An Exoskeletal Robot for Human Elbow Motion Support—Sensor Fusion, Adaptation, and Control

Kazuo Kiguchi, *Member, IEEE*, Shingo Kariya, Keigo Watanabe, *Member, IEEE*, Kiyotaka Izumi, *Member, IEEE*, and Toshio Fukuda, *Fellow, IEEE*

***Abstract*—In order to help everyday life of physically weak people, we are developing exoskeletal robots for human (especially for physically weak people) motion support. In this paper, we propose a one degree–of–freedom (1 DOF) exoskeletal robot and its control system to support the human elbow motion. The proposed controller controls the angular position and impedance of the exoskeletal robot system based on biological signals that reflect the human subject's intention. The skin surface electromyogram (EMG) signals and the generated wrist force by the human subject during the elbow motion have been fused and used as input information of the controller. In order to make the robot flexible enough to deal with vague biological signal such as EMG, fuzzy neuro control has been applied to the controller. The experimental results show the effectiveness of the proposed exoskeletal robot system.**

***Index Terms*—Electromyogram, exoskeletal robots, fuzzy–neuro control, human motion support, impedance control, sensor fusion.**

I. INTRODUCTION

A DECREASE in the birthrate and aging are progressing in Japan and several countries. In that society, it is important that physically weak people are able to take care of themselves. We are developing exoskeletal robots to support motion of the physically weak people such as elderly persons. It is important for elderly persons to take care of themselves in everyday life. It is also important for them to use their own body functions to keep them healthy. Recent progress of robotics technology brings a lot of benefits not only in the industries, but also in many other fields such as welfare, medicine, or amusement. In the field of welfare, for example, much research has been carried out for the disabled people who lost their original function in order to support their motion [1], [2], or to make up their lost function [3]–[10]. The electromyogram (EMG), contains biological information to understand the patient's muscle activities, can be used as input information for the robotic prosthetic devices [6], [7], [10]. This EMG signal is important for those devices to understand how the human subject intends to move. The EMG can also be used as an effective interface between human and robot manipulators in teleoperation [5], [11].

It is difficult, however, to obtain the same EMG signal for the same motion even from the same patient since the EMG signal is a biologically generated signal. Many factors such as fatigue of patients affect the biological signal [12]. Furthermore, another patient generates different level of the EMG signal. Consequently, it is important that the system has ability to adapt itself to the physiological condition of each human subject online [13], [14]. The online adaptation to the physiological condition can also be realized using evolvable hardware [15]. These online adaptation techniques have been proposed for motion pattern classification of prosthesis hands based on EMG signals.

In this paper, we propose a one degree–of–freedom (1 DOF) exoskeltal robot system and its control system for the purpose of human elbow motion support as the first step toward an exoskeletal robot for the whole body motion support in everyday life. A study of exoskeletal robots was started more than four decades ago [16]. The exoskeletal robots, which are sometimes called as power suits, man amplifiers, man magnifiers, or power assist systems, have been studied for the purpose of military or industry use [17], [18]. Hardiman [18] was the first whole body exoskeletal robot. It was actuated by hydraulic actuators and supposed to be controlled (driven) by a human operator in it. In order to control (drive) the exoskeletal robot, the operator had to grip the handle attached to the tip of the exoskeletal robot. So that it was not suitable for human motion support in everyday life, and besides, its legs did not work properly. Another exoskeletal robot for human legs has been designed for rehabilitation of walking and clinically evaluated [19]. It was actuated by periodic signals using pneumatic actuators or dc motors. In addition to these studies, some power assist systems have been proposed recently to extend the strength of the human [20], [21]. In those systems, however, human subjects have to manipulate the robot system using extender systems. Furthermore, unexpected and/or undesired motion for human subjects might be generated when unexpected external force accidentally acts on the force sensors in those systems since only the signals from the force sensors are used to control the robot systems. In this study, the proposed robot system is mainly supposed to help the motion of physically weak people in everyday life. Since the robot is supposed to be used for everyday life of human subjects in living space, its motion has to be flexible enough. Furthermore, subjects' intention has to be directly reflected to the robot movement. Unlike previously proposed exoskeletal robots [16]–[21], the proposed exoskeletal robot in this study is supposed to generate flexible human-like motion based on biological signals that directly reflect the subject's intention. The skin surface EMG signals and the force generated between the exoskeletal robot and the human subject's wrist (the generated wrist force)—i.e., the force caused from the motion difference

Manuscript received October 5, 2000; revised February 3, 2001 and April 24, 2001. This paper was recommended by Associate Editor N. Pal.

K. Kiguchi, S. Kariya, K. Watanabe, and K. Izumi are with the Department of Advanced Systems Control Engineering, Saga University, Saga 840-8502, Japan (e-mail: kiguchi@ieee.org).

T. Fukuda is with the Center of Cooperative Research in Advanced Science and Technology, Nagoya University, Nagoya 464-8603, Japan.

Publisher Item Identifier S 1083-4419(01)05972-6.

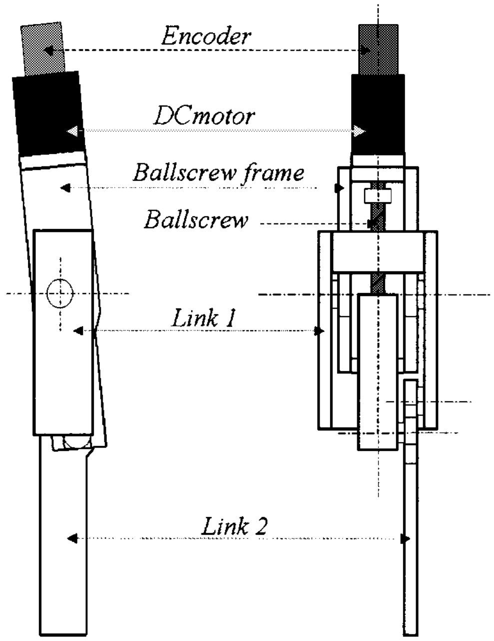


Fig. 1. Designed exoskeletal robot.

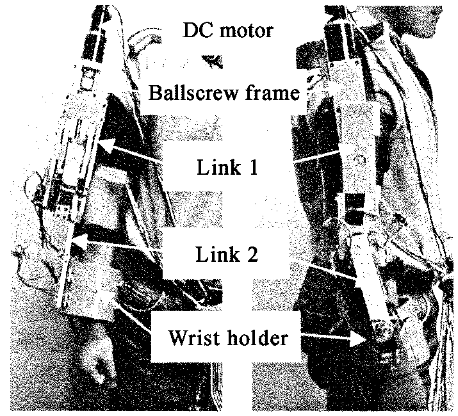


Fig. 2. Attached exoskeletal robot.

