

# Implementation of Real-Time Motion and Force Capturing System for Tele-manipulation based on sEMG Signals and IMU Motion Data

MinKyu Kim, Kwanghyun Ryu, Yonghwan Oh, Sang-Rok Oh, and Keehoon Kim

**Abstract**—In this paper, we present a real-time motion and force capturing system for tele-operated robotic manipulation that combines surface-electromyogram (sEMG) pattern recognition with an inertia measurement unit(IMU) for motion calculation. The purpose of this system is to deliver the human motion and intended force to a remote robotic manipulator and to realize multi-fingered activities-of-daily-living (ADL) tasks that require motion and force commands simultaneously and instantaneously. The proposed system combines two different sensors: (i) the IMU captures arm motion, (ii) and the sEMG detects the hand motion and force. We propose an algorithm to calculate the human arm motion using IMU sensors and a pattern recognition algorithm for a multi-grasp myoelectric control method that uses sEMG signals to determine the hand postures and grasping force information. In order to validate the proposed motion and force capturing system, we used the in-house developed robotic arm, K-Arm, which has seven degrees-of-freedom (three for shoulder, one for elbow, and three for wrist), and a sixteen degrees-of-freedom robotic hand. Transmission Control Protocol Internet Protocol (TCP/IP)-based network communication was implemented for total system integration. The experimental results verified the effectiveness of the proposed method, although some open problems encountered.

## I. INTRODUCTION

For several decades, tele-operation systems have been applied for applications in hazardous or dangerous environments where humans cannot carry out tasks, such as near a radiation leak [1]. Recently, tele-robotic systems have been used in more general environments for activities-of-daily-living (ADL), that require human-robot and robot-robot interactions, e.g., imitating human motion and tracking kitchen work with humanoids [2]. A key technology to realizing tele-robotic manipulation systems for ADL is to decode human motion and force intention simultaneously and instantaneously. In addition, the decoding device should be user-friendly: it should be compact, easy to equip/un-equip, and robust for stable signal detection without complex components such as data gloves and motion capturing systems that require carefully mounted optical markers.

Previous studies have attempted using motion data from Inertia Measurement Unit (IMU) sensors [3], visual data [4], and optical markers [5], with diverse methods and algorithms

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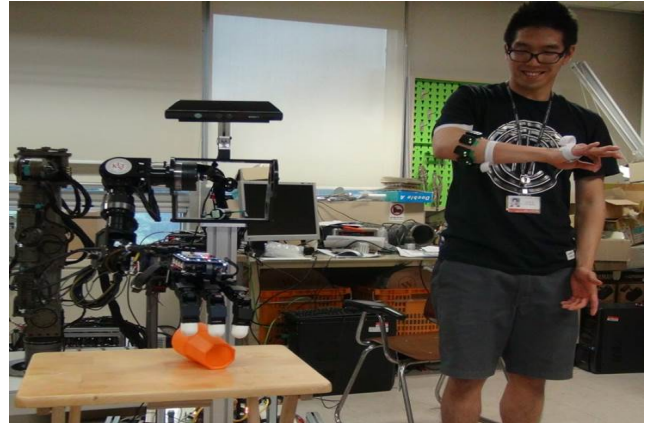


Fig. 1. The implemented tele-manipulation system using the proposed real-time motion and force capturing system

to realize human motion tracking systems. IMU-based motion capture systems are considered superior to the others [6], in terms of the ease of tele-robotic manipulation for ADL by non-expert users, but disadvantages include sensor drift and magnetic distortions. Although kinematic motions can be detected successfully, dynamic behavior such as handling objects and manipulation with physical interactions has not reached a satisfactory level because there are limitations on the force information that can be extracted from IMU sensors.

There have been numerous attempts to realize dynamic motion with robotic devices so that they can interact with real environments. An effective approach has been adopted the force information from the muscle signals of a user based on surface-electromyogram (sEMG) signals, which are widely utilized as a control input for human-robot and human-computer interfaces such as prosthetic hands [7-10], exoskeletons, rehabilitation applications, and tele-operation systems [11]. A prominent advantage of sEMG signals is that the motion intention can be detected prior to actual movements. Thus, they can be used to develop an efficient interface for tele-operating systems that solves time-delay problems.

