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User independent hand motion recognition for robot arm manipulation

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Abstract In the present work, tele-manipulation of robot arm and gripper is experimentally performed using inertia measurement unit (IMU) and electromyogram (EMG)-based human motion recognition. The movement of robot arm and motion of robot gripper is determined based on the measured IMU and EMG data, respectively. To overcome user dependence which is one of main disadvantage of EMG-based motion recognition, reference voluntary contraction method-based normalization of measured EMG data is carried out. Training and test data of EMG are obtained from experiments for four kinds of hand motion of four experimental participants. After extraction of feature vectors, artificial neural network is applied for the EMG-based hand motion recognition. Even when training data and test data are obtained from different participants, it is confirmed that classification accuracy can be greatly improved through the proposed simple normalization method. Finally, a real-time tele-manipulation of 6-degree-of-freedom robot arm is demonstrated successfully by adopting the proposed user independent human motion recognition method.

1. Introduction

Recently, various efforts have been made to utilize a robot in a dangerous environment, such as a medical system requiring precise and delicate work or a disaster site where direct access is difficult for humans [1, 2]. Various studies have been conducted to develop an excellent robot capable of solving a problem by recognizing the situation and acting autonomously, but there are still problems to be solved. As a front step of a fully autonomous robot, a lot of research has been conducted to perform a given task by remotely controlling the robot in various ways. Research on da Vinci, a robot for surgery, can be said to be representative [3]. Joystick is used as the most common human-robot interface for remote control of robots, but it has disadvantages such as unintuitive usage, and cannot be used by people with hand or arm disorders. Research to remotely control a robot using motion recognition as an intuitive human-robot interface method is also actively being conducted. Motion recognition using a camera is the most representative, and research using Microsoft's KINECT has been conducted in various ways, but the disadvantage is that the spatial limitation is large [4, 5]. Recently, studies on motion recognition techniques using EMG also have been actively conducted [6]. Electromyography is a signal for microscopic action potentials generated in the muscles and nervous system during muscle contraction of skeletal muscles and can be easily measured through electrodes on the skin surface. In particular, research is being conducted on the number of robots recognizing the user's intention by using a characteristic in which the EMG can be measured even in the remaining muscles of the body [7]. The EMG-based human-robot interface system can be classified according to whether the pattern is recognized. The first is a method of using a threshold value of the EMG signal as a control input signal such as force and torque, and has a limitation in extending multiple motion control commands [8-10]. The second pattern recognition-based method has the advantage of being able to distinguish multiple motions by extracting linear and nonlinear features to perform motion recognition or by recognizing motion using images of surface EMG signals. Chu et al. proposed a novel real-time EMG pattern recognition for the control of a multifunction myoelectric hand from four channel EMG signals [11]. They also propose a linear-nonlinear feature projection composed of principal component analysis (PCA) and a self-organizing feature map. Geng et al. presented that the patterns inside the instantaneous values of high density EMG enables gesture recognition to be performed merely with surface EMG signals at a specific instant [12]. Francesco et al. reported that it is possible to decode individual flexion and extension movements of each finger (ten movements) with greater than 90 % accuracy in a transradial amputee using only noninvasive surface myoelectric signals [13]. Englehart et al. proposed wavelet-based continuous classification scheme to achieve greater classification accuracy for multifunction myoelectric control [14]. Bi et al. investigated on EMG based motor intention prediction of continuous human upper limb motion for human-robot collaboration [15]. Tavakoli et al. proposed a minimalistic approach with only 2 EMG channels to achieve comfort and lightness of wearable device and adopted support vector machine as a classifier to construct robust hand gesture recognition system [16].

There are disadvantages to the motion recognition technique using EMG. The first is that the signal characteristics may be different for the same motion due to a decrease in magnitude caused by muscle fatigue when used for a long time. The second point is that the characteristics of the EMG may vary depending on the location of the electrode. Third, because the person's age, gender, skin thickness, and size of muscle cross-sections are different, the measured EMG amplitude is different when the user is different even when measuring for the same motion at the same electrode location. In order to compensate for these shortcomings, a normalization method for EMG has been proposed. The most common method is maximum voluntary isomeric contraction (MVIC), which is based on the maximum electromyogram measured when a subject applies maximum contraction to the muscle, and indicates the level of the remaining signal corresponding to the percentage of the maximum value. MVIC is mainly used as a normalization method for motions where a large force is applied. The reference voluntary contraction (RVC) method determines the maximum value measured when a specific motion is taken as a reference value, and indicates the percentage of the remaining signal corresponding to the level of the maximum value. This is a method that increases the sensitivity to motions that do not apply large force. Matsubara proposed a bilinear model, consist of user dependent factor and motion dependent factor, of EMG signal to extract user-independent features for multi-user myoelectric interface [17]. Zhang et al. proposed user-independent feature classification of forearm using EMG signals by using back propagation neural networks [18]. However, there have been few reports of research on real-time tele-manipulation of six-degree-of-freedom robots without user dependence using EMG-based motion recognition.

