Estimation of User's Motion Intention of Hand based on Both EMG and EEG Signals

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Abstract: A surface EMG signal is one of the most widely used signals as input signals for wearable robots. However, EMG signals are not always available to all users. On the other hand, an EEG signal has drawn attention as input signals for those robots in recent years. However, the EEG signal does not have straightforward relationships with the corresponding brain part. Therefore, it is more difficult to find the required signals for the control of the robot in accordance with the user's motion intention using the EEG signals compared with that using the EMG signals. In this paper, both the EMG and EEG signals are used to estimate the user's motion intention. The EMG signals are used as main input signals because the EMG signals have higher relative to the motion of a user. The EEG signals are used as sub signals in order to cover the estimation of the user's motion intention when all required EMG signals cannot be measured. The effectiveness of the proposed method has been evaluated by performing experiments.

1 INTRODUCTION

In advanced countries, aging of the society with low birthrates is a serious problem. It is very important to assist the daily living of physical weak persons in order to make them live the independent lives. To assist daily life motions of the physically weak persons such as elderly, injured, or disabled persons, many kinds of power-assist robots and robotic artificial limbs have been developed (Yang et al., 2008); (Escudero et al., 2002). Those robots are required to generate the proper motion according to a user's motion intention because the robots need to prevent a user from uncomfortableness. To activate the robots according to a user's motion intention, the biological signals are often used as input signals for those robots.

In the biological signals, a surface electromyogram (EMG) signal is one of the most widely used signals as input signals for wearable robots. An EMG signal is an electric signal which is generated when a muscle is activated. Therefore, the robots can estimate a user's motion intention and assist the estimated motion in real-time by measuring multiple EMG signals. However, EMG signals that are needed to estimate the motions of a human upper-limb are not always available to every user. For example, persons who lost their limb due to an accident or a sickness are not able to prepare EMG signals because they lost some necessary muscles. Furthermore, paralyzed patients are also not able to prepare EMG signals. In addition, the correct locations of the electrodes are difficult to find for some surface EMG signals. If all required EMG signals for the control of the robots cannot be measured, other input signals must be prepared instead of EMG signals.

On the other hand, electroencephalogram (EEG) signals are used as input signals for various robots in recent years. An EEG signal is an electric signal that can be measured along a scalp. Therefore, the EEG signals can be measured even with amputees and paralyzed patients who are not able to generate some (or all) EMG signals. An EEG signal is one of the strong candidates for the additional input signals for wearable robots, and it will be able to allow more users to use those wearable robots. The interface between a robot and EEG signals is called as Brain Computer Interface (BCI). Until EEG signals were used for the control of the robots, the researches on offline analysis of EEG signals were mainly carried out. To detect event-related potential, evoked potential, and so on, the averaging method, frequency analysis and principal component analysis

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are widely used in offline analysis. However, many of those analyses require a certain length of time-series data of EEG signals. Therefore, in general, those analyses are not suitable for the real-time control of the robots. On the other hand, some classification methods that are used to control the robotic systems in real-time were proposed (Novi et al., 2007), (Fabiani et al., 2004). In addition, the hand velocity is estimated from EEG signals in recent years in the limited condition (Lv et al., 2010), (Bradberry et al., 2010).

In the case of a surface EMG signal, although an electrode is located on the skin, the measured EMG signal has almost straightforward relationships with the corresponding muscle as long as the electrode is located correctly. On the other hand, in the brain, various electric signals are generated at multiple locations and are conveyed to the scalp. The sum of those conveyed electrical signals on the scalp is recorded as the EEG signal. Therefore, in the case of an EEG signal, the measured EEG signal does not have straightforward relationships with the corresponding brain part. It is more difficult to find the required signals for the control of the robot in accordance with the user's motion intention using the EEG signals compared with that using the EMG signals.

In this paper, both the EMG and EEG signals are used as input signals for wearable robots, and estimated the user's motion intention of the upper-limb based on the measured EMG and EEG signals. In the proposed method, the EMG signals are used as main input signals because the EMG signals have higher relative to the motion of a user in comparison with the EEG signals. The EEG signals are used as sub signals in order to cover the estimation of the user's motion intention when all required EMG signals cannot be measured. The effectiveness the proposed method has been evaluated by performing experiments.

2 MEASUREMENT OF EMG AND EEG SIGNALS

In this study, to estimate a user's upper-limb motion, EMG and EEG signals are used. A human's upper-limb basically has 7 degrees of freedom (shoulder vertical and horizontal fle./ext. motion, shoulder int./ext. rotation motion, elbow fle./ext. motion, forearm supination/pronation motion, wrist fle./ext. motion and wrist radial/ulnar deviation motion).

