Torque Estimation of Knee Flexion and Extension Movements From a Mechanomyogram of the Femoral Muscle

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***Abstract*— A mechanomyogram is a visualization of the mechanical signal from the surface of a muscle when the muscle is contracted. The setup of the mechanomyography (MMG) measurement is simpler than the setup for surface electromyography (sEMG) measurement and is less affected by sweating. However, torque estimation based on a mechanomyogram involves significant noise, which is an important issue. Therefore, we propose a regression analysis method to estimate the torque of the knee joint during voluntary movement based on the MMG signal. The proposed method differs from conventional methods because it integrates the MMG sensor responses at four locations: anterior, posterior, and medial/lateral just above the main operating muscle. This method focuses on the acceleration response characteristics, which change slightly depending on the location of the MMG sensor. Support vector regression was performed on the root mean square (RMS) of the MMG signals, which were processed by a low-pass filter. Two-channel estimation with an increased number of MMG sensors for the leading and antagonist muscles improved the conventional method, and four-channel estimation with medial and lateral sensors further improved the performance. These results show that the estimation performance of the proposed method does not significantly differ from that of the surface electromyogram.**

***Index Terms*— Human–machine interface (HMI), joint torque estimation, knee torque, mechanomyogram, motor intention prediction (MIP).**

I. Introduction

HUMAN-MACHINE interface (HMI) technology is indispensable in the operation of artificial limbs, and rehabilitation and is being actively researched. Various HMI technologies have been studied and investigated for operating human support systems at the operator's will [1]–[4]. Typical examples are electroencephalography (EEG), which records cortical action potentials through the skull and scalp; electromyography (EMG), which detects action potentials from muscles; nystagmus movement (electrooculography [EOG]); and electrocardiography (ECG). In particular, research using EEG and EMG, which are biological signals that directly include the operator's intended motion, has increased in recent years [5]. In the case of motion-assist systems, EMG is most often used as an input signal, and studies have been reported that use EMG to identify and classify intended motions and output the results [2]–[4]. Surface electromyography (sEMG), which detects EMG activity from the skin surface, can be recorded more easily than using other biological signals, such as using the noninvasive MYO Armband (MYB) [6]. It has been the subject of more research and analysis than EEG, which has a complicated measurement method. Although sEMG is easy to use, it is affected by changes in skin impedance, such as due to perspiration, which negatively impact its ability to accurately detect EMG signals after prolonged use [7]. It is also susceptible to external noise and requires a reference electrode to measure the potential difference in muscle-action potential, which requires skill in mounting and measurement. Furthermore, EMG signals are not suitable for quantifying dynamic muscle movement [8].

The mechanomyograms (MMG) are pressure waves associated with changes in muscle fiber dimensions generated by muscle contraction and record muscle activity [9]. MMG is a visual representation of the signal that reflects the mechanical activity of muscles and is not affected by skin impedance due to sweating. This signal reflects (1) the lateral movement of muscle fibers during the initial phase of muscle contraction, (2) subsequent oscillations in the resonator, and (3) changes in muscle dimensions [8]. Although 90% of the energy in the evoked myogram measured with an accelerometer is between 20 and 390 Hz, the main frequency component in the mechanomyogram during voluntary contraction is said to be less than 100 Hz, and a sampling frequency of 200 Hz or higher is sufficient [10], [11]. MMG can be used to evaluate and measure muscle activity during and after exercise.

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Saitama University Ethical Review under Approval No. R2-E-5 and the University of Human Sciences Ethical Review under Approval No. 620.

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Previous studies on MMG have been reported in subjects with myotonic diseases and it is a physiological signal that can be fully exploited [8], [11].