The main contribution of this work is demonstration of a tele-

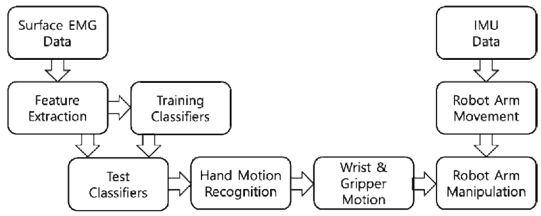
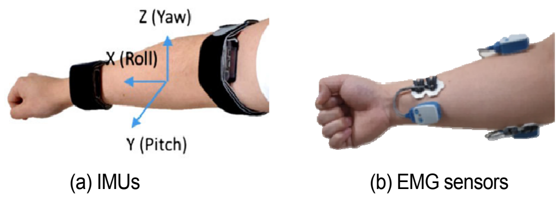


Fig. 1. Process of hand motion recognition and robot arm manipulation.



(a) IMUs (b) EMG sensors

Fig. 2. Measurement devices.

manipulation of robot arm and gripper by using user independent human hand motion recognition. The movement of human arm is measured by using two IMUs which are attached on the upper and lower arm. The motion of human hand is measured by using three EMG sensors which are attached on the lower arm. To apply machine learning algorithm for the recognition of human hand motion, features are extracted from the measured EMG data. To achieve user independence of EMG based motion recognition, feature vectors are normalized using reference voluntary contraction method. Training and test data are obtained from experiments for four kinds of hand motions from four experimental participants. When learning is performed using the measurement data of one experimental participant and the classification is performed using the measurement data of remaining three participants, it is confirmed that the classification accuracy is greatly increased by using the normalized feature vectors. The effectiveness of the proposed method is experimentally demonstrated by performing a real-time tele-manipulation of a 6-degree-of-freedom robot arm, and it is clearly confirmed that user independence can be secured using a normalization technique.

2. Data acquisition

The proposed process of tele-manipulation of robot arm and gripper using hand motion recognition is presented in Fig. 1. The movement of robot arm is controlled by using IMU data of human upper arm and forearm. The motion of robot wrist and gripper is controlled by using results of human hand motion recognition based on surface EMG data. After measurement of surface EMG data, features are extracted according to hand motions. Hand motion recognition is conducted after training and testing of machine learning-based classifier. The measurement devices which are worn on human arm are shown in Fig. 2. As shown in Fig. 2(a), one IMU sensor is attached on forearm to measure the Euler angle in pitch direction and another IMU sensor is attached on upper arm to measure the

Table 1. Sensor specifications.

Specifications	EMG	IMU
Manufacturer	NORAXON	E2BOX
Channels	Max. 8 CH	3-axis acc. 3-axis gyro 3-axis magnetometers
Sampling rate	Max. 4000 Hz	1000 Hz
Cut-off frequency of low pass filter	500/1000/1500 Hz	5-250 Hz
Sensitivity	0.3 uV	Gyro 250-2000 dps
Wireless communication	2.4 GHz Bluetooth	2.4 GHz RF

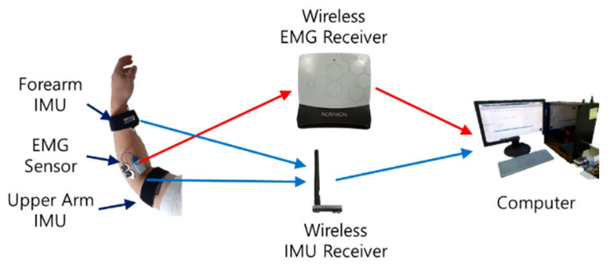


Fig. 3. Experimental setup for data acquisition from EMG and IMUs.

Euler angle in pitch and yaw direction. As shown in Fig. 2(b) three EMG sensors are attached on forearm to measure the wrist and hand motions. The positions of the sensor are selected where the muscles related to the wrist and hand movements, such as flexor digitorum profundus, flexor digitorum superficialis, flexor pollicis longus, extensor digitorum, extensor pollicis longus, and abductor pollicis longus, are located. The experimental setup for data acquisition using EMG sensor and IMU is presented in Fig. 3. The measured data from EMG sensors and IMUs which are attached on human arm is transmitted to data receiver via wireless communication. The obtained IMU data is transmitted to computer via USB cable and computer. After changing to analog signal, the obtained EMG sensor data is transmitted to computer through wireless data receiver. The principal specifications of EMG sensor and IMU are listed in Table 1. In this work, the sampling rate is 1000 Hz and 2000 Hz for IMU and EMG sensor, respectively.