Another distinctive characteristic of sEMG signals is that they allow human force information to be decoded during a motion. An sEMG pattern recognition system can be applied to determine the hand grasping posture and force for tasks such as grasping an object. Providing simultaneous and proportional control signals for a multifunction prosthesis is one of the most challenging issues for myoelectric control [12],

since sEMG is basically a time-varying signals that depends on physical condition of the users. To address this issue, the velocity command of sEMG signals has been utilized to estimate the grasping force [13-16], but this mapping is not natural and makes the grip force more difficult to control.

In this paper, we report on our efforts to design a real-time motion and force capturing system that combines the advantages of sEMG signals and IMU motion data. The human arm motion is fully tracked by a wearable IMU and sEMG-integrated capturing interface. The arm motion of a robot at a remote site with seven degrees-of-freedom (DOF) - at the shoulder, elbow, and wrist joints - is operated by human motion commands through IMU sensors. Hand commands are calculated from a pattern recognition system using the sEMG signals from the forearm of the human user. Two motions (power and pinch grasp) are implemented and each motion has a strong or weak force level. The properties of sEMG signals in the transient state, are used to immediately determine the motion, while the force level of the grasping motions is calculated from the steady-state signal pattern. To verify our system, we tried grasping numerous objects with a robotic manipulator.

This paper is organized as follows. Section II describes the implemented tele-manipulation systems consisting of IMU sensors and sEMG systems for the motion and force capturing system. Section III presents the detailed algorithms of each subsystem and the overall framework are presented. In Section IV, the proposed methodology is validated through experiments. This is followed by conclusion and discussion of open problems encountered while performing experiments as future works in Section V.

## II. SYSTEM DESCRIPTION

This section describes the implemented tele-manipulation systems, which consists of IMU sensors and sEMG systems for the motion and force capturing system, and the K-Arm robotic manipulator with the Allegro hand at a remote site (Fig. 2).

### A. IMU sensors

With recent developments in motion tracking systems, tiny and wearable IMU sensors are being widely applied to obtain rotation information of the human body. In this study, four IMU sensors (EBIMU24G, E2BOX Co.) were attached to the human torso, upper arm, forearm, and hand to obtain the joint angles of the shoulder, elbow, and wrist. The maximum sampling rate is 100 Hz; each sensor used wireless radio frequency (RF) communication to provide rotation information in the form of Euler angles or quaternions. For sensor attachment, the locations are not specified but arbitrarily determined by the user. In the calibration process (see Section III-A), the relative transformation from the body frame link and the sensor frame is obtained and the joint angles of the human arm are estimated for the desired joint angles of the K-Arm manipulator.

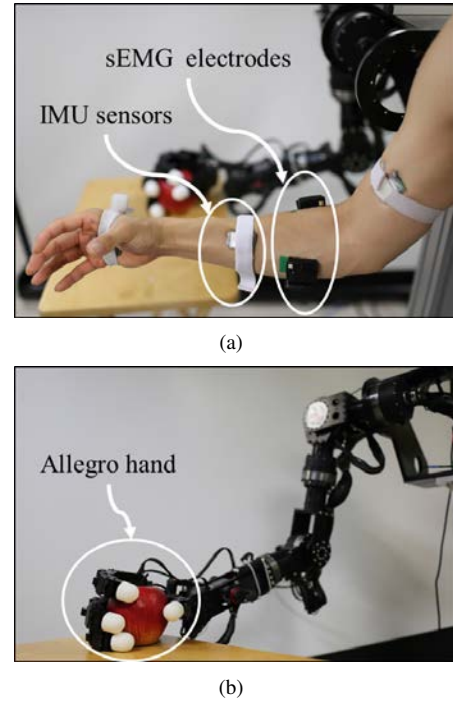


Fig. 2. Human arm and the K-Arm manipulator (a) the location of IMU sensors and sEMG systems attached to human arm. (b) grasping an apple with K-Arm and Allegro hand;

### B. sEMG system

sEMG signals were recorded using surface electrodes (Trigno wireless, Delsys Inc.). Four electrodes were used for sEMG signal acquisition, as shown in Fig. 2.(a). The electrodes were arbitrarily attached to the forearm. In training session (see Section III-B), the proposed classifier learned the features. The sEMG signals were acquired at a 1 kHz sampling rate using wireless communication protocols.