As an example of motion identification based on MMG, Tsuji *et al.* reported a study of the control of a prosthetic hand using muscle sound [7]. Using four accelerometers, features were extracted from MMG signals. Four motions (opening and closing of the fingers, palmar flexion, and dorsiflexion of the wrist joint) were identified, and the identification rate was 94.3% in five healthy subjects. Similarly, Ding *et al.* used accelerometer-based MMG to identify five tapping movements of the thumb, index, middle, ring, and little fingers, showing the effectiveness of a support vector machine (SVM) [13]. As a technique for estimating muscle activity during full-body movements and not just limited to small movements at the end of the upper limb, a method for MMG of the lower limb during walking with a sixth-order model has been proposed [14].

Pradhan *et al.* proposed a linear regression technique that divides the EMG signal into frequencies to control a prosthetic hand and stated that control by linear regression prediction provides accurate and robust control [15]. Similar to Pradhan *et al.*, Smith *et al.* reported that linear regression control can be an alternative to conventional methods [16]. Chen *et al.* used polynomial regression to analyze joint torque and muscle activity using EMG, MMG, and sonography, respectively, and found that EMG and MMG had no effect on convergence speed [17]. Anders *et al.* used polynomial regression analysis to identify patterns in EMG and MMG of the vastus lateralis muscle signals during leg extension and found that there were few intra-individual effects such as fatigue but observed that differences between individuals should be noted [18]. The best performance of MMG-based regression analysis is given in [19]. Estimating muscle torque with support vector regression (SVR) from MMG signals evoked by electrical stimulation showed a coefficient of determination (R^2) of 94% for training and 89% for testing. However, this study was conducted under limited conditions in which vibrations were induced by electrical stimulation.

In this paper, we propose a regression analysis method to estimate knee joint torque during voluntary movement using the MMG signal. The main difference between the proposed method and the conventional method is the integration of sensor responses placed at four locations (anterior, posterior, and medial/lateral just above the main operating muscle). It focuses on the characteristics of the acceleration response, which change slightly depending on the location of the MMG sensor. Support vector regression was performed on the root mean square (RMS) of the MMG signals processed by a low-pass filter. The performance of the proposed method was compared with two baseline methods: sEMG and conventional MMG, using one channel.

II. Materials and Methods

A. Overview of the Study

In this study, we validated the method of muscle torque estimation for the flexion-extension motion of the lower limb and knee joint. We measured the activities of the rectus femoris (RF) muscle of the thigh, which is the main flexion-extension muscle of the knee joint, and the hamstring (HM), which is the antagonist muscle group, from four directions, and analyzed the feature values during the flexion-extension movement. A regression analysis was performed using the number of flexion and extension movements as objective variables. From the results of the regression analysis, the knee joint flexion/extension joint torques was predicted from the MMG of the thigh, and the accuracy was verified.

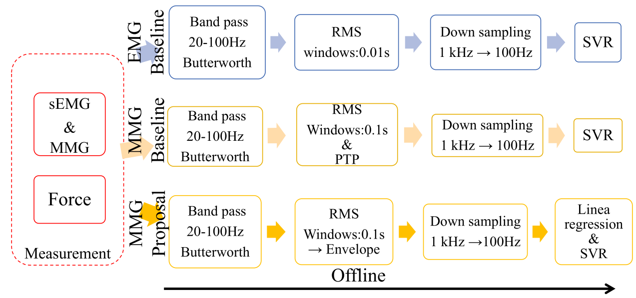

Fig. 1. Overview of the signal processing.

Four accelerometers were used in the experiment, and a two-channel electromyograph was used for comparison. Figure 1 shows an overview of the signal processing. First, the MMG signal obtained from the accelerometer was passed through a bandpass filter. The RMS of a 100 ms window was calculated for the signal and the envelopment process was performed. To reduce the amount of computation, a regression process was performed after 1/10 downsampling. The conventional sEMG and MMG methods were employed as comparators for the evaluation. The conventional sEMG is a regression analysis method that uses the RMS of the two-channel surface electromyogram of the RF and HM as the feature value. The conventional MMG is a regression method using the RMS and peak-to-peak (PTP) features of the mechanomyogram of the RF muscle to achieve the same conditions as in the literature [19].