2.1 IMU data

As a first step, movement tracking performance of robot arm according to measured 3-axis Euler angle of IMU is evaluated experimentally. By matching the coordinate system of the IMU with the coordinate system of the robot arm, the Euler angle measured by the IMU is used as the angle the human arm moved without an additional conversion process. The relationship between angles of IMUs attached on human arm and joints of slave robot arm is shown in Fig. 4. The measured Euler angles of human arm and measured angles of robot arm from robot arm joints are presented in Fig. 5. The error between measured Euler angle of human arm and followed angle of robot arm is calculated by following equation.

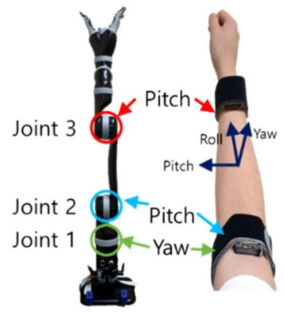
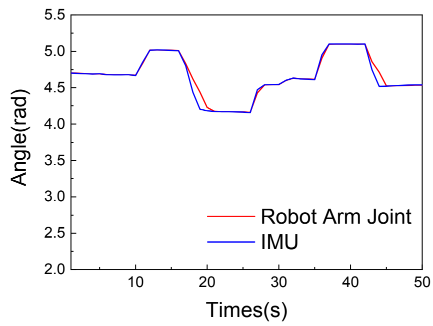
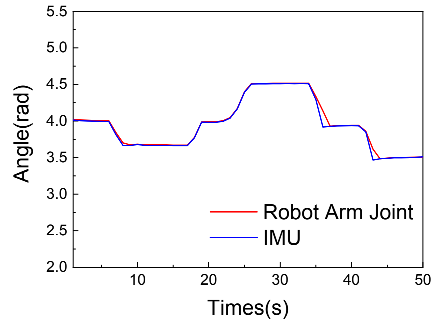


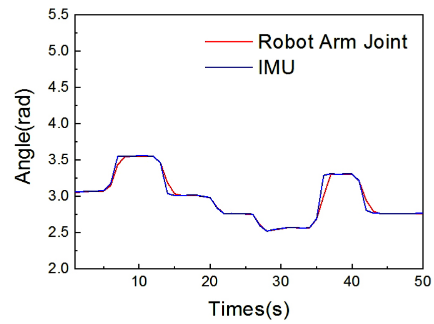
Fig. 4. The relationship between robot joint and Euler angle of IMU.



(a) Joint 1



(b) Joint 2



(c) Joint 3

Fig. 5. The measured angle of human arm and robot arm.

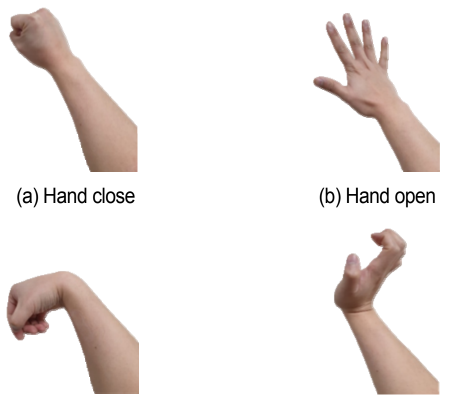
$$\text{Error} = \left| 1 - \frac{\text{Robot Joint Angle}}{\text{IMU Euler Angle}} \right| *100 \, . \tag{1}$$

Table 2. Error between human arm and robot arm movement.

Joint	Average error	Maximum error
Joint 1	0.45	5.62
Joint 2	0.39	5.67
Joint 3	0.59	8.59

Table 3. Basic information for participants.

Participants	Age	Gender
A	27	Male
B	27	Male
C	23	Female
D	23	Female



(a) Hand close (b) Hand open

(c) Wrist flexion (d) Wrist extension

Fig. 6. Target hand motions.

Average and maximum error for three robot joints are summarized in Table 2. It is clearly observed that the average error are very small and this result means that the movement of robot arm is perfectly matched to movement of human arm by using IMU data. The maximum error is due to the time difference when the robot arm moves according to significantly changed Euler angle.