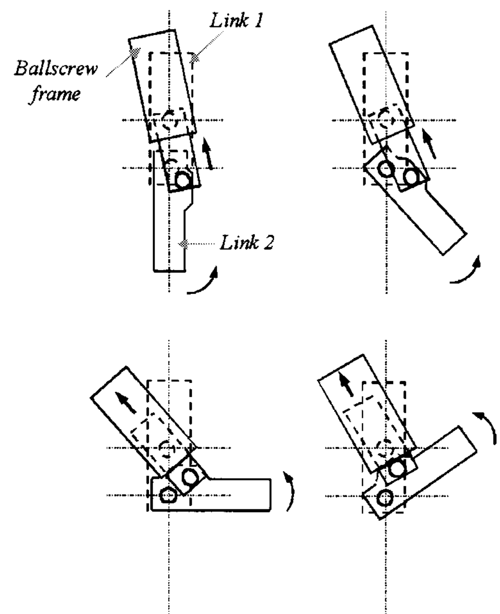


Fig. 3. Generation of flexion motion of the robot.

between the exoskeletal robot and the human subject—during the human elbow motion are fused and used for input information of the control system in order to control the robot system based on human subject's intention. By applying sensor fusion with the skin surface EMG signals and the generated wrist force signal, error motion caused by little EMG levels or the external force affecting the human arm can be avoided. It is known that the human can moderately control the elbow angle and elbow impedance [22], [23]. Therefore, the proposed controller is supposed to control both the elbow angle and impedance of the exoskeletal robot like human in accordance with the EMG signals and the generated wrist force signal. In order to make the controller deal with and adapt to these signals, which contain some intrinsic variance that makes their use as a control signal a challenging task, fuzzy–neuro control has been applied and a teaching system is introduced for the proposed robot control system. The effectiveness of the proposed exoskeletal robot system and control system has been evaluated by experiment.

II. EXOSKELETAL ROBOT SYSTEM

We have designed the 1 DOF exoskeltal robot (Fig. 1) for human elbow motion support. This exoskeltal robot is supposed to be attached directly to the lateral side of a human arm as shown in Fig. 2. This robot consists of two links, a ballscrew drive shaft, a ballscrew support frame, a dc motor [RH14C-3002-E1000D0, Harmonic Drive System Co.], and force sensors (strain gauges). The dc motor drives the ballscrew drive shaft to make the link-2 flex or extend. The link-2 is flexed (or extended) by contracting (or expanding) the prismatic joint along the ballscrew drive shaft in the ballscrew support frame, which is attached to the link-1, as shown in Fig. 3. The generated wrist force (i.e., the force caused from the motion difference between the exoskeletal robot and the human subject's wrist) during the human elbow motion is measured by the strain gauge based force sensor. In this force sensor, strain gauges are attached on the beams between the wrist holder outer cover, which is connected to the exoskeltal robot, and the wrist holder inner cover, which is connected to the human subject (Fig. 4). The signal from the force sensor is sampled at a rate of 2 kHz and low-pass filtered at 4 Hz. The measured force by these force sensors are used to understand the force externally acting on the human subject's forearm.

The skin surface EMG signals of biceps and triceps, which imply the human subject's intention, are another input information to control the robot. The location of electrodes on biceps and triceps (two channels for biceps and another two channels for triceps) is depicted in Fig. 5. The electrodes on the medial and lateral side of biceps and those on the lateral and medial side of triceps are connected to channel 1, channel 2, channel 3, and channel 4, respectively. The details of the method of control with these signals are explained in Section IV.

Usually, the movable range of human elbow is between -5 and $145°$. Considering the safety of the human subject, the elbow motion of the proposed robot is limited between 0 and

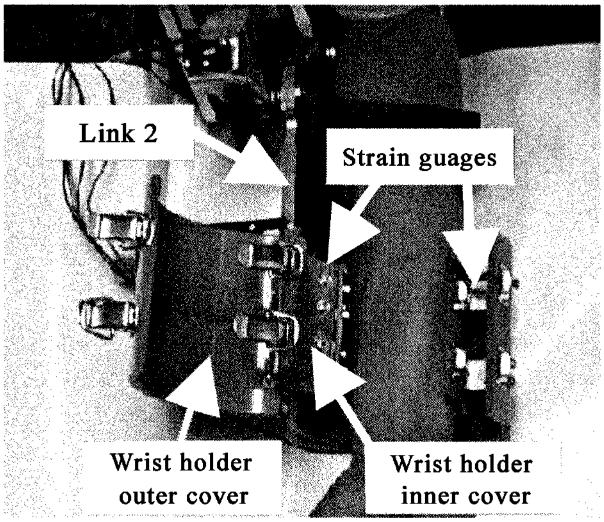


Fig. 4. Strain gauge based force sensor.

120° in this system. The maximum angular velocity of the motor is limited by the hardware. The maximum torque of the robot (i.e., the maximum current of the motor) is also limited by both the hardware and software for safety. Furthermore, there is an emergency stop switch beside the robot.

III. Human Elbow Motion

Agonist-antagonist muscles exist in many human joint such as elbow, knee, wrist, ankle, etc. Such human joint is usually activated by many muscles. Human elbow is mainly actuated by two antagonist muscles: biceps and triceps, although it consists of more muscles. The origin of the long head of biceps is connected to supraglenoid tubercle of the scapula, and that of the short head of biceps is connected to coracoid process of the scapula. The other side of biceps is connected to tuberosity of the radius and the bicipital aponeurosis. In the case of triceps, the origin of the long head is connected to infraglenoid tubercle of the scapula, that of the lateral head is connected to posterior surface and lateral border of the humerus and the lateral intermuscular septum, and that of the medial head is connected to posterior surface and medial border of the humerus and the medial intermuscular septum. The other side of triceps is connected to posterior part of the olecranon process of the ulna and the deep fascia of the dorsal forearm. Consequently, biceps and a part triceps are bi-articular muscles. Many studies have been performed to investigate the effects of bi-articular muscles [22], [24]. By adjusting the amount of force generated by these muscles, the elbow angle and impedance can be arbitrary controlled [3]. The muscle activity level can be described by the EMG signal. In order to design the control system of the exoskeltal robot, the skin surface EMG signals and the generated wrist force signal during the human elbow motion have been analyzed by the pre-experiment. Table I shows the analyzed human elbow motion patterns in the pre-experiment. The amplified EMG signals are sampled at a rate of 2 kHz. Since it is difficult to use law data of EMG for input information of the controller, features have to be extracted from the law EMG data. There are many kinds of feature extraction methods, e.g., mean absolute value, mean absolute value slope, zero crossings, slope sign changes, or waveform length [4]. We have tested all these feature extraction methods, and found out that Waveform Length (WL) is the most suitable feature to express the EMG levels for the fuzzy–neuro control. This is the cumulative length of the waveform over the time segment. The equation of WL is written as

$$\mathrm{WL} = \sum_{k=1}^{N} |x_k - x_{k-1}| \tag{1}$$

where

x_k kth sample voltage value;

Δx_k difference in consecutive sample voltage values $(x_k - x_{k-1})$;

N number of samples in segment.

