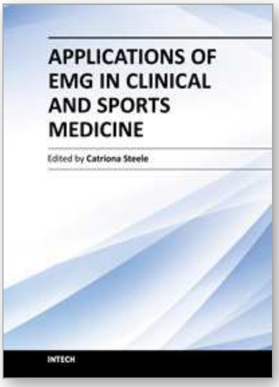

Applications of EMG in Clinical and Sports Medicine
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This second of two volumes on EMG (Electromyography) covers a wide range of clinical applications, as a complement to the methods discussed in volume 1. Topics range from gait and vibration analysis, through posture and falls prevention, to biofeedback in the treatment of neurologic swallowing impairment. The volume includes sections on back care, sports and performance medicine, gynecology/urology and orofacial function. Authors describe the procedures for their experimental studies with detailed and clear illustrations and references to the literature. The limitations of SEMG measures and methods for careful analysis are discussed. This broad compilation of articles discussing the use of EMG in both clinical and research applications demonstrates the utility of the method as a tool in a wide variety of disciplines and clinical fields.

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