In the case of EMG signals, 16 EMG signals are used to estimate 7 DOFs' motion of a user's upper-limb (Kiguchi et al., 2012). Table 1 shows the muscles in which 16 EMG signals are measured. At least two muscles are related to each upper-limb motion. EMG signals are measured by using electrodes (NE-101A, Nihon Koden Co.). The EEG signals are measured by Net Station System (Geodesic Sensor Nets, Electrical Geodesics, Inc.) as shown in Figure 1. This sensor system can measure EEG signals of 256 channels. EMG and EEG signals are measured with the sampling frequency of 1 kHz.

Table 1: Muscle for each EMG channel.

Ch.	Name of muscle	Related major motion
ch. 1	Deltoid-anterior	Shoulder vertical fle. Shoulder horizontal fle. Shoulder int. rotation
ch .2	Deltoid-posterior	Shoulder vertical ext. Shoulder horizontal ext. Shoulder ext. rotation
ch. 3	Pectoralis major-clavicular	Shoulder vertical fle. Shoulder horizontal fle.
ch. 4	Teres major	Shoulder int. rotation Shoulder vertical ext.
ch. 5	Infraspinatus	Shoulder ext. rotation
ch. 6	Teres minor	Shoulder ext. rotation
ch. 7	Biceps-short head	Elbow fle. Forearm supination
ch. 8	Biceps-long head	Elbow fle. Forearm supination
ch .9	Triceps-long head	Elbow ext.
ch. 10	Triceps-lateral head	Elbow ext.
ch. 11	Pronator teres	Elbow ext. Forearm pronation
ch. 12	Supinator	Forearm supination
ch. 13	Extensor carpi radialis brevis	Wrist ext. Wrist radial deviation
ch. 14	Extensor carpi ulnaris	Wrist ext. Wrist ulnar deviation
ch. 15	Flexor carpi radialis	Wrist fle. Wrist radial deviation
ch. 16	Flexor carpi ulnaris	Wrist fle. Wrist ulnar deviation

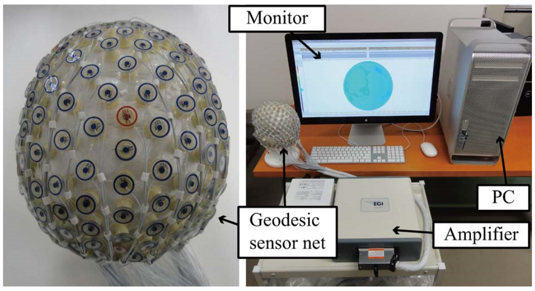

Figure 1: Net Station System.

3 MOTION ESTIMATION

3.1 Motion Estimation by using EMG Signals

The raw EMG signals are not suitable for input signals for the robots. Therefore, a feature extraction from raw EMG signals is necessary. There are some methods to extract the features of raw EMG signals. Root mean square (RMS) is one of those methods. The RMS values of each EMG signal are calculated as follows.

$$Ch_i = \sqrt{\frac{1}{N_s}\sum_{j}^{N_s} v_{i,j}^2} \tag{1}$$

where $v_{i,j}$ is the raw EMG signal of ith channel at jth sampling, Ch_i is the RMS value of ith channel, and N_s is the number of segments. Each joint torque is calculated by the linear sum of the RMS values of the muscles that relate to moving the joint. For example, in the case of shoulder joint, each torque is calculated as follows.

$$\begin{bmatrix} \tau_v \\ \tau_h \\ \tau_r \end{bmatrix} = \begin{bmatrix} w_{sv1} & \cdots & w_{sv10} \\ w_{sh1} & \cdots & w_{sh10} \\ w_{sr1} & \cdots & w_{sr10} \end{bmatrix} \begin{bmatrix} Ch_1 \\ \vdots \\ Ch_{10} \end{bmatrix} \tag{2}$$