The electrode signals were transferred to the mainboard of the sEMG system and A/D data acquisition board (S526, Sensoray Co.) on a PC-104 (Neptune SBC, Diamond System Co.) sequentially. The signal processing and pattern recognition were operated by a MATLAB simulink Xpc real-time operating system (Mathworks Co.).

### C. K-Arm Robotic Manipulator with Allegro Hand

TABLE I  
DH PARAMETERS OF K-ARM

Link	$\alpha_i(\text{rad})$	$a_i(\text{m})$	$d_i(\text{m})$	$\theta_i(\text{rad})$
1	$\pi/2$	0	0.12	$q_1 + \pi/2$
2	$\pi/2$	0	0	$q_2 - \pi/2$
3	$-\pi/2$	0	0.3	$q_3 + \pi/2$
4	$\pi/2$	0	0	$q_4$
5	$-\pi/2$	0	0.3	$q_5$
6	$-\pi/2$	0	0	$q_6 - \pi/2$
7	0	0.155	0	$q_7$

K-Arm is a robotic manipulator with seven degrees-of-freedom (three for shoulder, one for elbow, and three for

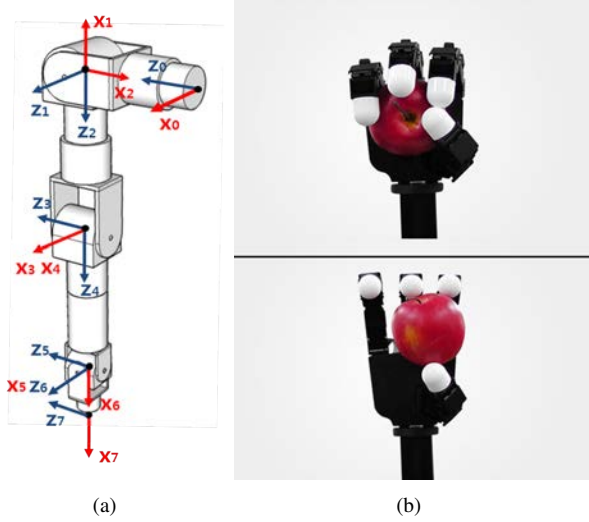


Fig. 3. K-Arm manipulator with Allegro hand: (a) Kinematic structure of K-Arm manipulator; (b) Grasping motions of Allegro hand

wrist) and Allegro Hand is a robotic hand with 16 degrees-of-freedom (Fig. 3.(b)). Fig. 3.(a) and TABLE I describe the kinematic structure and DH parameters, respectively, of K-Arm. The payload of the robot arm is approximately 50 N. The total length and weight are 0.72m and 15kg, respectively.

Allegro Hand (SimLab Co.) is a four-fingered torque-controlled robotic hand (four DOF in each finger for 16 DOF total). Diverse grasping postures are available according to the object shape with a maximum payload of 50 N maximum payload. It was equipped at the wrist joint of K-Arm.

The K-Arm and Allegro Hand controller works in a real-time operating system with a sampling rate of 1 kHz. In order to maintain a 1 kHz sampling rate for the combined K-Arm with Allegro Hand, an EtherCAT communication protocol between the control PC and real robot was implemented.

### III. MOTION AND FORCE CAPTURING ALGORITHM

This section describes the algorithms for the proposed motion and force capturing system. Section III-A describes the calibration process to calculate the human arm motion from IMU sensors on the upper limb. Section III-B proposes a fast sEMG pattern recognition technique to decode the human hand configuration and force and can be generalized to decode a number of features if there are enough electrodes. Section III-C describes the controller for K-Arm and Section III-D presents the overall control framework.