The number of samples is set to be 100 in this study. An example of the WL of biceps obtained in the pre-experiment is shown in Fig. 6. One can see that the biceps are activated during the elbow flexion motion from the magnitude of the WL.

IV. Sensor Fusion, Adaptation, and Control of the Exoskeletal Robot

Fuzzy–neuro control method is proposed to control both the angle and impedance of the exoskeletal robot based on both the skin surface EMG signals of biceps and triceps and the generated wrist force. So that the robot can be controlled in accordance with the human subject's intention. The fuzzy IF-THEN control rules of the fuzzy–neuro control are designed based on the analyzed human subject's elbow motion patterns in the pre-experiment. The properties of human elbow impedance studied in another research [25], [26] are also taken into account. Although the relationship between the EMG signals and joint torque has been studied for long years [27], [28], the reliable relationship has yet to be established [29]. In this study, the *EMG*-to-*joint impedance and desired angular motion* relationship is modeled as IF-THEN fuzzy rules. Furthermore, the *generated wrist force*-to-*joint impedance and desired angular motion* relationship is also modeled as IF-THEN fuzzy rules. In the proposed control rules, we consider the generated wrist force is more reliable when the subject activates the muscles little (when the EMG levels of the subject are low), and the EMG signals are more reliable when the subject activates the muscles a lot (when the EMG levels of the subject are high). Consequently, error motion caused by little EMG levels or the external force affecting to human arm can be avoided by applying both the skin surface EMG signals and the generated wrist force.

The input variables of the fuzzy–neuro control are the WL of biceps (two channels) and triceps (two channels) and the force measured by the wrist force sensor. Three kinds of fuzzy linguistic variables (ZO: zero, PS: positive small, and PB: positive big) are prepared for the WL of EMG and five kinds of fuzzy linguistic variables (NB: negative big, NS: negative small, ZO: zero, PS: positive small, and PB: positive big) are prepared for the generated wrist force data. The outputs of the fuzzy–neuro control are the desired joint angle and impedance

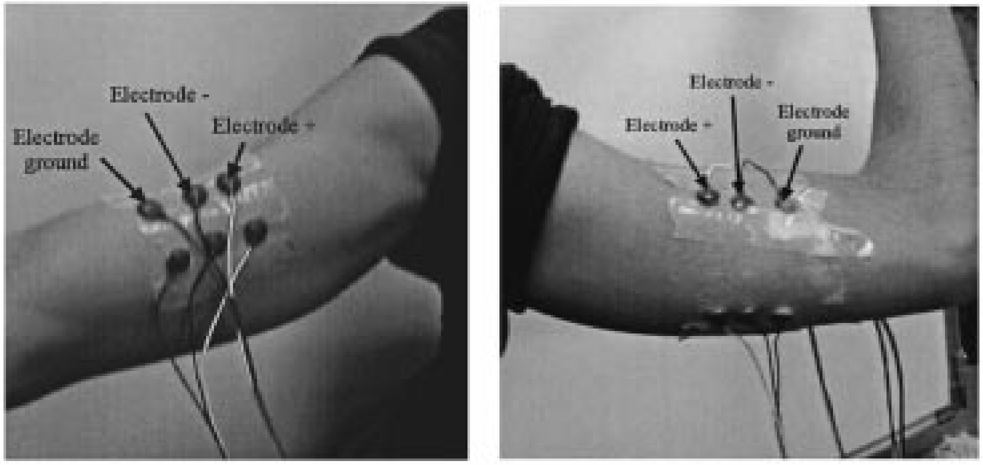


Fig. 5. Location of electrodes.

TABLE I
ANALYZED HUMAN ELBOW MOTION PATTERNS IN THE PRE-EXPERIMENT

1.	Flexion/extension motion without a weight in a hand
2.	Flexion/extension motion with a 7kg weight in a hand
3.	Hold motion with a 7kg weight in a hand
4.	Flexion motion with a 18kg weight in a hand (overweight)
5.	Flexion/extension against the fixed constraint

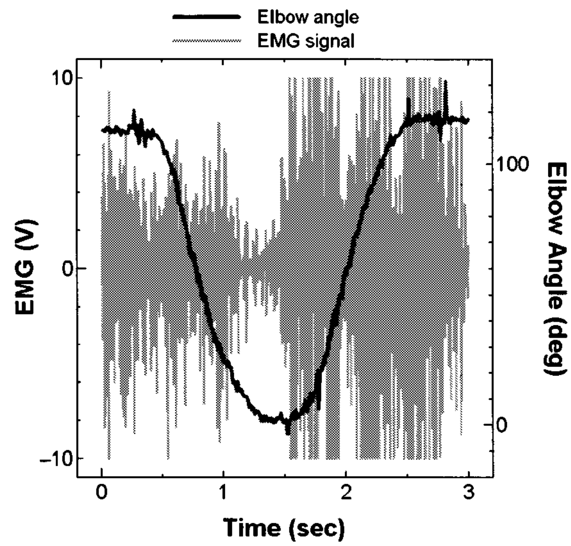
of the exoskeletal robot. In this method, impedance control is performed to follow the generated desired joint angle using the generated desired impedance coefficients. Consequently, both the angle and impedance of the exoskeletal robot are controlled like human beings do. The equation of impedance control is written as

$$\tau_e = M_e(\ddot{q}_d - \ddot{q}) + B_e(\dot{q}_d - \dot{q}) + K_e(q_d - q) \qquad (2)$$