B. Participants

The study included six healthy adults with no history of neuromuscular disease, three males and three females, with a mean age of 21 ± 5.2 years. The dominant side was confirmed orally, and the extensor and flexor muscles of the thigh on the dominant side were targeted. The purpose of this study was fully explained to the subjects, and their consent and cooperation were obtained. This study was approved by the Saitama University Ethical Review (R2-E-5) and the University of Human Sciences Ethical Review (No. 620).

C. Measurement Method

MMG signals were acquired using the MPU-6050 (InveSnse) accelerometer on a TSND121 composite sensor (ATR). The acceleration (ACC) in the x-, y-, and z-axes was extracted from the obtained 6-axis information. The anterior and posterior sensors were placed on the anterior and posterior

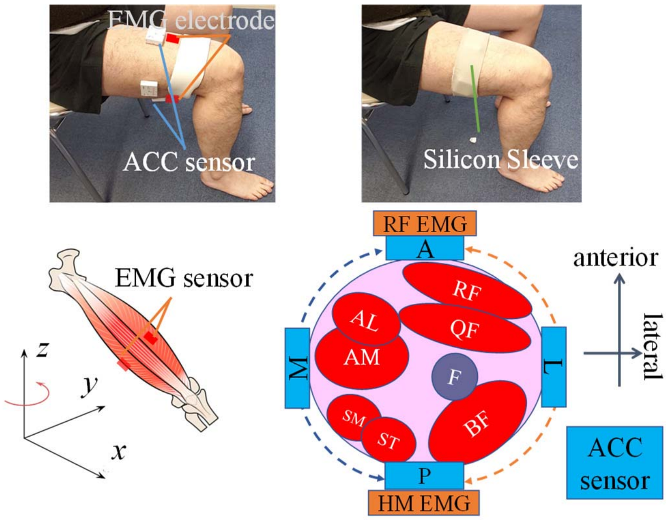

Fig. 2. Attachment of the sensors (top), orientation of the sensors (bottom), and position of the sensor in relation to the thigh muscle.

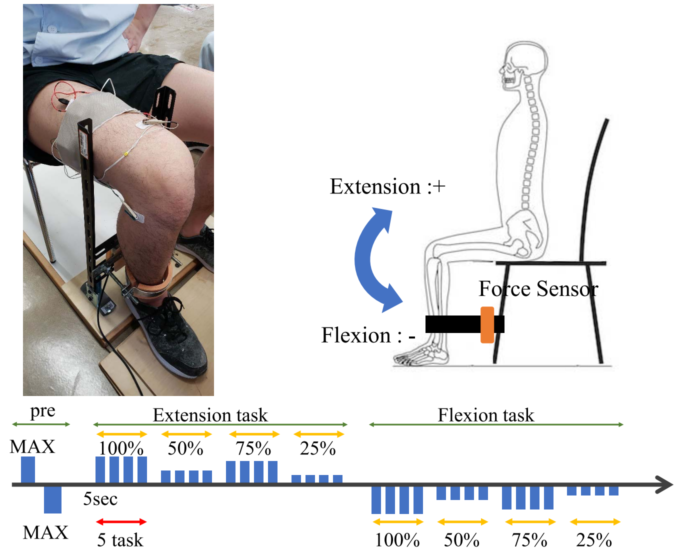

Fig. 3. Overview of the measurement (top) and flow of the task (bottom).

surfaces of the mid-thigh, and the medial and lateral sensors were placed on the middle of the anterior and posterior sensors on the thigh. The sensors were fixed with a silicone sleeve (Fig. 2).

sEMG signals were also acquired simultaneously for comparison with the MMG signals. Electrodes were placed across the distal 30 mm to the RF and biceps femoris muscles, and the reference electrode was the ipsilateral peroneal head. The electromyogram was amplified by TSEMG01 (ATR) and recorded on TSND121.

The flexion moment and extension moment forces were derived from the force information measured by the 6-axis sensor SFS055YA500U6 (Leptrino) as a reference for obtaining the muscle torque estimation error. The maximum voluntary contraction (MVC) was measured before the main experiment, and the %MVC was calculated from these values.