#### A. IMU Sensor Calibration

As discussed above, we envisioned a motion capturing system that can be used by non-expert users. Thus, the locations of the IMU sensors are not specified but arbitrarily mounted by users. The calibration process should calculate the relative transformation from body frame link and sensor frame. Calibration process need three poses to know the predefined angles.

We need the rotation sensor information of three postures at the predefined angles for each joint. Hence, To facilitate

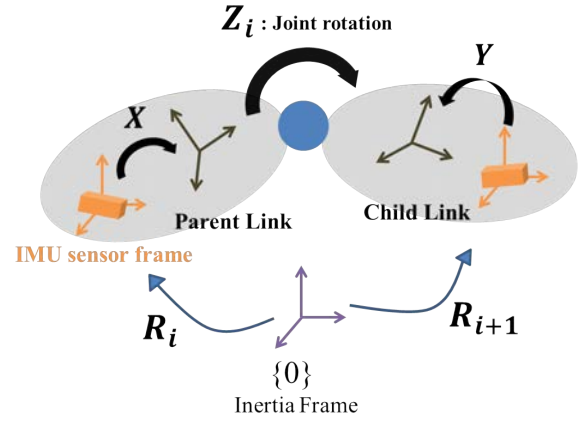


Fig. 4. Coordinate systems for IMU sensor calibration: inertia frame, IMU sensor frames, parent and child link frames.

#### Algorithm 1 IMU Sensor Calibration for $i$ th joint

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1: function CALIBRATION(  $Z_i^j, R_i^j, R_{i+1}^j$  )
2:   (where  $i$  = number of links ,  $j$  = number of posture)
3:   for  $j = 1 : 3$  do
4:      $R_i^j X Z_i^j = R_{i+1}^j Y$ 
5:   end for
6:    $A^k X = X B^k$  , (where  $k = 1, 2$ )    ▷ Eliminate  $Y$ 
7:   where  $A$  and  $B$  are,
8:    $A^k = [R_i^{j+1}]^{-1} R_{i+1}^{j+1} [R_{i+1}^j]^{-1} R_i^j$ 
9:    $B^k = Z^{j+1} [Z^j]^{-1}$ 
10:  For least squares solution, [17]
11:   $\tilde{A} = [\log A^1 \quad \log A^2 \quad \log A^1 \times \log A^2]$ 
12:   $\tilde{B} = [\log B^1 \quad \log B^2 \quad \log B^1 \times \log B^2]$ 
13:   $X = \tilde{A} [\tilde{B}]^{-1}$ 
14:   $Y = [R_{i+1}^j]^{-1} R_i^j X Z^j$ 
15:  return  $X, Y$ 
16:  ▷ Rotation from the sensor to the parent & child link
17: end function

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implementation, the shoulder and elbow joints are calibrated together, and the wrist joint is then independently calibrated. In Fig. 4,  $Z_i$  is the rotation matrix that originates from the rotation of the predefined angle along the predefined axis, and  $R_i$  and  $R_{i+1}$  are the sensor frame rotations of the parent and child links, respectively, at known postures. These parameters can be calculated from three predefined postures for the calibration. The goal of the calibration process is to determine the relative rotation from the sensors to the link frame:  $X$  and  $Y$ . The calibration process is as follows: (i) save the sensor data of the predefined angles in three postures for the  $i$ th joint. (ii) solve the equation to obtain the relative orientation from the IMU sensor frame to the parent and child links [17][18].

The results of the calibration process, are used to obtain the transformation matrix from the IMU sensor frame to the parent and child link frames. With this information, we can calculate the relative rotation matrix from the parent

link frame to child link frame. With an inverse EulerZYX function, we can acquire all joint angles of the model.