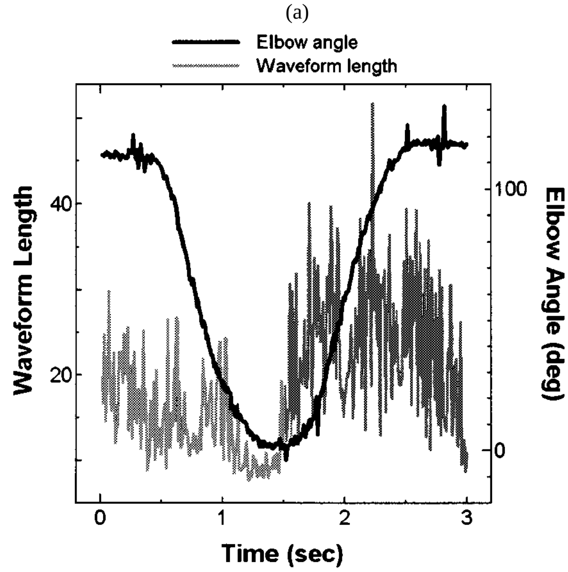
where

- τ_e torque command for the exoskeletal robot joint;
- M_e moment of inertia of link 2 and human subject's forearm;
- B_e viscous coefficient generated by the fuzzy–neuro controller;
- K_e spring coefficient generated by the fuzzy–neuro controller;
- q_d desired joint angle generated by the fuzzy–neuro controller;
- q measured joint angle of the exoskeletal robot.

The torque command for the exoskeletal robot joint is then transferred to the torque command for the driving motor. In the fuzzy–neuro controller, 20 kinds of fuzzy IF–THEN rules are prepared to generate the desired joint angle and impedance of the exoskeletal robot. The initial fuzzy IF–THEN control rules are written in Table II and the architecture of the fuzzy–neuro controller is depicted in Fig. 7. Here, Σ means sum of the inputs, Π means multiplication of the inputs. The fuzzifier layer, in which each neuron represents a membership function for the input, consists of 17 neurons, the rule layer consists of 20 neurons and the defuzzifire layer consists of four neurons.



(a)



(b)

Fig. 6. Example of WL and EMG during elbow motion. (a) EMG. a(b) Waveform length of EMG.

TABLE II
INITIAL FUZZY IF–THEN CONTROL RULES

	IF	THEN
Rule 1:	EMG ch.1 is PB and EMG ch.2 is PB	q_d is 4.2, B_e is 1.359, and K_e is 9.0
Rule 2:	EMG ch.1 is PB and EMG ch.2 is PS	q_d is 3.6, B_e is 0.906, and K_e is 4.0
Rule 3:	EMG ch.1 is PS and EMG ch.2 is PS	q_d is 3.0, B_e is 0.453, and K_e is 1.0
Rule 4:	EMG ch.1 is ZO, EMG ch.2 is ZO, and EMG ch.4 is PB	q_d is -1.0, B_e is 1.359, and K_e is 9.0
Rule 5:	EMG ch.1 is ZO, EMG ch.2 is ZO, and EMG ch.4 is PS	q_d is -0.65, B_e is 0.906, and K_e is 4.0
Rule 6:	EMG ch.1 is PB, EMG ch.2 is ZO, and EMG ch.4 is PB	q_d is 0.0, B_e is 1.359, and K_e is 9.0
Rule 7:	EMG ch.1 is PB, EMG ch.2 is ZO, and EMG ch.4 is PS	q_d is 0.0, B_e is 0.906, and K_e is 4.0
Rule 8:	EMG ch.1 is PB, EMG ch.2 is ZO, EMG ch.4 is PB, and Wrist Force is ZO	q_d is 0.0, B_e is 1.359, and K_e is 9.0
Rule 9:	EMG ch.1 is PB, EMG ch.2 is ZO, EMG ch.4 is PS, and Wrist Force is ZO	q_d is 0.0, B_e is 0.906, and K_e is 4.0
Rule 10:	EMG ch.1 is ZO, EMG ch.2 is ZO, EMG ch.3 is ZO, and EMG ch.4 is ZO	q_d is 0.0, B_e is 0.22, and K_e is 0.5
Rule 11:	Wrist Force is ZO	q_d is 0.0, B_e is 0.22, and K_e is 0.5
Rule 12:	EMG ch.1 is not PB and Wrist Force is PS	q_d is 0.7, B_e is 0.22, and K_e is 0.5
Rule 13:	EMG ch.1 is not PB and Wrist Force is PB	q_d is 1.1, B_e is 0.453, and K_e is 1.0
Rule 14:	EMG ch.1 is not PB and Wrist Force is NS	q_d is -0.7, B_e is 0.22, and K_e is 0.5
Rule 15:	EMG ch.1 is not PB and Wrist Force is NB	q_d is -1.7, B_e is 0.453, and K_e is 1.0
Rule 16:	EMG ch.3 is PB and EMG ch.4 is PB	q_d is -1.6, B_e is 1.359, and K_e is 9.0
Rule 17:	EMG ch.3 is PS and EMG ch.4 is PB	q_d is -1.3, B_e is 0.906, and K_e is 4.0
Rule 18:	EMG ch.3 is PS and EMG ch.4 is PS	q_d is -0.9, B_e is 0.453, and K_e is 1.0
Rule 19:	EMG ch.3 is PB and EMG ch.4 is PS	q_d is -1.0, B_e is 0.453, and K_e is 1.0
Rule 20:	EMG ch.3 is PS, EMG ch.4 is PS, and Wrist Force is NB	q_d is -0.4, B_e is 0.22, and K_e is 0.5

Two kinds of nonlinear functions (f_G and f_S) are applied to express the membership function of the fuzzy–neuro controller:

$$f_s(u_s) = \frac{1}{1+e^{-u_s}} \tag{3}$$
$$u_s(x) = w_0 + w_i x \tag{4}$$
$$f_G(u_G) = e^{-u_G^2} \tag{5}$$
$$u_G(x) = \frac{w_0 + x}{w_i} \tag{6}$$

where w_0 is a threshold value and w_i is a weight. In the Gaussian function f_G, w_0 is a mean value and w_i is a deviation of the membership function. The process of the fuzzy–neuro controller is the same as that of ordinal simplified fuzzy controllers. Consequently, the output of the fuzzy–neuro controller is calculated with the following equation:

$$O = \frac{\sum_i w_{ri} y_{ki}}{\sum_i y_{ki}} \tag{7}$$

where
- O output vector;
- y_{ki} degree of fitness of ith rule;
- w_{ri} weight for ith rule.