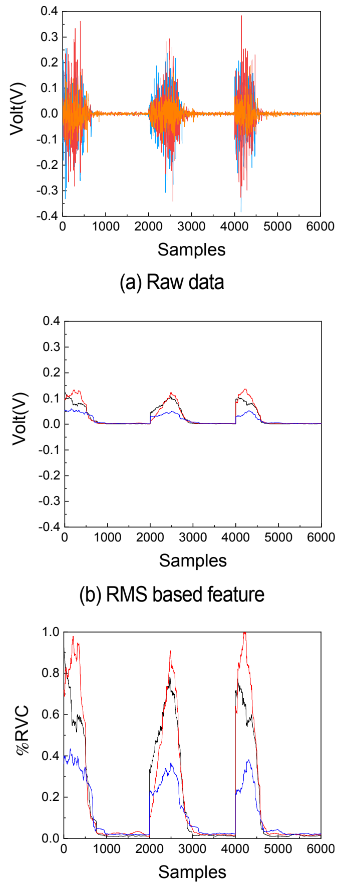
2.2 EMG data

For the control of gripper motion of slave robot, EMG data for predefined hand motions are collected by using EMG sensors. The predefined four target hand motions such as hand close, hand open, wrist flexion and wrist extension, are presented in Fig. 6. To recognize hand motions, EMG data of each hand motion are obtained for four participants in this work. The basic information for the participants is presented in Table 3. Since, the method of measuring the surface EMG has a disadvantage that it is affected by the impedance of the skin rather than using an invasive electrode, the disposable alcohol cotton is used to remove foreign substances from the skin to lower the impedance of the skin. In addition, since the characteristics of the EMG signal may be changed according to the location of the electrode, the exact location is designated so that the electrode can be attached to the same location. In this study, the most used silver electrode of 1 cm size is used. Three channels of EMG are measured from each experimental participant, and the measured EMG is in μV. In this study, a gain of 4000, a high pass filter of 20 Hz, a low pass filter of 500 Hz, and a sampling rate of 2000 Hz are applied. Participants are allowed to measure EMG with their arms relaxed in a sitting position. EMG measurement is performed in the following order: hand close, hand open, wrist flexion, and wrist extension. Each hand motion is repeated 5 sets, 10 times per set. During the repetition, the motion is performed for 1 second, paused for 5 seconds, and the metronome is used to allow the participant to recognize the proper timing. Between each set, sufficient rest time is given for more than 5 minutes to minimize errors caused by muscle fatigue. The EMG signals collected for each operation are stored in the form of a 2000 by 3 matrix using MATLAB program.

The measured raw data of EMG is shown in Fig. 7(a), and it is not easy to find the characteristics of each hand motion from this waveform. In order to apply the measured EMG to machine learning, it is necessary to extract features from raw data. In this study, the moving RMS method, which is widely used in the time domain, is applied. The moving RMS contains the amplitude information of the measured signal and is expressed by the following equation.

$$RMS(t) = \sqrt{\frac{1}{M_{RMS}} \sum_{k=0}^{M_{RMS}-1} raw^2(t-k)} \ . \tag{2}$$

Here, t is sampling index and $raw(t)$ is the raw data of the EMG signal when the t-th sample is measured. M_{RMS} represents the size of the moving window. If the size of the window is too small, the amount of data to be measured decreases and recognition accuracy decreases. In this work, the window size is 200 ms and the extracted RMS based feature is presented in Fig. 7(b). In order to reduce the real-time calculation speed of MATLAB program, the data stored in a matrix of 2000 by 3 is converted into a 1200 by 3 matrix by storing only the data up to the 1200th sample as the starting point where 30 % of the maximum value of the collected data occurs. Even though the EMG signal is measured under the same conditions, it has a characteristic that varies depending on the person, and thus it is difficult to apply the motion recognition method using EMG to several people. If the person who provided training data and the person who provided test data are different, it is impossible to accurately classify. In this study, the reference voluntary contraction (RVC) normalization technique is applied to overcome this disadvantage. The RVC normalization method has the feature that it can increase the sensitivity even at a small amplitude when a specific action is taken without requiring much force. In the proposed RVC method, after finding the maximum value in the matrix of 1200 by 3 where the rms value is calculated, and the entire matrix is divided by the maximum

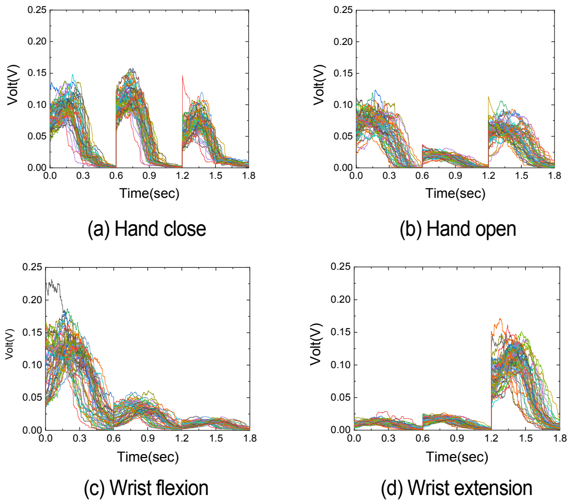


(a) Raw data

(b) RMS based feature

(c) Normalized feature

Fig. 7. Measured EMG data and extracted features.



