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# Muscle Modeling between Upper Arm and Lower Arm for Wearable Haptic Sleeve for Force Feedback of Virtual Reality

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**Abstract:**

In the realm of virtual environments, hand haptic technology plays a crucial role in capturing the nuanced movements of a user's hands and fingers. This is complemented by a haptic sleeve that bridges the gap between the arm and hand, effectively translating these movements into corresponding actions performed by a robot avatar within the virtual space. Furthermore, these innovative devices are adept at relaying the force and texture felt by the robot avatar as it interacts with objects in the virtual environment back to the user. This interaction crafts an immersive experience, mirroring the sensation of physically touching and manipulating the objects. The prediction of wearer's joint torques uses the Hill-type model and is made through the flexion movement of the elbow joint.

As the user engages in object manipulation through the robot avatar, the haptic feedback disseminates throughout the entire arm, enriching the user experience with a wide spectrum of tactile sensations. This advancement in haptic technology significantly enhances the realism of robot operation, thereby improving the dynamics of human-robot interaction.

**Keywords:** hand haptic; haptic sleeve; hill type model; human-robot interface (hri); intent signal

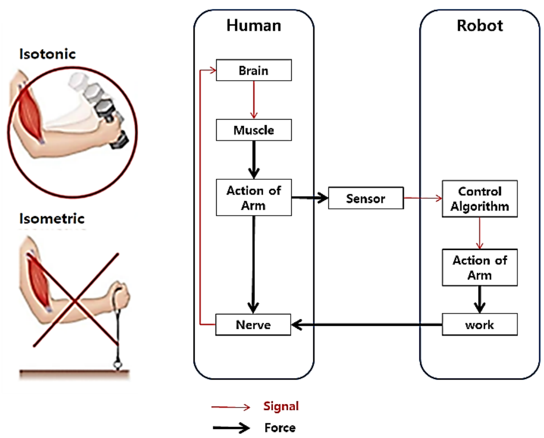
## Introduction

Hand haptic systems and haptic sleeves enable remote robot operations by providing realistic physical sensations to the wearer across various environments. In these setups, a robot avatar in a virtual environment controls the posture, situational awareness, and motion signals of the robot's artificial intelligence component. These devices primarily receive motion signals from the wearer and amplify the workforce through the robot avatar in the virtual environment, serving this specific purpose. [1] They typically have an exoskeleton form that mimics human joints and deliver haptic feedback through methods such as vibration, pressure, and movement. This allows users to feel as if they are touching or manipulating objects in the virtual environment using a device worn on their arm. [2-6]

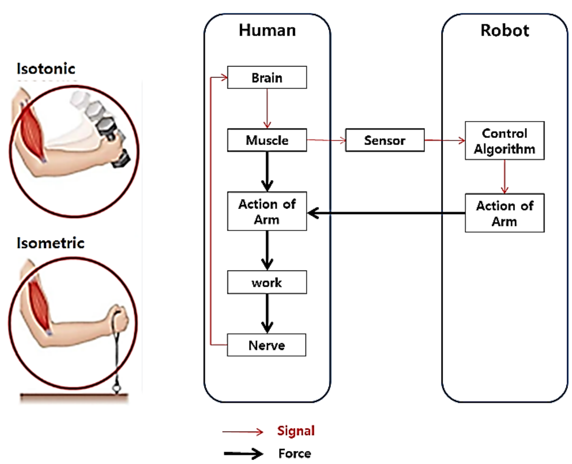
Human movements through haptic devices can be categorized into isotonic movements, where muscles change length and joints move as muscles are activated, and isometric movements, where muscles are activated but joints do not move. [8,9] Figure 1 illustrates the process of human and robot movements based on the type of sensors used. Figure 1 (a) depicts the use of force signals as motion signals, utilizing Force/Torque sensors to measure force signals. These sensors gauge the relative force between the wearer and the robot caused by the wearer's upper limb movements. While Force/Torque sensors can detect the wearer's intention of isotonic movements, they cannot capture the intention of isometric movements. Consequently, during the wearer's isometric movements, the haptic device cannot directly assist in robot operations, and operations are instead performed using the gripper at the robot's end-effector. However, wearable haptic devices allow wearers to immediately receive feedback on position, speed, and force generated during robot operation, facilitating task execution with minimal force using the robot's strength in various working environments.