### B. Pattern Recognition using sEMG signals

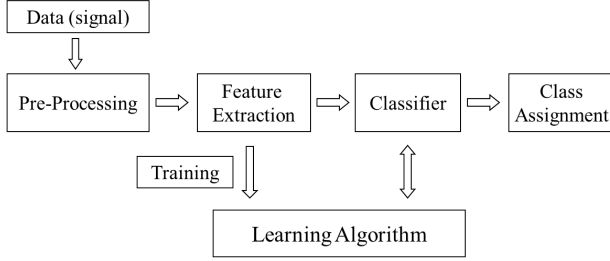


Fig. 5. Process for sEMG pattern recognition

The general pattern recognition system using sEMG signals consists of three main processes as shown in Fig. 5: (i) preprocessing, (ii) feature extraction, and (iii) classification (classifier, learning algorithm, class assignment). In the training session, the features of the data are learned by the classifier with the learning algorithm. After the training process, the classifier determines the class of motion for new data through learning algorithms based on the feature data.

1) *Preprocessing and Feature Extraction* : The signal has to be pre-processed before meaningful feature are extracted. The proposed pre-processing includes a band pass filter range of 15 to 500 Hz and a squared function to ensure non-negative properties before extracting time domain feature. The mean absolute value (MAV) is one of the most popular time domain features and was adopted as a feature.

$$MAV = \frac{1}{N} \sum_{i=1}^N |x_i| \quad (1)$$

2) *Training session*: Two types of grasp postures are used: power grasp and pinch grasp. In the training session, a randomly selected motion is displayed on screen with cue signs. The user then begins to follow that motion. Each signal is recorded for 3s, and the rest session is also 3s. The motion is repeated three times to obtain distinctive features.

3) *Classification*: For classification, an extreme learning machine (ELM) with a voting classifier was introduced. The hidden parameters can be independently determined from the training data, and the output parameters can be determined by pseudo-inverse method using the training data. ELM learns extremely quickly compared to other learning algorithms [19][20]. The force level of each motion is classified into two states, strong and weak. The Force level is determined by how long the user maintains the motions. If the maximum value of the classified signals exceeds predefined threshold level, the force level for grasping was increased. Thus, four hand commands (power grasp - strong/weak, pinch grasp - strong/weak) were classified in the proposed pattern recognition system. It will be explained in section V-B in more detail.

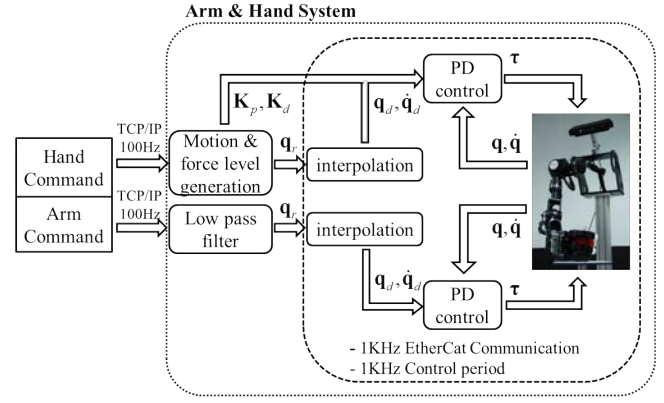


Fig. 6. Block diagram of control scheme for K-Arm with Allegro hand

### C. K-Arm Controller

Fig. 6 shows the control scheme for K-Arm with Allegro Hand. Since command signals calculated from IMU sensors for the 7 DOF joint angles contain high-frequency noise, low-pass filtered data are used as the command signals for K-Arm and Allegro Hand. The command signals are interpolated since the control frequency of K-Arm is 10 times faster than the 100 Hz command signal. The command signals for hand motion and force from the sEMG system execute the predefined hand motions of power grasp and pinch grasp while adjusting the grasping force level. The controller is based on the Proportional-derivative (PD) control with gravity and friction compensation in a joint space.

$$\tau = K_p \Delta q + K_d \dot{\Delta q} + g(q) + f(\dot{q}) \quad (2)$$

where  $\tau$  is the control torque,  $K_p$  and  $K_d$  are PD control gains,  $\Delta q$  is the control error,  $g(q)$  and  $f(\dot{q})$  are feedforward control inputs to compensate for gravity and friction, respectively.