It is important that the controller adapts itself to physiological condition of each human subject online, since the EMG signal is a biologically generated signal. The adaptation of fuzzy–neuro controller is carried out by adjusting each weight of the fuzzy–neuro to minimize the evaluation function. In this study, the antecedent part and some of the consequence part (i.e., fuzzy rules for the desired joint angle generation) of the fuzzy IF–THEN control rules are supposed to be adjusted by the back-propagation learning method in online manner.

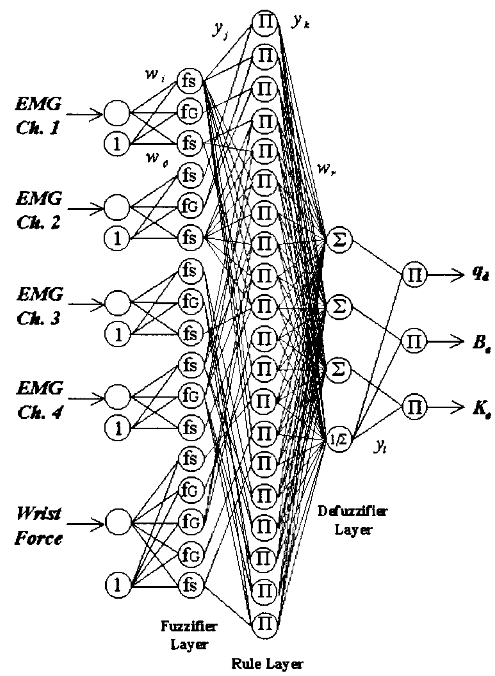


Fig. 7. Architecture of the fuzzy–neuro controller.

The back-propagation learning algorithm has been applied to minimize the squared error function written as follows:

$$\begin{cases} E = \frac{1}{2}(q_d - q)^2, & \text{IF } (q_d - q) \text{ is not ZERO} \\ E = 0, & \text{IF } (q_d - q) \text{ is ZERO} \end{cases} \tag{8}$$

where q_d is the angle of the desired motion and q is the measured joint angle of the exoskeletal robot. In order to avoid the useless adaptation caused from little error, the fuzzy variable: ZERO is applied to express the error of the exoskeletal robot is about zero. The desired motion of the exoskeletal robot, which

Fig. 8. Teaching equipment.

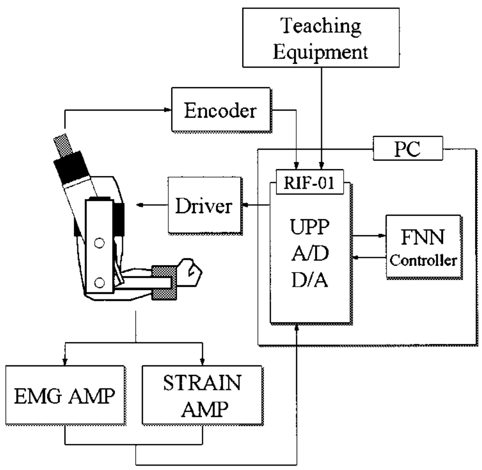


Fig. 9. Experimental setup.

is required for the evaluation function of the back-propagation learning, is demonstrated by the teaching equipment (see Fig. 8) attached on the other arm. In the teaching time, the subjects are supposed to generate the same elbow motion in both arms. Consequently, the difference between the right elbow angle and the left elbow angle is the control error of the exoskeletal robot system.

V. Experiment

In order to evaluate the effectiveness of the adaptation ability of the proposed exoskeletal robot system, experiments have been performed with three healthy human male subjects (subject A and B are 23 years old and subject C is 24 years old). Fig. 9 shows the experimental setup. In this experiment, the subjects are supposed to carry out flexion/extension elbow motion without any weight at first, grab a heavy weight (7 kg) when they extend their elbow at the second time, and then manipulate the weight by hand in order to evaluate the effect of the exoskeletal robot.

Figs. 10 and 11 show the experimental results of EMG signals during elbow motion with and without support of the proposed exoskeltal robot, respectively. Since the biceps are supposed to be the most active muscle during this experiment, only the EMG signal of channel 1 (medial side of biceps) is depicted in Figs. 10 and 11. The EMG levels of biceps during the heavy weight manipulation are supposed to be lower if the proposed exoskeletal robot supports the human motion properly. Comparing the results in Figs. 10 and 11, one can see that the EMG levels of biceps during the heavy weight manipulation are much lower when the human motion is supported by the exoskeletal robot. One can also see that the EMG levels during flexion/extension elbow motion without the weight are almost the same in Figs. 10 and 11. This means that the exoskeletal robot does not constrain the elbow motion of the subjects.

These results show that the proposed exoskeletal robot system can effectively support the elbow motion of any subjects using its adaptation ability.

Next, the target following experiments have been carried out with and without support of the exoskeletal robot in order to evaluate the accuracy of the system. In this experiment, the subject A is supposed to make his elbow flexion angle follow the target trajectory shown on the display with a heavy weight (7 kg) in his hand. The target flexion angle of the elbow angle is given as sinusoidal trajectory: $60\sin(0.2t)$ [deg]. Since the human subject try to adjust his elbow flexion angle to follow the target trajectory shown on the display, a little motion error is inevitable. Figure 12 shows the experimental result of the target following with and without support of the exoskeletal robot. In this figure, the desired joint angle (trajectory), the generated desired joint angle by the fuzzy–neuro controller (i.e., one of the output of the fuzzy–neuro controller: q_d) and the measured joint angle with support of the exoskeletal robot, and the measured joint angle without support of the exoskeletal robot are depicted. One can see that the appropriate desired joint angle, which is similar to natural joint motion (i.e., the measured joint angle without support of the exoskeletal robot), is generated by the fuzzy–neuro controller and it is accurately realized by impedance control. These results show that the human subject's intention can be reflected properly into the supported motion by the proposed exoskeletal robot.