where τ_v, τ_h, and τ_r are the shoulder vertical fle./ext., horizontal fle./ext., and int./ext. rotation torques, respectively. w_{svi}, w_{shi}, and w_{sri} are the weight values of the RMS value of ith channel. Similarly, elbow joint torque (τ_e), forearm torque (τ_f), and wrist torques (τ_{wf}, τ_{wd}) are calculated based on the RMS values of ch. 7-ch. 10, ch. 11-ch. 12, and ch. 13-ch. 16, respectively. The EMG signals are changed according to the upper-limb posture. Therefore, the weight values are adjusted by using the neuro-fuzzy modifiers trained for each user (Kiguchi et al., 2012). The neuro-fuzzy modifier for the shoulder joint is shown in Figure 2 as an example. As shown in Figure 2, the inputs are some joint angles. In fuzzifier layer, two sigmoid functions and a gaussian function are used. CW_{svi}, CW_{shi}, CW_{sri} which are the outputs of neuro-fuzzy modifier are the gains for each initial weight value. The weight values in eq. (2) are calculated by multiplying the gains with the initial weight values. In the neuro-fuzzy modifiers, the weight value is learned for each user before operation using the error back propagation learning algorithm.

3.2 Motion Estimation by using EEG Signals

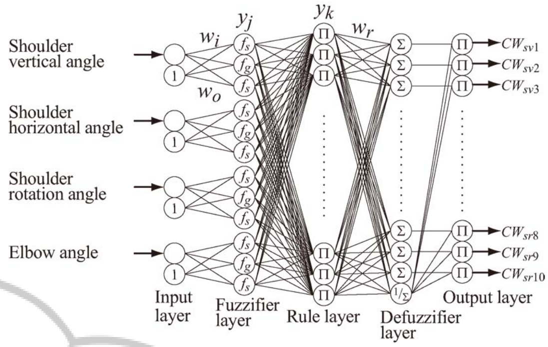

Figure 2: Neuro-fuzzy modifier for shoulder joint.

The raw EEG signals are also not suitable as input signals of the wearable robots such as power-assist robots. Hence, some features must be extracted from the raw EEG signals in order to use the EEG signals as input signals for those robots. There are many kinds of methods to extract the features of EEG signals. For example, the averaging method and the fast Fourier transformation (FFT) are basic methods to treat EEG signals on offline analysis. Because those methods require a lot data of EEG signals, in general, those methods are not suitable for the real-time control method. In this paper, to extract the feature of the raw EEG signals, band pass filter (BPF) is used at first. Since relatively-low frequency in EEG signals contains the important feature of the motion and they are used instead of alpha wave or beta wave in order to estimate the hand velocity in some methods (Lv et al., 2010), (Bradberry et al., 2010), the frequency between 0.3 and 4 Hz is used in the method. The hand velocity is estimated from the EEG signals after the BPF with 0.3-4Hz. In general, electrodes are located based on International 10-20 system. On the other hand, in this study, we can measure 256 EEG signals. However, the EEG signals of 256 channels are too many, and all of them are not required as input signals for the controller. Therefore, 40 important EEG channels are selected from 256 channels. In 256 channels, 61 electrodes are located on the cheeks and bottom of the head. Since those electrodes might detect other signals such as EMG signals except EEG signals, they are excluded from the channel selection preliminarily. To select the channels of EEG signals, at first, we measure EEG signals as the pre-experiment. In the pre-experiment, the subjects perform the various motions of upper-limb. After BPF processing, an angle between two EEG signal vectors is calculated based on inner product as follows.

$$\cos\theta_{ij} = \frac{\langle \boldsymbol{V}_i \cdot \boldsymbol{V}_j \rangle}{|\boldsymbol{V}_i||\boldsymbol{V}_j|} \tag{3}$$

where $\boldsymbol{V}_i = [v_{i0}\ v_{i1}\ \cdots\ v_{iN}]^{\mathrm{T}}$ represents the vector which consist of EEG signals of ith channel (N is the time count), θ_{ij} is the angle between vector $\boldsymbol{V}_i$ and vector $\boldsymbol{V}_j$, and <·> represents inner product. If vector $\boldsymbol{V}_i$ is perpendicular to vector $\boldsymbol{V}_j$, inner product and $\cos\theta_{ij}$ between $\boldsymbol{V}_i$ and $\boldsymbol{V}_j$ become zero. On the other hand, if $\boldsymbol{V}_i$ is nearly parallel to $\boldsymbol{V}_j$, inner product between $\boldsymbol{V}_i$ and $\boldsymbol{V}_j$ has a certain value that is not equal to zero, and absolute value of $\cos\theta_{ij}$ becomes almost one. The sum of $\cos\theta_{ij}$ becomes smaller if $\boldsymbol{V}_i$ is becoming perpendicular to the other vectors. Therefore, the evaluation E_{1i} function is defined as follows.