### D. Overall Control Framework

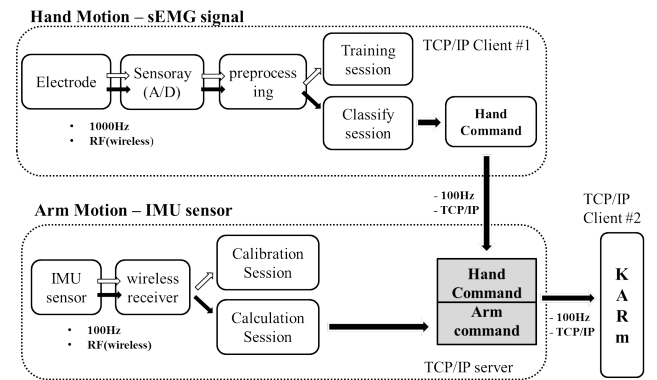


Fig. 7. The whole framework of the integrated system

Fig. 7 shows the overall control framework for the proposed system. The IMU-based arm tracking control framework for K-Arm is implemented in C++ language with



the RTX (venturecom) real time operating system and the sEMG pattern recognition framework is implemented using the MATLAB XPC real-time operating system. We selected TCP/IP protocol as the network protocol to integrate subsystems into a single unified system. All subsystems are connected through the TCP/IP network in the overall framework.

The maximum sampling rate for the IMU sensor is 100 Hz and the sampling rate for the sEMG signal is 1 kHz. Thus, the overall system implements 100 Hz sampling rate.

#### IV. EXPERIMENTAL RESULTS

In this section, we discuss the experimental results for verifying the proposed system in terms of arm motion tracking (Section IV-A) and hand motion and force tracking (Section IV-B).

##### A. Arm tracking

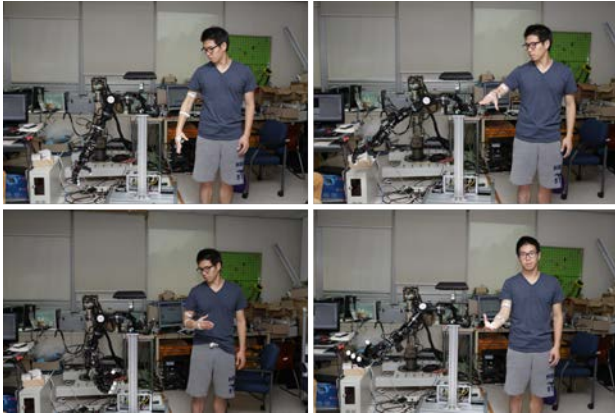


Fig. 8. The human arm motion tracking with K-Arm

Fig. 8 shows that K-Arm with Allegro Hand followed the desired human command using the proposed real-time motion and force capturing system.

Fig. 9 shows the 7-DOF human arm motion data from the IMU sensors and the actual joint angles of K-Arm. K-Arm successfully tracked the human motion. Since the cutoff frequency of low-pass filter was 10 Hz, and the desired joint angles were reproduced through linear interpolation because the sampling frequency of IMU (100 Hz) was slower than the control frequency of the K-Arm (1 kHz), there was a time delay of approximately 100 milliseconds between human motion and actual joint. angles (Fig. 10).

##### B. Hand Motion and Force tracking

Fig. 11 shows the filtered sEMG signals from four electrodes on a forearm for power and pinch grasping. The signal patterns collected in the training session and these MAV features were tested to check if the two motions were significantly different. As shown in Fig. 12, the MAV patterns for the two motions showed low variations in the transient and steady-state periods. After the proposed ELM process, the two motions were classified very well for some of the subjects. This is not surprising since only two motions

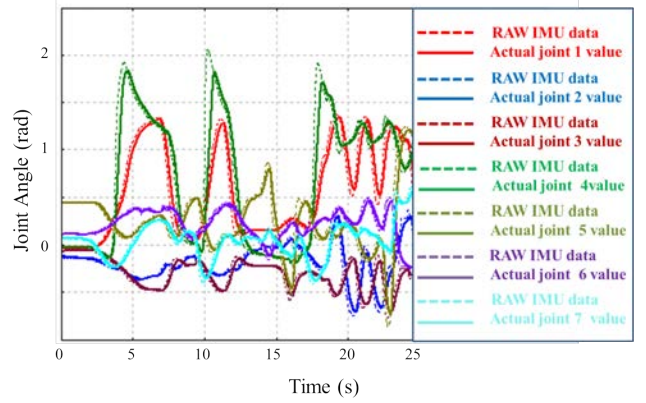


Fig. 9. Raw IMU sensor data and actual joint values of all joints.