VI. Discussion

It is important to realize natural and flexible movement by the exoskeletal robot for everyday life of physically weak persons. In this study, the natural and flexible movement of the exoskeletal robot and the effective motion support have been realized by generating the physiological joint impedance [25], [26] and the desired angular motion using fuzzy–neuro impedance control based on human subject's intention. The online adaptation ability of fuzzy–neuro enables the exoskeletal robot to adapt its interface to physiological condition of any human subject. Since fuzzy–neuro is equivalent to trained neural networks based on our knowledge, experience, and previous research results, it is more efficient than neural networks [30]. The back-propagation learning method has been applied in online manner for adaptation in this study. We have confirmed the effectiveness of the adaptation ability of the proposed exoskeletal robot system by the experiment with several subjects. Application of another adaptation method such as evolvable hardware [15] to

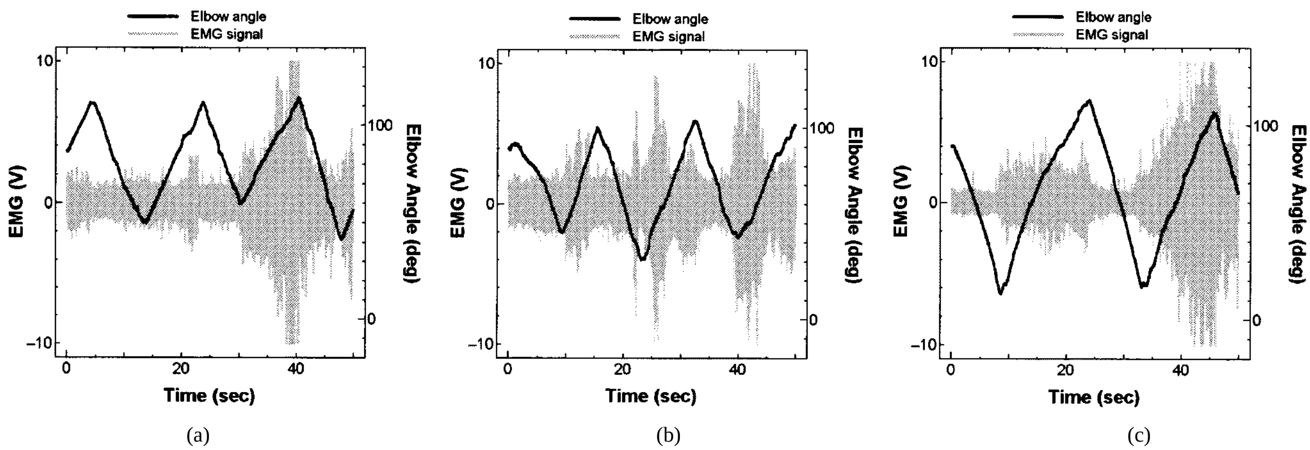


Fig. 10. Experimental results with support of the exoskeletal robot. (a) Subject A, (b) subject B, and (c) subject C.

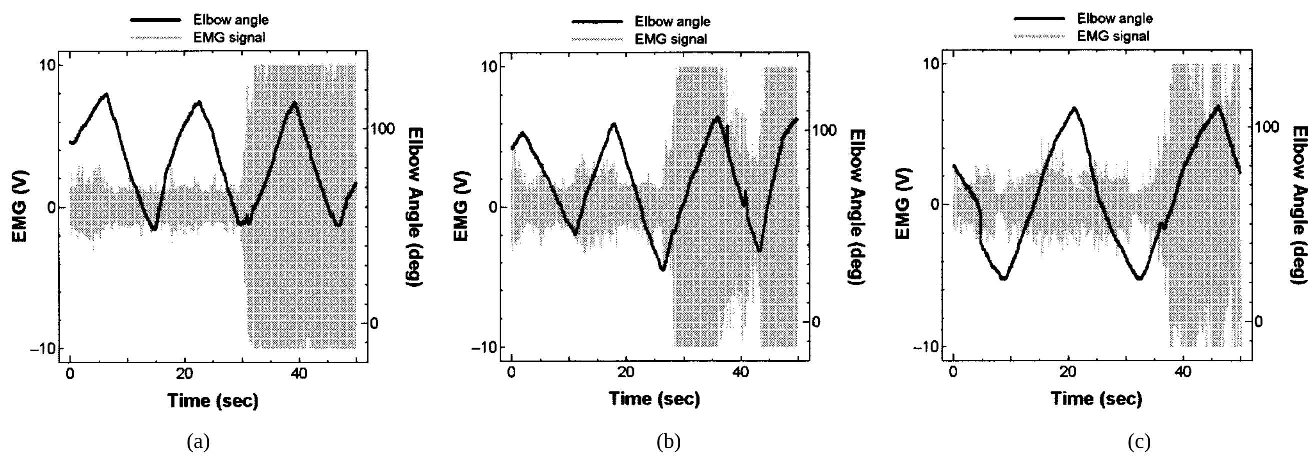


Fig. 11. Experimental results without support of the exoskeletal robot. (a) Subject A, (b) subject B, and (c) subject C.

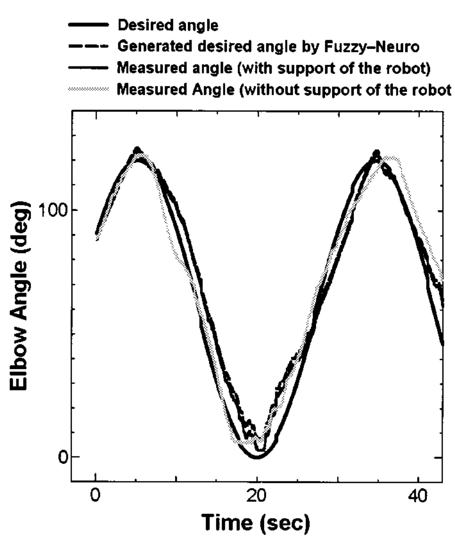


Fig. 12. Experimental results of target following.

the fuzzy–neuro controller is not appropriate since the structure of fuzzy–neuro computation process and some knowledge stored in the fuzzy–neuro should not be changed.

Many human joints yield complex motion. A human knee joint is a typical example. It is known that the knee joint yields complex 6DOF motion. In the case of a human elbow, however, the joint is modeled as a uniaxial hinge joint [31], although it consists of three bones (humerus, ulna, and radius). Therefore, as far as the axis of the exoskeletal robot joint is set to be the same as the subject's elbow joint axis passing through the centers of the arcs formed by the capitellum and the trochlear sulcus, the motion of the exoskeletal robot is supposed to be the same as the subject's elbow motion (i.e., the exoskeletal robot does not constrain the subject's elbow motion). We have confirmed that the exoskeletal robot does not constrain the elbow motion of the subjects in experiment.

VII. Conclusion

An exoskeletal robot system has been proposed for assisting human elbow motion as the first step toward the development of a full motion support exoskeletal robot. The effective control method has been proposed to realize adaptive ability to the biological signals. The skin surface EMG signals of biceps and triceps and the generated wrist force during the human elbow motion is fused and used for input information of the controller of the robot as the signals implying the human subject's intention. In order to control both the angle and impedance of the exoskeletal robot according to the vague biological signals, a fuzzy–neuro control method has been proposed. The experimental results showed the effectiveness of the proposed control system. The hardware of the proposed exoskeletal robot system needs further improvement such as weight reduction, size reduction, and improvement of attachment feeling. We would like to continue this study toward the realization of a full motion support exoskeletal robot.