Systems that utilize force signals as command signals offer advantages such as easier signal measurement and the ability to measure reliable signals compared to systems that use bio-signals. However, these systems often have drawbacks such as being fixed in place, limiting user mobility, or being costly due to extensive use of expensive sensors and electronic equipment. Figure 1 (b) describes systems that utilize bio-signals as input, primarily employing tactile sensors for signal measurement. Tactile sensors can capture signals for both isotonic and isometric movements, allowing for the acquisition of movement intentions for all movements of the human arm. Consequently, the robot can directly transmit power during isotonic movements by the haptic wearer, enabling tasks to be performed with the human hand and amplifying the wearer's muscular strength to perform movements. However, bio-signals are measured differently based on the sensor's attachment location and the worker's muscle activity, leading to individual differences among people. [5,8] To address these disadvantages, researchers have used bio-signals measured by EMG (electromyogram) normalized as inputs to a muscle model using the Hill-type model to predict human joint torques. To mitigate uncertainty caused by individual differences, they optimized muscle modeling parameters.

This research aims to generate intention signals for wearable robots based on bio-signals, with the initial step being the prediction of wearer's joint torques using the Hill-type model. Consequently, this paper models the Biceps brachii, the primary muscle involved in the Flexion movement of the elbow joint, and conducts simulations to verify this model.




(a) Use of force signals




(b) Use of bio-signals

**Figure 1** Conceptual organization of HRI technologies

## Materials and Methods

The Hill-type model uses the current length and speed of the muscle as inputs. Typically, motion capture equipment is used to measure the position and speed of human joints, and related software is used to obtain information such as the length, speed, and moment arm of the muscles. However, wearable robots are not suitable for using such equipment. [9] Therefore, a kinematic approach is needed to simplify human joints to determine the muscle length and speed. Figure 2 schematically simplifies the human elbow joint and the Biceps brachii. Since wearable robots are attached to the person, the wearer's joint angles can be known from the robot's encoders.

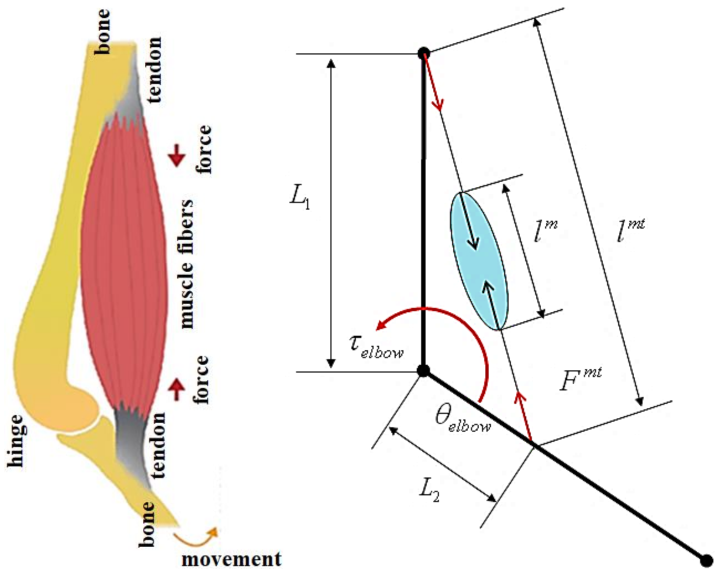
In Figure 2, the muscle-tendon length ($l^{mt}$) can be calculated through the kinematic model as shown in Equation (1), where the length of the upper limb ($L_1$) and the attachment position of the biceps brachii ($L_2$) are used based on human baseline data. [10]

$$l^{mt} = {L_1}^2 + {L_2}^2 - 2L_1L_2\cos\theta \quad (1)$$

From the calculated $l^{mt}$, the length of the muscle ($l^m$ ) can be calculated as shown in Equation (2). [12]

$$l^m = \sqrt{(l_o^m \sin\emptyset_o)^2 + \left(l^{mt} - l^t\right)^2} \quad (2)$$

where, $l^t$ is the length of the tendon, $\phi_o$ is the pennation angle at maximum muscle force, and $l_o^m$ is the muscle length at maximum force generation (optimal fiber length). This paper assumes that the tendon does not undergo deformation and uses human baseline data. [10, 11]