$$E_{1i} = \sum_{k=1}^{195} |\cos\theta_{ik}| \tag{4}$$

The first channel in which E_{1i} becomes a minimum value is selected. After that, channels are selected based on the evaluation E_{2i} function as follows.

$$E_{2i} = \sum_{k=1}^{N_s} |\cos\theta_{in[k]}| \tag{5}$$

where $n[k]$ is the array which consists of the selected channels. N_s is the number of selected channels. The channel which E_{2i} becomes a minimum value among non-selected channels is selected. Then the selected channel number is added to array $n[k]$ and N_s is increased until N_s becomes 40. The channels which are becoming near perpendicular to the already selected channels are selected by using eq. (5). The examples of the selected electrode's locations are shown in Figure 3. In Figure 3, red circles represent the selected channels based on eqs. (4) and (5). Note that the selected channels are different between each subject as shown in Figure 3. After the selection of the EEG channels, the average values of EEG signals are calculated as follows in order to extract the feature.

$$v_{avg,it} = \frac{1}{N_a} \sum_{k=t-N_a+1}^{t} v_{ik} \tag{6}$$

where v_{it} represents the EEG signals of ith channel after filtering at tth sampling, and N_a is the sampling number (N_a=200). $v_{avg,it}$ represents the EEG signals of ith channel after calculation at tth sampling. A neural network is used to estimate a user's hand

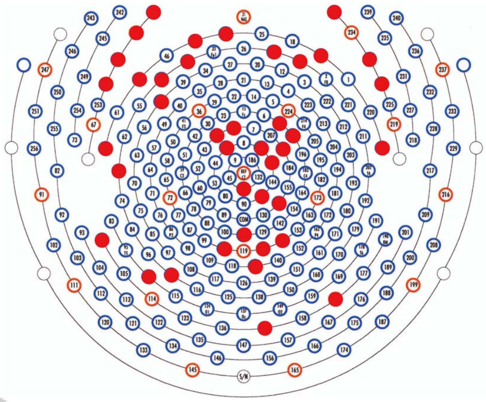

Figure 3: Example of selected channels.

motion from EEG signals. The neural network which estimates a user's hand velocity consists of three layers (input layer, hidden layer, and output layer). There are 40 neurons in the input layer, 100 neurons in the hidden layer and 6 neurons in the output layer. $v_{avg,it}$ is used as input signals to estimate the user's hand velocity. The error back propagation learning algorithm has been applied to train the neural network. A nonlinear sigmoid function is used as the activation function for the neurons in the hidden layer.

3.3 Motion Estimation by using EMG and EEG Signals

The EMG signals that are needed to estimate the motions of a human upper-limb are not always able to measure from all users. Therefore, The EMG and EEG signals are used to estimate the upper-limb's motion of a user. In this study, the EMG signals are used as main input signals because the EMG signal has straightforward relationships with the corresponding muscle. In addition, the EEG signals are used as sub signals to cover the estimation of the user's motion intention.

In the case that a user can measure the all EMG signals which are needed to control the upper-limb power-assist robot, the hand force vector which represents the user motion intention is calculated as follows.

$$\boldsymbol{F}_{hand} = \boldsymbol{J}^{-\mathrm{T}}\boldsymbol{\tau} \tag{7}$$

where $\boldsymbol{\tau}$ is the joint torque vector, $\boldsymbol{J}$ is the Jacobian matrix, and $\boldsymbol{F}_{hand}$ is the hand force vector. On the other hand, if the EMG signals which are needed to control the robot cannot be measured, a part of joint torques of upper-limb is not able to calculate by using eq. (2). In this case, the hand force vector is expressed as follows.

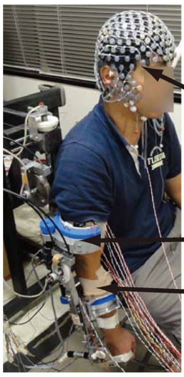

Figure 4: Experimental condition.

$$\boldsymbol{F}_{hand} = \boldsymbol{F}_{emg} + \boldsymbol{F}_r = \boldsymbol{J}_p^{-\mathrm{T}} \boldsymbol{\tau}_p + \boldsymbol{F}_r \quad (8)$$

where $\boldsymbol{F}_{emg}$ is the part of the hand force vector which can be calculated by the EMG signals, $\boldsymbol{\tau}_p$ is the joint torque vector in which each joint torque can be estimated by the measured EMG signals, $\boldsymbol{J}_p$ is the Jacobian matrix for $\boldsymbol{\tau}_p$. $\boldsymbol{F}_r$ is the part of the hand force vector which cannot be calculated by the EMG signals. Then, the hand velocity is calculated based on $\boldsymbol{F}_{hand}$.