REFERENCES

[1] K. Nagai, I. Nakanishi, H. Hanafusa, S. Kawamura, M. Makikawa, and N. Tejima, "Development of an 8 DOF robotic orthosis for assisting human upper limb motion," *Proc. IEEE Int. Conf. Robotics and Automation*, pp. 4386–4391, 1998.

[2] W. H. Finger and H. H. Asada, "Design and control of an active mattress for moving bedridden patients," *Proc. IEEE Int. Conf. Robotics and Automation*, pp. 2044–2050, 1999.

[3] C. J. Abul-Haj and N. Hogan, "Functional assessment of control systems for cybernetic elbow prostheses—Part I and II," *IEEE Trans. Biomed. Eng.*, vol. 37, pp. 1025–1047, Nov. 1990.

[4] B. Hudgins, P. Parker, and R. N. Scott, "A new strategy for multifunction myoelectric control," *IEEE Trans. Biomed. Eng.*, vol. 40, pp. 82–94, Jan. 1993.

[5] K. A. Farry, I. D. Walker, and R. G. Baraniuk, "Myoelectric teleoperation of a complex robotic hand," *IEEE Trans. Robot. Automat.*, vol. 12, pp. 775–788, Sept. 1996.

[6] O. Fukuda, T. Tsuji, A. Ohtsuka, and M. Kaneko, "EMG-based human-robot interface for rehabilitation aid," *Proc. IEEE Int. Conf. Robotics and Automation*, pp. 3942–3947, 1998.

[7] D. Nishikawa, W. Yu, H. Yokoi, and Y. Kakazu, "EMG prosthetic hand controller using real-time learning method," *Proc. IEEE Int. Conf. Systems, Man, and Cybernetics*, pp. I-153–I-158, 1999.

[8] J. A. Cozens, "Robotic assistance of an active upper limb exercise in neuro logically impaired patients," *IEEE Trans. Rehab. Eng.*, vol. 7, no. 2, pp. 254–256, 1999.

[9] C. Pfeiffer, K. DeLaurentis, and C. Mavroidis, "Shape memory alloy actuated robot prostheses: Initial experiments," *Proc. IEEE Int. Conf. Robotics and Automation*, pp. 2385–2391, 1999.

[10] H. Huang and C. Chen, "Development of a myoelectric discrimination system for a multi-degree prosthetic hand," *Proc. IEEE Int. Conf. Robotics and Automation*, pp. 2392–2397, 1999.

[11] S. Suryanarayanan, "An intelligent system for surface EMG-based position tracking of human arm movements for the control of manipulators," Ph.D. dissertation, Univ. Akron, OH, 1996.

[12] E. Park and S. G. Meek, "Fatigue compensation of the electromyographic signal for prosthetic control and force estimation," *IEEE Trans. Biomed. Eng.*, vol. 40, Oct. 1993.

[13] T. Tsuji, Y. Kawaguchi, and M. Kaneko, "An adaptive training method for human-robot systems using neural networks," *J. Robotics Soc. Jpn.*, vol. 18, no. 5, pp. 683–389, 2000. in Japanese.

[14] S. Fujii, D. Nishikawa, and H. Yokoi, "Development of prosthetic hand using adaptive control method for human characteristics," in *Intelligent Autonomous Systems*. Sapporo, Japan: IOS Press, 1998, pp. 360–367.

[15] I. Kajitani, M. Murakawa, D. Nishikawa, H. Yokoi, N. Kajihara, M. Iwata, D. Keymeulen, H. Sakanashi, and T. Higuchi, "An evolvable hardware chip for prosthetic hand controller," in *Proc. Seventh Int. Conf. Microelectronics for Neural, Fuzzy, and Bio-Inspired Systems (MicroNeuro99)*, 1999, pp. 179–186.

[16] R. S. Mosher and B. Wendel, "Force-reflecting electrohydraulic servomanipulator," *Electro-Technology*, pp. 138–141, Dec. 1960.

[17] W. Cloud, "Man amplifiers: Machines that let you carry a ton," *Popular Sci.*, vol. 187, no. 5, pp. 70–73 & 204, 1965.

[18] R. S. Mosher, *Handyman to Hardiman*: Soc. Automotive Eng., 1967, Publ. MS670 088.

[19] M. Vukobratovic, *Legged Locomotion Robots and Anthropomorphic Mechanisms*. Tokyo, : The Nikkan Kogyo Shimbun Ltd., 1975. Translated into Japanese by I. Kato and T. Yamashita.

[20] H. Kazerooni and S. L. Mahoney, "Dynamics and control of robotic systems worn by humans," *Trans. ASME, J. Dynam. Syst., Meas. Contr.*, vol. 113, no. 3, pp. 379–387, 1991.

[21] Y. Hayashibara, K. Tanie, and H. Arai, "Design of a power assisted system with consideration of actuator's maximum torque," in *IEEE Int. Workshop on Robot and Human Communication*, 1995, pp. 379–384.

[22] F. A. Mussa-Ivaldi, N. Hogan, and E. Bizzi, "Neural, mechanical, and geometric factors subserving arm posture in humans," *J. Neurosci.*, vol. 5, no. 10, pp. 2732–2742, 1985.

[23] H. Gomi and M. Kawato, "The change of human arm mechanical impedance during movements under different environment conditions," in *Soc. Neurosci. Abst.*, vol. 21, 1995, p. 686.

[24] A. J. van Soest *et al.*, "The influence of the biarticularity of the gastrocnemius muscle on vertical-jumping achievement," *J. Biomech.*, vol. 26, pp. 1–8, 1993.

[25] C. J. Abul-Haj and N. Hogan, "An emulation technique for developing improved elbow-prosthesis designs," *IEEE Trans. Biomed. Eng.*, vol. BME-34, pp. 724–737, 1987.

[26] D. J. Bennett, J. M. Hollerbach, Y. Xu, and I. W. Hunter, "Time-varying stiffness of human elbow joint during cyclic voluntary movement," *Exper. Brain Res.*, vol. 88, pp. 433–442, 1992.

[27] S. Bouisset, "EMG and muscle force in normal motor activities," *New Develop. Electromyography Clin. Neurophys.*, vol. 1, pp. 547–583, 1973.

[28] A. L. Hof and Jw. Van den Berg, "EMG to force processing I-III," *J. Biomech.*, vol. 14, no. 11, pp. 747–792, 1981.