(a) Arm musculoskeletal model (b) Simplified arm kinematic model

**Figure 2.** Schematic arm model

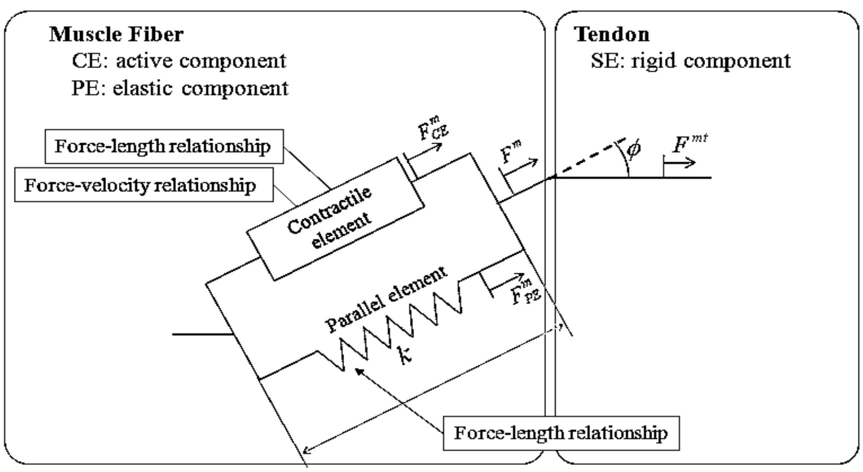



**Figure 3.** Simplified muscle-tendon modeling

| Muscle | PCSA ($cm^2$) | Peak force (N) | Optimal fiber length (cm) | Tendon slack length (cm) | Pennation (degree) | Moment arm average (cm) |
|---|---|---|---|---|---|---|
| **Triceps** | | | | | | |
| Long | 5.7 | 795.5 | 13.4 | 14.3 | 12 | -2.1 |
| Lateral | 4.5 | 624.3 | 11.4 | 9.8 | 9 | -2.1 |
| Medial | 4.5 | 624.3 | 11.4 | 9.1 | 9 | -2.1 |
| Anconeus | 2.5 | 350.0 | 2.7 | 1.8 | 0 | -1.2 |
| Supinator | 3.4 | 476.0 | 3.3 | 2.8 | 0 | -0.7 |
| **Biceps** | | | | | | |
| Long | 4.5 | 624.3 | 11.6 | 27.2 | 0 | 3.6 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Short | 3.1 | 435.6 | 13.2 | 19.2 | 0 | 3.6 |
| Brachialis | 7.1 | 987.3 | 8.6 | 5.4 | 0 | 1.8 |
| Brachioradialis | 1.9 | 261.3 | 17.3 | 13.3 | 0 | 5.7 |

**Table 1.** Muscle modeling parameters for elbow joint movement (sampling data measured)

Human muscles, as briefly mentioned in the previous section, are composed of muscles and tendons. Hill modeled these into three components: CE (contractile element), PE (parallel element), and SE (serial element). Here, the CE corresponds to an actuator that generates force according to human intention as active muscle force, and the muscle's force can be expressed through its relationship with force-length and force-velocity. The PE is a component that generates passive muscle force, and as the muscle is stretched, it can be modeled as an elastic object. Lastly, the SE, which models the tendon, can be modeled as a visco-elastic or elastic object [18], and is typically modeled as a nonlinear spring. However, tendons do not generate force but rather transmit the force generated by muscles. Additionally, at maximum muscle force generation, the tendon's strain is about 3% [12], meaning that for a tendon length of 200mm, a slight deformation of about 60mm occurs. Therefore, this paper models the muscle using only the CE and PE elements, excluding the SE element. Figure 3 schematically represents this. The force generated from the muscle-tendon ($F^{mt}$) can be expressed as in Equation (3), assuming the tendon as a rigid body.

$$F^{mt} = F^{m} cos\emptyset \tag{3}$$

where, $F^{m}$ represents the force generated in the muscle, as shown in Equation (4).

$$F^{m} = F^{m}_{CE} + F^{m}_{PE} \tag{4}$$

The active muscle force ($F^{m}_{CE}$) generated in the muscle by the CE (contractile element) is as follows.

$$F^{m}_{CE} = f(v)g(l)a(t)F^{m}_{o} \tag{5}$$

where, $a(t)$ represents the normalized muscle activation signal, $f(v)$ is the force-velocity relationship, and $g(l)$ is the force-length relationship, each defined as follows.