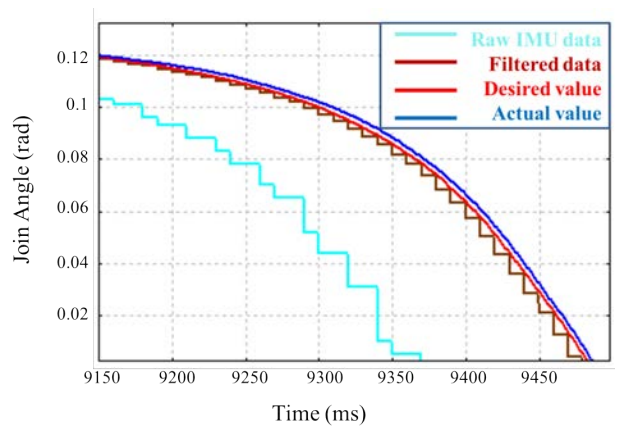


Fig. 10. Raw IMU data, filtered IMU data with the desired and actual value of 7th joint angle

were tested to simplify the experimental protocols and the signals were very distinctive and well-posed. However, in the experiments, the magnitude of signal tended to decrease gradually, thus, it was hard to maintain a constant grasping force when performing tasks over long periods. There seemed to be a fatigue problem in the muscles. Muscle artifacts were produced depending on the arm configuration, and there was a mental burden on the users to keep muscles contracted without feedback on the grasping force. These problems are discussed in detail in Section V.

Thus, we introduced visual feedback with a graphical user interface(GUI) where users can simultaneously see the current equalizer of the sEMG signals and the force level bar during the experiment, as shown in Fig. 13. The red line in Fig. 13 indicates the threshold of duration to the next force level. If the force bar exceeds the threshold, the controller gain of the robotic hand increases. The measured force level is reset when a rest signal arrives consecutively or the classified motion changes. Fig. 14 shows that the joint torques of the robotic hand were controlled by diverse force commands from the user with negligible errors.