[29] E. A. Clancy and N. Hogan, "Relating agonist-antagonist electromyograms to joint torque during isometric, quasiisotonic, nonfatiguing contractions," *IEEE Trans. Biomed. Eng.*, vol. 44, pp. 1024–1028, Oct. 1997.

[30] K. Kiguchi and T. Fukuda, "Intelligent position/force controller for industrial robot manipulators application of fuzzy neural networks," *IEEE Trans. Ind. Elect.*, vol. 44, no. 6, pp. 753–761, 1997.

[31] J. T. London, "Kinematics of the elbow," *J. Bone Joint Surgery*, vol. 63-A, no. 4, pp. 529–535, 1981.

Kazuo Kiguchi (S'92–M'93) received the B.E. degree in mechanical engineering from Niigata University, Japan, in 1986, the Master of Applied Science degree in mechanical engineering from the University of Ottawa, Ottawa, ON, Canada, in 1993, and the Dr.Eng. degree from Nagoya University, Japan, in 1997.

He was a Research Engineer with Mazda Motor Co. between 1986 and 1989, and with MHI Aerospace Systems Co. between 1989 and 1991. He was with the Department of Industrial and Systems Engineering, Niigata College of Technology, between 1994 and 1999. He is currently an Associate Professor, Department of Advanced Systems Control Engineering, Graduate School of Science and Engineering, Saga University, Japan. His research interests include biorobotics, intelligent robots, machine learning, application of soft computing for robot control, and application of robotics in medicine.

Dr. Kiguchi received the J. F. Engelberger Best Paper Award at WAC2000. He is a member of the Robotics Society of Japan, the IEEE SMC, R&A, EMB, IE, and CAS societies), the Japan Society of Mechanical Engineers, the Society of Instrument and Control Engineers, the Japan Society of Computer Aided Surgery, International Neural Network Society, Japan Neuroscience Society, the Virtual Reality Society of Japan, and the Japanese Society for Clinical Biomechanics and Related Research.

Shingo Kariya was born on January 14, 1977. He received the B.E. degree from Saga University, Saga, Japan, in 2000, and is currently pursuing the M.E. degree with the Department of Advanced Systems Control Engineering, Saga University.

Keigo Watanabe (M'93) received B.E. and M.E. degrees in mechanical engineering from the University of Tokushima, Japan, in 1976 and 1978, respectively, and the Dr.Eng. degree in aeronautical engineering from Kyushu University, Japan, in 1984.

From 1980 to March 1985, he was a Research Associate at Kyushu University. From April 1985 to March 1990, he was an Associate Professor in the College of Engineering, Shizuoka University. From April 1990 to March 1993, he was an Associate Professor, and from April 1993 to March 1998, a full Professor in the Department of Mechanical Engineering, Saga University, Japan. Since April 1998, he has been with the Department of Advanced Systems Control Engineering, Graduate School of Science and Engineering, Saga University. His research interests are in stochastic adaptive estimation and control, robust control, neural network control, fuzzy control, genetic algorithms and their applications to the machine intelligence and robotic control. He has published more than 270 technical papers in transactions, journals and international conference proceedings, and is author or editor of 14 books, including *Adaptive Estimation and Control* (Englewood Cliffs, NJ: Prentice-Hall), *Stochastic Large-Scale Engineering Systems* (New York: Marcel Dekker) and *Intelligent Control Based on Flexible Neural Networks* (Norwell, MA: Kluwer). He is an active reviewer of many journals or transactions, the editor-in-chief of *Machine Intelligence and Robotic Control*, and editorial board member of the *Journal of Intelligent and Robotic Systems* and the *Journal of Knowledge-Based Intelligent Engineering Systems*.

Dr. Watanabe is a member of the Society of Instrument and Control Engineers, the Japan Society of Mechanical Engineers, the Japan Society for Precision Engineering, the Institute of Systems, Control and Information Engineers, the Japan Society for Aeronautical and Space Sciences, the Robotics Society of Japan, and the Japan Society for Fuzzy Theory and Systems.

Kiyotaka Izumi (M'00) received the B.E. degree in electrical engineering from the Nagasaki Institute of Applied Science, Japan, in 1991, the M.E. degree in electrical engineering from the Saga University, Japan, in 1993, and the Dr.Eng. degree in faculty of engineering systems and technology from the Saga University in 1996.

From April in 1996 to March in 2001, he was a Research Associate, Department of Mechanical Engineering, Saga University. In April 2001, he joined the Department of Advanced Systems Control Engineering, Graduate School of Science and Engineering, Saga University His research interests are in robust control, fuzzy control, behavior-based control, genetic algorithms, evolutionary strategy and their applications to the robot control.

Dr. Izumi is a member of the Society of Instrument and Control Engineers, the Japan Society of Mechanical Engineers, the Robotics Society of Japan, Japan Society for Fuzzy Theory and Systems, the Institute of Electronics, Information and Communication Engineers, and the Japan Society for Precision Engineering.

Toshio Fukuda (M'83–SM'93–F'95) graduated from Waseda University in 1971 and received the M.S and Dr.Eng. degrees from the University of Tokyo, Japan, in 1973 and 1977, respectively. He also studied at the graduate school of Yale University, New Haven, CT, from 1973 to 1975.

In 1977, he joined the National Mechanical Engineering Laboratory and became Visiting Research Fellow at the University of Stuttgart, Germany, from 1979 to 1980. He joined the Science University of Tokyo in 1982 and then joined Nagoya University, Japan, in 1989 Currently, he is a Professor at the Center for Cooperative Research in Advanced Science & Technology, as well as the Department of Micro System Engineering and the Department of Mechano-Informatics and Systems, Nagoya University, mainly engaging in the research fields of intelligent robotic system, cellular robotic system, mechatronics and micro robotics. He is an author of six books, editing five books and has published over 1000 technical papers in microsystems, robotics, mechatronics, and automation areas.

Dr. Fukuda was named SICE Fellow in 1995, received the IEEE Eugene Mittlemann Award in 1997, the Banki Donat Medal form Polytechnic University of Budapest, Hungary, in 1997, the Medal from the City of Sartillo, Mexico, in 1998, and the IEEE Millennium Medal in 2000. He was the Vice President of IEEE Industrial Electronics Society (1990–1999), the IEEE Neural Network Council Secretary since 1992, IFSA Vice President since 1997, IEEE Robotics and Automation Society President in 1998–1999, and is currently Editor-in-Chief of IEEE/ASME TRANSACTIONS ON MECHATRONICS and IEEE Division X Director..