$$g(l) = -6.25\left(\tilde{l}^{m}\right)^{2} + 12.5\left(\tilde{l}^{m}\right) - 5.25\ ,\ \tilde{l}^{m} = {l^{m}}/{l^{m}_{o}} \tag{6}$$

$$f(v) = \frac{F^{m}_{o} b - a v_{m}}{b + v_{m}} \tag{7}$$

$v_{m}$ represents the velocity of muscle movement, where a positive value indicates a reduction in muscle length. $a$, $b$, $F^{m}_{o}$ are factors that determine the characteristics of $g(l)$, which are decided and used as follows.

$$a \cong 2.5\ F^{m}_{o},\ b = \frac{a}{F^{m}_{o}} v^{m}_{o} \tag{8}$$

$v^{m}_{o}$ represents the maximum contraction velocity of the muscle, and this value is commonly approximated and usable as $10\ {l^{m}_{o}}/{t}$.

Additionally, the passive muscle force $F^{mt}_{PE}$ generated by the PE (parallel element) acts like a nonlinear spring when the muscle is stretched, and can be expressed using an exponential function as the equation below.

$$F^{m}_{PE} = \frac{e^{10(\tilde{l}^{m}-1)}}{e^{5}} \tag{9}$$

As previously explained, $F^{mt}$ can be calculated using Equations (5) and (9), and when assuming the tendon to be a rigid body, the force $F^{mt}$ transmitted from the muscle to the bone was calculated using Equation (3). Using this, the joint torque can be calculated as shown in Equation (10).

$$\tau_{elbow} = F^{mt} \cdot b \tag{10}$$

where, $b$ represents the moment arm of the joint.

The joints of the human upper and lower arms are not perfect rotary joints, and therefore the moment arm is not linear with respect to the joint angle. If the human joints were perfect rotary joints, no joint torque would be generated when the elbow joint angle is 0 degrees, even if the muscles are activated. Figure 5 shows the change in the length of the moment arm according to the elbow angle.