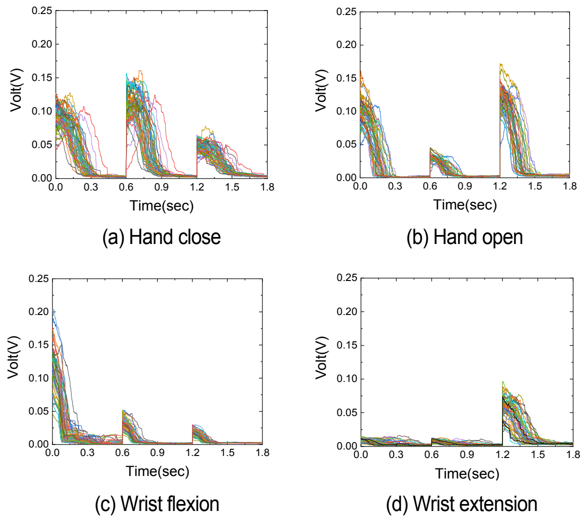
(a) Hand close (b) Hand open

(c) Wrist flexion (d) Wrist extension

Fig. 8. RMS feature vector for EMG data of participant A.

value so that the all the element in the matrix has a value between 0 and 1. The results of normalization of the RMS obtained from Fig. 7(b) is presented in Fig. 7(c).

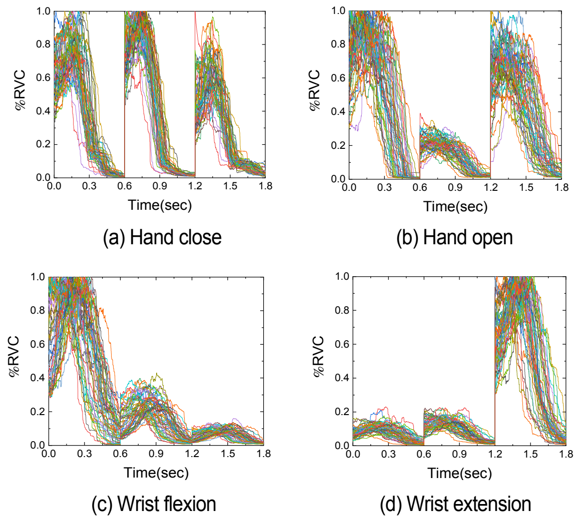
The RMS based features of 50 repeated measurements of the four hand motions of participants A and B are shown in Figs. 8 and 9, respectively. It is clearly observed that the magnitude of RMS features of participant A and B for each hand motion is much different. The normalized features of the four hand motions of participants A and B are shown in Figs. 10 and 11, respectively. Comparing Figs. 10 and 11 clearly shows that the features for each hand motion are much similar, rather than comparing Figs. 8 and 9. The RMS and normalized feature for participants C and D are provided in Appendix from Figs. A.1-A.4.



(a) Hand close (b) Hand open

(c) Wrist flexion (d) Wrist extension

Fig. 9. RMS feature vector for EMG data of participant B.



(a) Hand close (b) Hand open

(c) Wrist flexion (d) Wrist extension

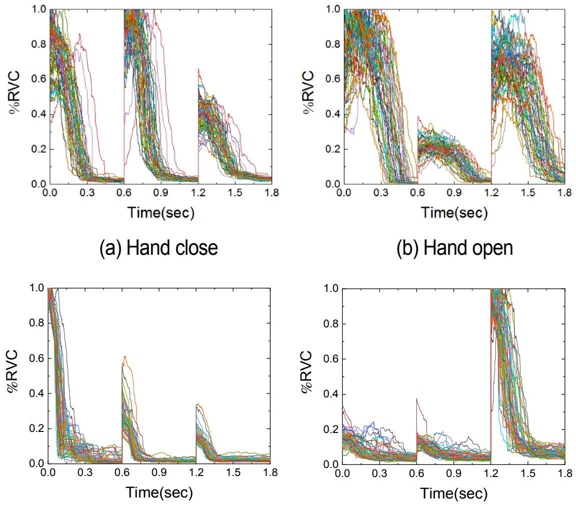
Fig. 10. Normalized feature vector for EMG data of participant A.

3. Classification

For the hand motion recognition using EMG data, artificial neural network (ANN) is applied in this work. In this study, a classifier is constructed using Neural Net Pattern Recognition Application of Deep Learning Toolbox of MATLAB program. This application configures the classifier by learning through the scaled conjugate gradient backpropagation algorithm by

Table 4. Averaged classification accuracies for participant A.

Number of hidden neurons	Accuracy with RMS features	Accuracy with normalized features
1	49.0	48.7
10	97.6	97.7
20	98.1	98.6
30	98.3	98.6
40	98.6	98.7
50	98.3	98.0
60	98.2	98.5