$$\boldsymbol{a}_{hand} = \boldsymbol{M}^{-1}\boldsymbol{F}_{hand} = \boldsymbol{M}^{-1}\left(\boldsymbol{F}_{emg} + \boldsymbol{F}_r\right) \quad (9)$$

$$\begin{aligned} \boldsymbol{v}_{hand} &= \int \boldsymbol{a}_{hand}\, dt = \int \boldsymbol{M}^{-1}\left(\boldsymbol{F}_{emg} + \boldsymbol{F}_r\right) dt \\ &= \boldsymbol{v}_{emg} + \boldsymbol{v}_r \end{aligned} \quad (10)$$

where $\boldsymbol{a}_{hand}$ and $\boldsymbol{v}_{hand}$ are the hand acceleration and velocity vectors, respectively. $\boldsymbol{M}$ is the mass matrix. In eq. (10), $\boldsymbol{v}_{emg}$ is estimated based on EMG signals. In the case of the estimation of $\boldsymbol{v}_r$ by using the EMG and EEG signals, the part of the direction of the hand velocity is estimated based on the neural network as the same way in section 3-B. In the case of section 3-B, the input layer of the neural network has 40 neurons (the number of selected EEG channels). In contrast, in the case of estimation based on EMG and EEG signals, the number of neurons of input layer is equal to the number of selected EEG channels (40) and the number of joint torques which can be estimated by the EMG signals. After the estimation of the direction of hand velocity, $\boldsymbol{v}_r$ in eq. (10) is defined so that the resultant torque of the absolute values of each joint torque which cannot be estimated by the EMG signals becomes minimum value.

4 EXPERIMENT

To verify the effectiveness of estimation method, the experiments were carried out. In the experiments, the subjects wore the 7-DOF upper-limb power-assist robot Kiguchi et al., 2012) and performed some combined motions of upper-limb. The power-assist robot has encoders and potentiometers in order to measure each joint angle. Therefore, we can calculate the position and orientation of the subjects' hand based on each joint angle. In the experiments, the robot just followed the subject's motion and did not perform the power-assist. The EMG and EEG signals of the subject were measured during the upper-limb motions. The subjects were healthy young men who can measure all EMG signals (16 channels). The experimental condition is shown in Figure 4. In the estimations, we assume that some EMG signals of the subjects could not be measured, and estimate the hand motion intention by using the EEG and the remaining EMG signals.

In the first case, we assume that EMG signals of ch.11 and ch.12 cannot be measured. Those two channels are difficult to find the correct locations of electrodes. In this case, although the robot can estimate the torques of 6 joints, the robot cannot estimate the torque of the subject's forearm if the input signals are only EMG signals. Therefore, the EMG and EEG signals are used for the estimation. The example of estimation results is shown in Figure 5. Figure 5 shows the hand velocities. The black line is the result which is estimated based on 16 EMG signals (Only EMG case), the red line is the result which is estimated based on 14 EMG signals and EEG signals (EMG and EMG case). In the case of Figure 5, the subject moved the elbow joint and the forearm mainly. The origin of the coordinate frame in Figure 5 is shoulder joint. *x* axis is the dorsoventral axis, *y* axis is dorsoventral axis, and *z* axis is the craniocaudal axis. From Figure 5, the estimation results by the EMG and EEG signals represent the subject's motion.

In the second case, we assume that EMG signals from ch.11 to ch.16 cannot be measured. This assumption means that a user is above elbow amputee. In this case, forearm and wrist motions cannot be estimated based on only EMG signals. Figure 6 shows the estimation results. The subjects performed the motion to carry a cup to mouth to drink water. Compared with Figures 5 and 6, the case of Figure 6 is worse than the case of Figure 5 because less EEG signals are able to be measured in the case of Figure 6. From Figure 6, although there are some difference between the estimation result and the subject's motion, the subject's motion is described on some level by estimating based on EMG and EEG signals.