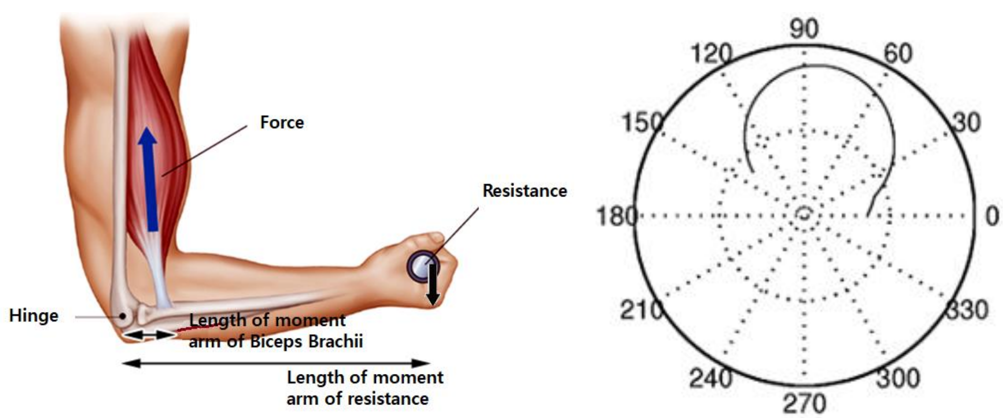


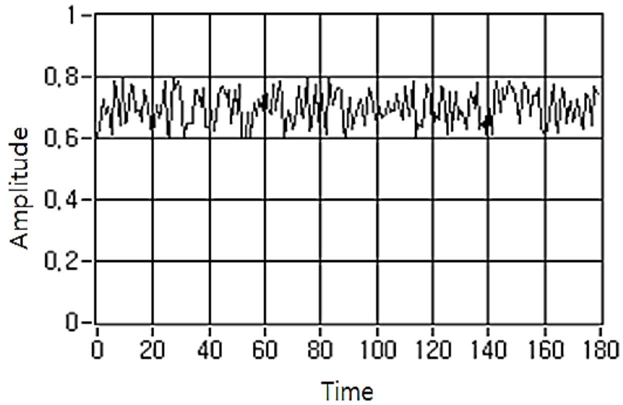

**Figure 4.** Length of the Moment Arm(cm) on the elbow operation angle(degree)

## Results

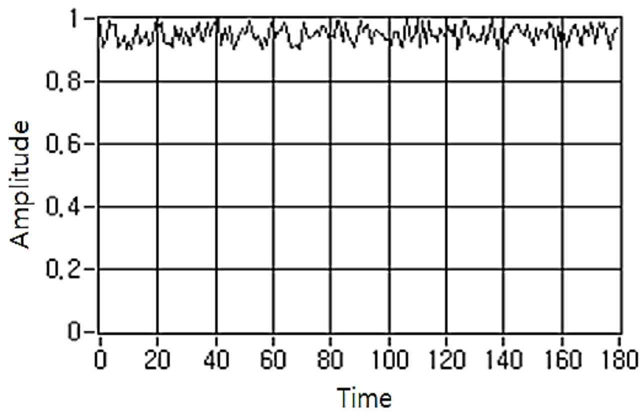
Human joints operate through the resultant force of multiple muscle forces, as described by the equation below.

$$\tau_{net} = \sum F_i^{mt} \cdot b_i \tag{11}$$

As a basic study for predicting joint torque, simulations were performed on Elbow F/E (Flexion/Extension) operated by the biceps brachii. For this purpose, the necessary muscle activation signals were generated as virtual signals, as shown in Figure 6.




(a) 70% Muscle Activatio




(b) 100% Muscle Activation

**Figure 5.** Virtual Muscle Activation Signals for Connecting Upper and Lower Arm(measured)

In an isometric state, the human elbow joint can produce maximum muscle force at an angle of 100~120 degrees, and at this point, the maximum muscle force of the biceps brachii is known to be about 870N. To validate the modeled muscle, the maximum muscle force was measured by changing the joint angle. For this measurement of muscle force in the isometric state, the component of muscle contraction speed was excluded. Figure 7 shows the simulation results, and approximately 840N is generated when the joint angle is 120 degrees. This indicates that both the joint angle at which the elbow joint can produce maximum muscle force and the maximum muscle force that the biceps brachii can produce are valid when compared to the experimental results of researchers in this field.

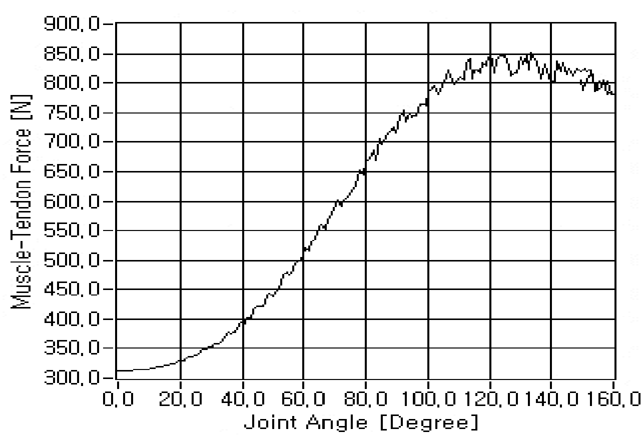
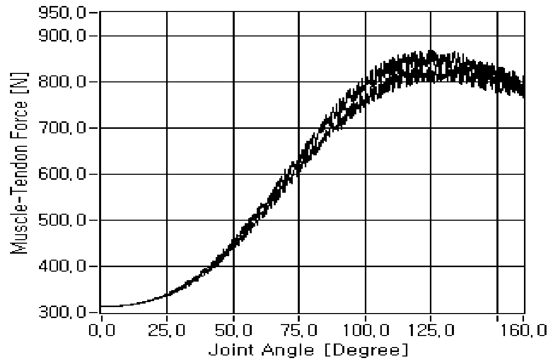
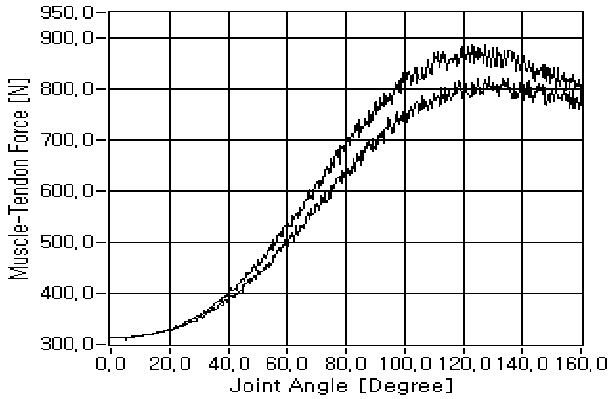