(a) Hand close (b) Hand open

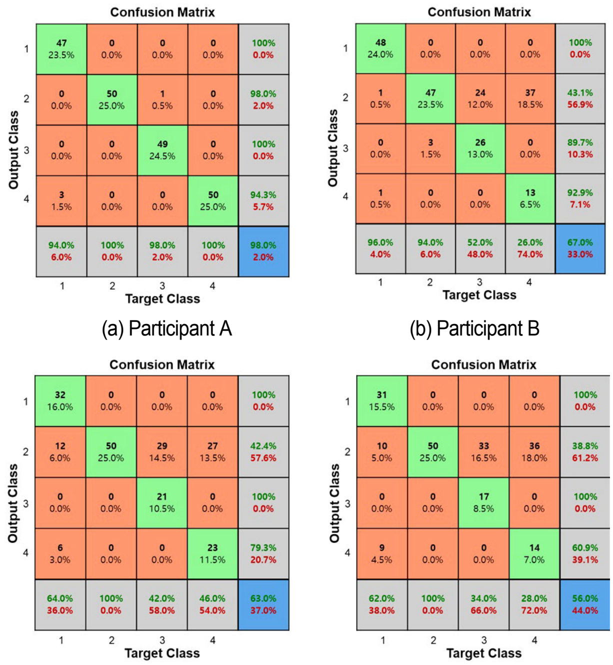
(c) Wrist flexion (d) Wrist extension

Fig. 11. Normalized feature vector for EMG data of participant B.

setting the input data matrix corresponding to the input layer neurons and the target data matrix representing the class information of the output layer and setting the number of hidden neurons. In artificial neural networks, the number of input layer neurons is the same as the number of input feature vectors, and the number of output layer neurons is the same as the number of classes to be classified. However, the number of hidden neurons can be freely set, and if insufficient or excessive, it may cause underfitting or overfitting, so a process of determining the optimal number is necessary. In this study, the method of finding the number of neurons with the highest classification rate by repeatedly adjusting the number of neurons in the hidden layer is applied. The input layer neurons of the artificial neural network used in this study are 3600 (1200 samples * 3 channels), and the output layer neurons are composed of 4 equals to the number of hand motions to be classified. The classification accuracies according to the number of hidden neurons is compared before and after normalization using 200 (4 motions * 50 data) training data and additionally measured 200 test data of the participant A. The classification accuracy is confirmed by changing the number of hidden layer neurons from 1 to 60, and the results are summarized in Table 4. The presented accuracies are the average of 10 replicate tests for each number of hidden neurons. It is confirmed that it has the highest classification accuracy when it has 40 hidden layer neurons. The similar classification accuracies before and after normalization is because the same participant's data are used for training and testing.

Table 5. Classification accuracies according to participants.

Test data provide	Accuracy with RMS features	Accuracy with normalized features
A	98.0	99.0
B	67.0	91.0
C	63.0	90.5
D	56.0	99.5
Training data: participant A, number of hidden neurons: 40		

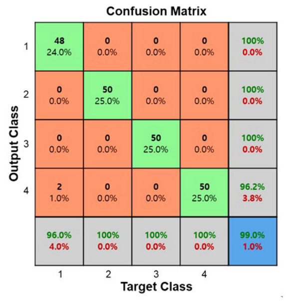


(a) Participant A (b) Participant B

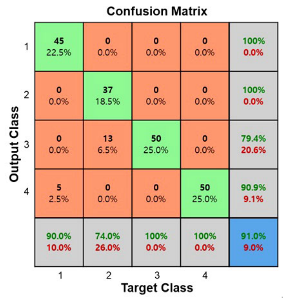
(c) Participant C (d) Participant D

Fig. 12. Confusion matrix with RMS features.

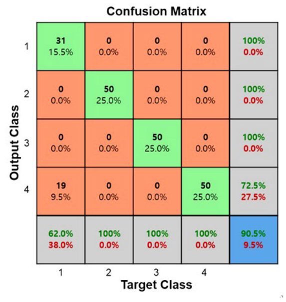
With the classifier learned using the data of participant A, the classification accuracy for the cases where the data of other participants is applied as test data without normalization are evaluated. The classification accuracy is listed in Table 5. It is clearly observed that the classification accuracy is significantly reduced compared to the case when the training data and the test data are of the same person. The confusion matrix for the classification with RMS features (without normalization) for participants A, B, C, and D are presented in Fig. 12. As shown in the confusion matrices, In the case of the hand open during the four hand gestures, it can be seen that although it does not normalize, it has relatively high classification accuracy, but the wrist flexion and wrist extension have very low classification accuracy. As mentioned earlier, the RMS-based feature without normalization is characterized by the magnitude of the



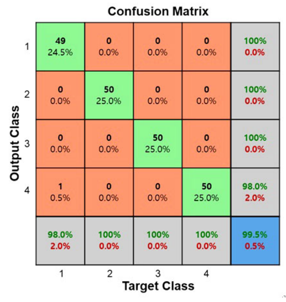
(a) Participant A



(b) Participant B



(c) Participant C



(d) Participant D

Fig. 13. Confusion matrix with normalized features.

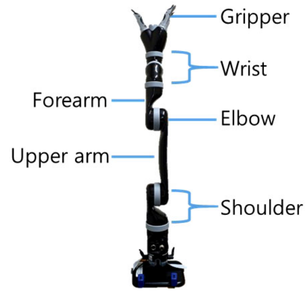


Fig. 14. Photograph of the slave robot.