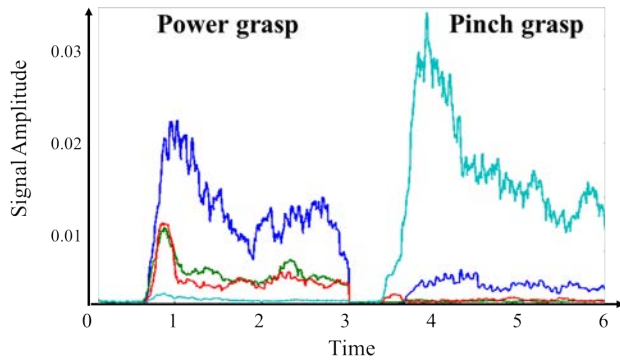


Fig. 11. Filtered sEMG signal for two motions : Power and Pinch grasp

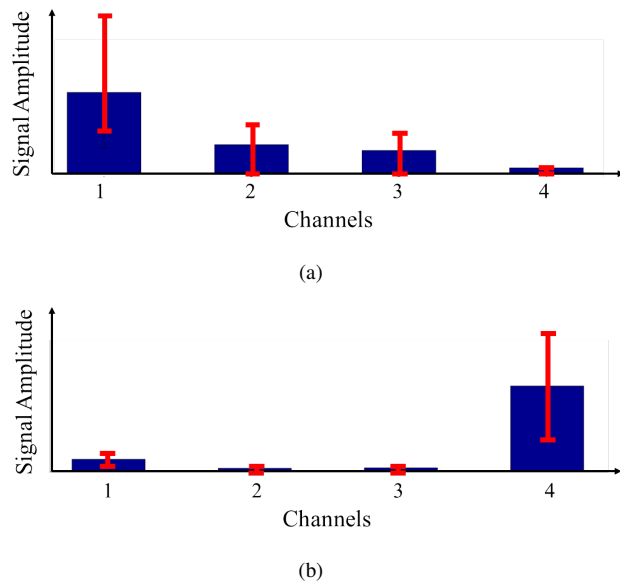


Fig. 12. MAV of two motions : (a) power grasp (b) pinch grasp

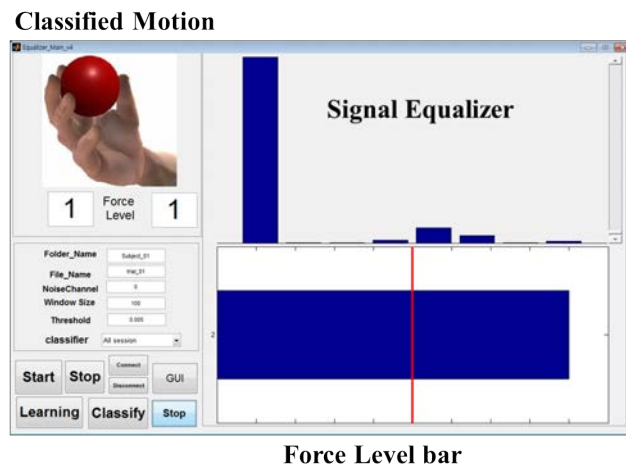


Fig. 13. Matlab GUI(Graphic User Interface) that provides visual feedback for current signals and force level

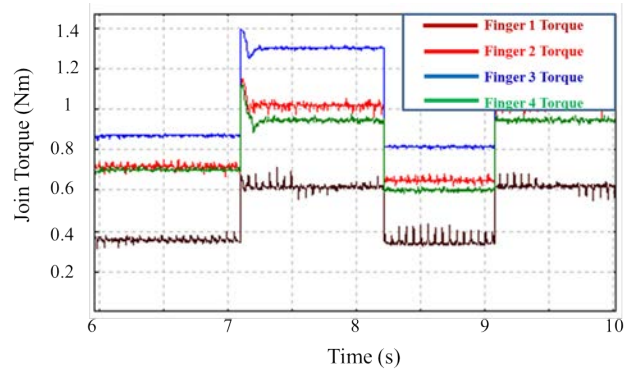


Fig. 14. The total sum of joint torques of each finger according to the command

## V. CONCLUDING REMARKS

We proposed a real-time motion and force capturing system for tele-operated robotic manipulation that combines sEMG pattern recognition with motion calculation using a IMU. A 7-DOF arm manipulator with a 16-DOF hand was successfully synchronized with the motion and force of human arm and hand motion and force. We confirmed that the sEMG signal can be adopted as an input signal to detect the human grasping motion and force in an arm motion capturing system combined with an IMU.

However, we encountered critical problems that were not anticipated before the system implementation. First, muscle artifacts occurred depending on the arm configuration. The forearm muscles contract to generate an anti-gravity torque, so the sEMG signal patterns can change even when the hand motion and grasping force are the same. In our experiment, users could handle the muscle contraction to maintain the same sEMG patterns recorded in the training session through visual feedback using a GUI as shown in Figure 13. However, in long term tasks, unconscious muscle contraction were generated. For the future work, the muscle artifacts produced by arm configuration and tasks should be considered.

Second, there were mental and physical fatigue problems. As discussed in Section IV-B, the magnitude of the sEMG signals diminished as the grasping motion and force were maintained. Also, users frequently dropped the object since it was a mental burden to concentrate on controlling the grasping force through visual feedback. In order to solve this problem, we concluded that haptic feedback is necessary for users to confirm if the robotic hand is holding an object with appropriate grasping force according to the surface conditions and weight of the objects.

Third, the control frequency of the overall system should be enhanced to offer more realistic tele-manipulation. The current system has a time delay of about 100ms, when performing grasping tasks. The system needs to operated at a much higher control frequency to perform grasping or manipulation tasks, while time delay of 100 - 200 ms is known to be acceptable for tasks using visual or kinesthetic feedback.

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