**Figure 6.** Maximum Muscle Force According to Changes in Joint Angle(measured)

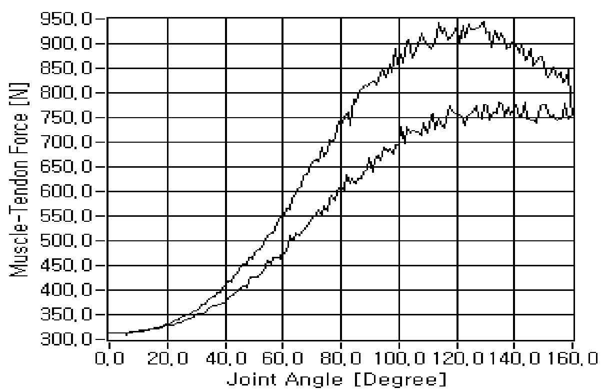
Figure 7 presents the simulation results for the magnitude of muscle force generated according to the speed of joint movement. In this simulation, the muscle is assumed to be 100% activated, and simulations were conducted for Extension/Flexion movements from 0 to 160 degrees at joint speeds of 10, 20, and 100 degrees per second. In each figure, the lower line represents the muscle force during Flexion, and the upper line represents the muscle force during Extension. The speed of the joint increases the muscle force during Extension and decreases the muscle force during Flexion. As shown in the figure, the slower the speed, the more similar the muscle force appears to the isometric state, and the faster the speed, the smaller the muscle force during Flexion and the larger during Extension.




(a) 10 degree/sec



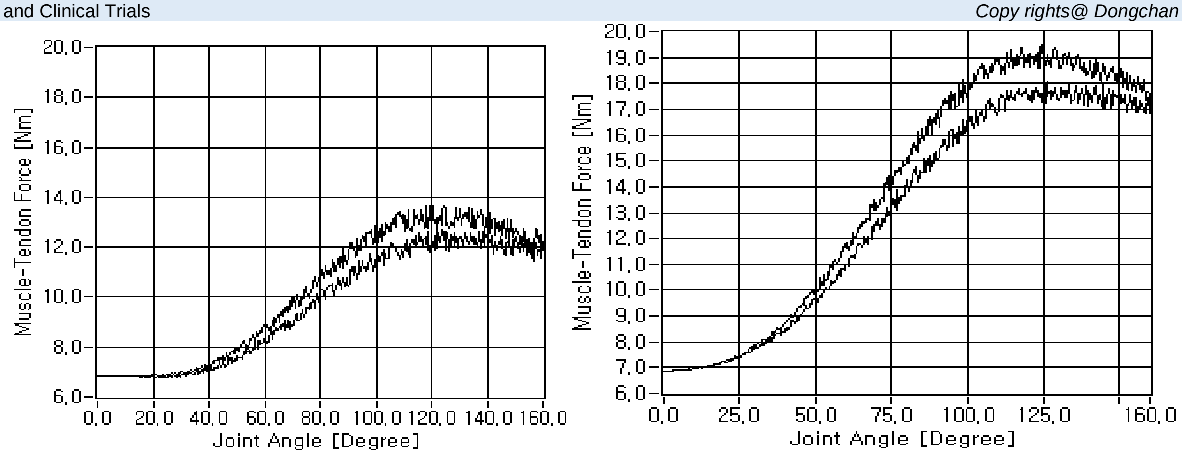

(b) 20 degree/sec




(c) 100 degree/sec

**Figure 7.** Changes in Muscle Force According to Speed(measured)

Figure 9. Simulation Results of Joint Torque According to the Degree of Muscle Activation. In this case, the joint speed was fixed at 20 degrees/sec, and simulations were conducted for conditions where the muscle was activated at 70% and 100%, respectively. The simulation results showed that when muscle activation decreased by 30%, muscle strength was reduced by approximately 32%.




(a) 70% Muscle Activation (b) 100% Muscle Activation

**Figure 8.** Joint Torque According to Muscle Activation between the Upper and Lower Arm(measured)

## Discussion

In this study, as an initial investigation into predicting human joint torque using bio-signals for potential use as motion intention signals in wearable robots, the biceps brachii was modeled using the Hill-type model. Simulations were conducted for the extension/flexion (E/F) movements of the elbow joint to explore the feasibility of the controller for wearable robots proposed in Figure 1. The simulation results were found to be similar to those of studies using SIMM (software for interactive musculoskeletal modeling). However, to predict joint torque more accurately, more kinematic information about human joint structures is required. It is anticipated that incorporating modeling of other muscles involved in elbow joint movements in the future could make it possible to use them as motion intention signals for wearable robots

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