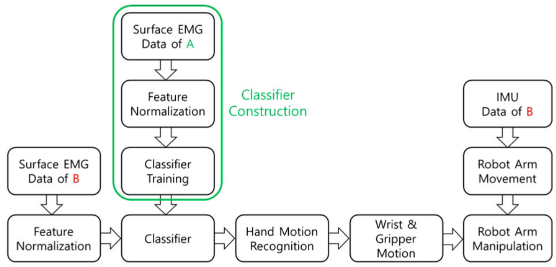


Fig. 15. Procedure of real-time tele-manipulation of robot arm.

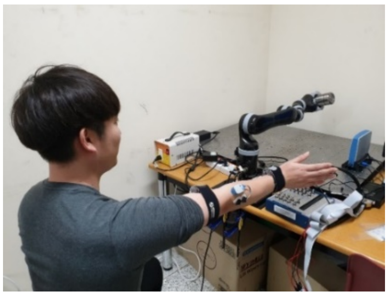


Fig. 16. Photograph of robot arm tele-manipulation.

measured EMG. Since there is a difference in the muscle mass of the participants, the shape of the feature vectors of each participant becomes different for the same motion, and the classification accuracy is decreased.

With the classifier learned using the data of participant A, the classification accuracy for the cases where the data of other participants is applied as test data after normalization are evaluated and the results are also listed in Table 5. When using the normalized test data, it can be clearly seen that the classification accuracy is significantly higher for all participants compared to the case where the normalization is not performed. It was confirmed that classification accuracy can be improved to 90 % or more by adopting normalization even when providers of training data and test data are different. The confusion matrix for the classification with normalized features for participants A, B, C, and D are presented in Fig. 13. In the case of participant B, although the classification accuracy for the hand open motion is slightly reduced, it can be seen that the wrist flexion and the wrist extension motion are classified 100 % accurately. In the case of participant C, the classification accuracy of the hand close and hand open motions is not significantly different from that before normalization, but it can be confirmed that in the case of the wrist flexion and the wrist extension motions, the classification accuracy is 100 % accurate. In the case of participant D, it can be seen that only one case is incorrectly classified in the hand close motion and all the other cases are correctly classified.

4. Experimental demonstration

To confirm the superiority of the proposed EMG based hand motion recognition technique featuring the normalization feature vector, real-time tele-manipulation of a 6-degree-of-freedom slave robot is performed. In this work, JACO2 model of KINOVA is used for slave robot and a description of the joints and links is presented in Fig. 14. The movement of robot arm is determined by forward kinematics using the 3-axis Euler angle data measured from IMU sensors mounted on the human upper arm and forearm. The motion of robot wrist and gripper is determined by using results of human hand motion recognition based on surface EMG data. The predefined hand motions are hand close, hand open, wrist flexion and wrist extension and the corresponding gripper motions are gripper close, gripper open, wrist rotation in left and wrist rotation in right, respectively. The procedure of real-time tele-manipulation is provided in Fig. 15. The IMU data of arm movement and EMG data of hand motion of is measured in real-time from operator, participant B. For the real-time hand motion recognition, artificial neural network algorithm-based classifier is constructed by using normalized EMG data of participant A. The classifier is realized by MATLAB program. The photograph of the robot arm tele-manipulation is presented in Fig. 16. The movie clips of real-time tele-manipulation of robot arm are presented in Refs. [19, 20]. Video in Ref. [19] is movie clip for tele-manipulation using RMS based features, without normalization of EMG data. It is observed that only five times of success is achieved in nine attempts as similar pattern as shown in Fig. 12(b). Video in Ref. [20] is movie clip for tele-manipulation using normalized features. It is also clearly observed that ten times of success is achieved in eleven attempts as similar as shown in Fig. 13(b). By comparing these two results, it is concluded that high classification accuracy can be achieved by applying normalization of measured EMG data when the training data and test data are obtained from different person. The effectiveness of the proposed method for real-time user independent tele-manipulation of robot arm is also clearly demonstrated.

5. Conclusions

The demonstration of a tele-manipulation of robot arm by using user independent human hand motion recognition was carried out in this work. The movement of a 6-degree-of-freedom robot arm was followed by measured human arm movement and the wrist and gripper motion of the robot was determined by recognizing human hand motions. The movement of human arm was measured by using IMUs which are attached on the upper and lower arm. The human hand motions were measured by using EMG sensors which are attached on the lower arm. For the recognition of predefined four kinds of hand motions, a classifier based on artificial neural network was constructed and utilized. To achieve user independent characteristics in hand motion recognition, normalization of RMS based feature vector had been proposed and its superiority was confirmed through experiments with four participants. By applying normalized feature vectors, it was verified that classification accuracy can be much improved to more than 90 percentage even though the training data and test data were obtained from different person. Finally, the effectiveness of the proposed method is demonstrated by performing a real-time tele-manipulation of a 6-degree-of-freedom robot arm, and it was clearly confirmed that the tele-manipulation of robot arm can be conducted successfully regardless of the user even when the EMG based motion recognition was used.