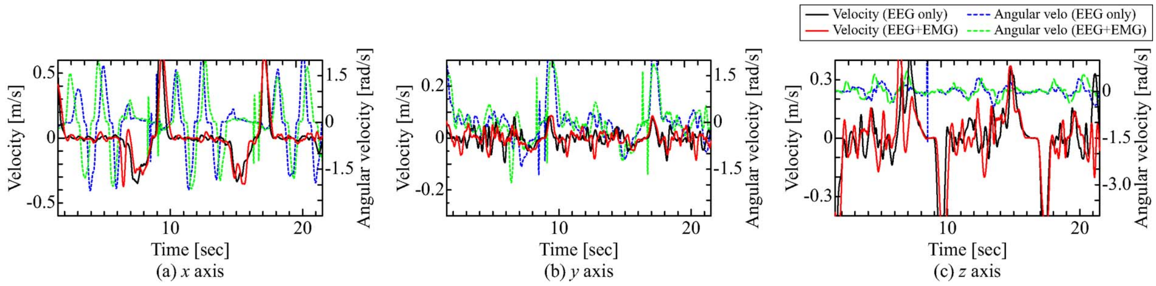

Figure 5: Experimental results (first case).

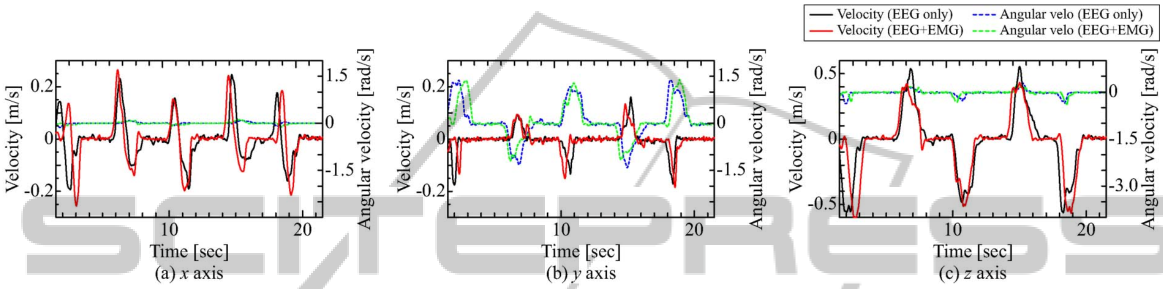

Figure 6: Experimental results (second case).

5 CONCLUSIONS

A surface EMG signal is one of the most widely used signals as input signals for wearable robots. However, EMG signals that are needed to estimate the motions of a human upper-limb are not always available to every user. On the other hand, in the case of an EEG signal, the measured EEG signal does not have straightforward relationships with the corresponding brain part. Therefore, it is more difficult to find the necessary signals for the control of the robot compared with the EMG signals. In this paper, we use the EMG and EEG signals as input signals for wearable robots, and estimated the user's motion intention of the upper-limb based on the measured EMG and EEG signals. The EMG signals are used as main input signals because the EMG signals have higher relative to the motion of a user in comparison with the EEG signals. The EEG signals are used as sub signals in order to cover the estimation of the user's motion intention when all required EMG signals cannot be measured. The experimental results show the effectiveness of the estimation method.

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REFERENCES

C. J. Yang, et al., 2008. A review of exoskeleton-type systems and their key technologies. *Proc. of IMechE, Journal of Mechanical Eng. Science, Part C*.

A. B. Zoss, et al., 2006. Biomechanical Design of the Berkeley Lower Extremity Exoskeleton (BLEEX). *IEEE/ASME Trans. on Mechatronics, 11(2)*.

H. Kobayashi, et al., 2004. Realization of all 7 motions for the upper limb by a muscle suit. *Journal of Robotics and Mechatronics, 16(5)*.

A. Z. Escudero, *et al.*, 2002. Development of a parallel myoelectric prosthesis for above elbow replacement. *Proc. of the Second Joint EMBS/BMES Conf.*

Q. Novi, *et al.*, 2007. Sub-band Common Spatial Pattern (SBCSP) for Brain-Computer Interface. *Proc. of 3rd Int. IEEE EMBS Conf. on Neural Eng.*

G. E. Fabiani, et al., 2004. Conversion of EEG activity into cursor movement by a brain-computer interface (BCI). *IEEE Trans. on Neural Systems and Reha. Eng., 12(3)*.

J. Lv, et al., 2010. Decoding hand movement velocity from electroencephalogram signals during a drawing task. *BioMedical Eng. OnLine, 9:64*.

T. J. Bradberry, et al., 2010. Reconstructing Three-Dimensional Hand Movements from Noninvasive Electroencephalographic Signals, *The Journal of Neuroscience, 30(9)*.

K. Kiguchi, et al., 2012. An EMG-Based Control for an Upper-Limb Power-Assist Exoskeleton Robot, *IEEE Trans. Systems, Man, and Cybernetics, Part B, 42(4)*.