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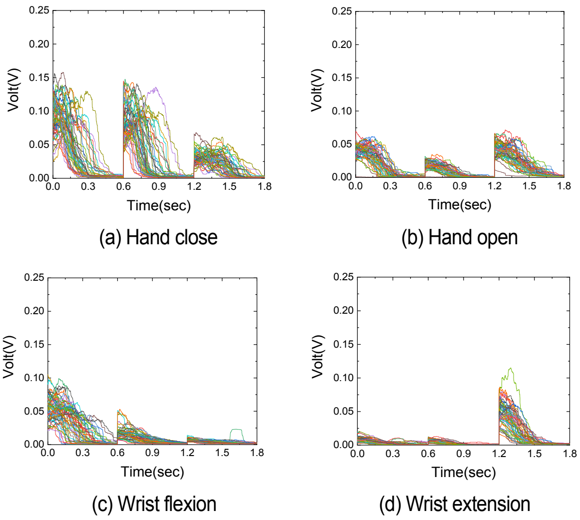
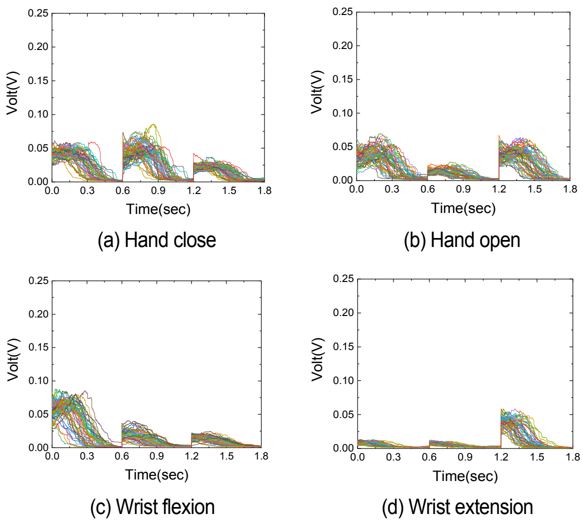
Appendix



(a) Hand close (b) Hand open

(c) Wrist flexion (d) Wrist extension

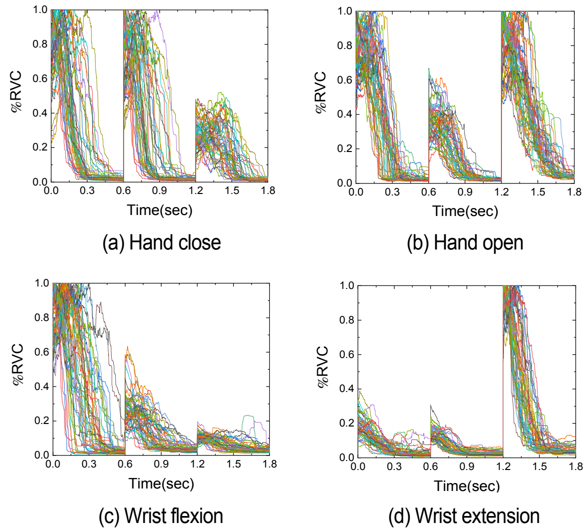
Fig. A.1. RMS feature vector for EMG data of participant C.



(a) Hand close (b) Hand open

(c) Wrist flexion (d) Wrist extension

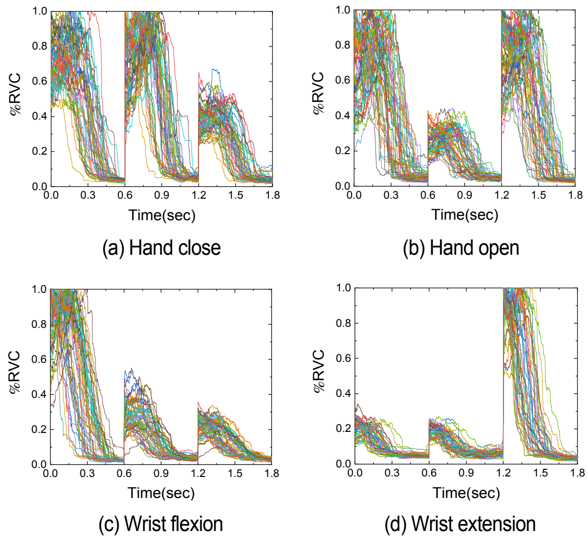
Fig. A.2. RMS feature vector for EMG data of participant D.



(a) Hand close (b) Hand open

(c) Wrist flexion (d) Wrist extension

Fig. A.3. Normalized feature vector for EMG data of participant C.



(a) Hand close (b) Hand open

(c) Wrist flexion (d) Wrist extension

Fig. A.4. Normalized feature vector for EMG data of participant D.

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