D. Given Task

The subject was seated in an upright position with the knee joint at 90°, and the force sensor was placed between the lower leg and the frame (Fig. 3, top). The subjects were verbally instructed to start the knee joint extension and flexion exercises. The task was divided into four stages. The four stages were 100%, 75%, 50%, and 25% of the maximum effort exercise. The subjects performed flexion and extension, respectively, for a total of eight trials. The force sensor values were presented to the subjects in order to confirm the exercise intensity. Each trial lasted approximately 5 s and was performed five times (Fig. 3, bottom). The motor tasks were divided into nine levels: 0% no activity; 100% extension; 75%, 50%, 25%, and 100% flexion; 75%, 50%, and 25%.

E. Analysis Methods

1) Filtering and Feature Extraction: The frequency response of induced MMGs ranges from 20-390 Hz, while the spontaneous MMGs in this study. It is known from the literature that the frequency response of the MMG signal concentrates at 10–50 Hz [7]–[10]. Reference [19] employed a 4th-order 0.1–50 Hz bandpass Butterworth filter for upper limb MMG. For the lower limbs, Morufu *et al.* used a 20–200 Hz filtering scheme [18]. With this information as a reference, a 4th-order 20–100 Hz bandpass Butterworth filter was used for 1 kHz sampling responses.

Then, the RMS and PTP features in a 100-msec window were extracted for torque estimation. Because the mechanomyogram contains a lot of noise due to vibration, these features were smoothed by using a second-order low-pass filter consisting of two first-order low-pass filters with time constants of 1.6 Hz. To reduce the computational cost of the regression, and because 100 Hz is sufficient for the sampling period of the torque estimation, downsampling from 1 kHz to 100 Hz was performed after the feature-smoothing process.

2) Regression Processing: To estimate the knee flexion/extension activity (%MVC) during voluntary knee movement, we processed the mechanomyogram obtained from four sensor channels located at the front, rear, inside, and outside of the thigh. Two baseline methods were tested for comparison: First, we evaluated SVR performance using the RMS of the surface electromyogram as an explanatory variable, which is the most commonly used method (Trial 1). Then we evaluated the SVR performance using the RMS and PTP features of one-channel MMG as explanatory variables, which is representative of conventional MMG-based methods [19] (Trial 2). These trials are compared in Table I.

The proposed method was tested in 4 ways: multiple regression analysis using all four channels (Trial 3), SVR using only the anterior and posterior two channels (Trial 4), SVR using only the medial and lateral two channels (Trial 5), and SVR using all four channels (Trial 6). This study employs an SVR with a radial-based function (RBF) as the kernel function [19].

TABLE I
LIST OF TRIALS

	Number of channel	Position	Feature type	Biological signal	Processing method
Trial 1	2	RF & HM	RMS	EMG	SVR
Trial 2	1	RF	RMS+ PTP	MMG	SVR
Trial 3	4	A-P& M-L	RMS	MMG	Multiple liner regression
Trial 4	2	A-P	RMS	MMG	SVR
Trial 5	2	M-L	RMS	MMG	SVR
Trial 6	4	A-P& M-L	RMS	MMG	SVR

The kernel function is as follows:

$$K\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right) = exp\left(-\gamma \left\|\boldsymbol{x}_i - \boldsymbol{x}_j\right\|^d\right).$$

Here, $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ denote the input data of the ith and jth samples, respectively. γ is a parameter that defines the width of the slope of the kernel function.

The regression model uses an optimization algorithm to find a set of coefficients for each input to the model that minimizes the following formula:

$$minimize \quad \frac{1}{2}\|\boldsymbol{w}\|^2 + C\sum_{i=l}^{k}\left(\xi_i + \xi_i^*\right)$$

$$subject\ to \begin{Bmatrix} y_i - \langle \boldsymbol{w}, x_i \rangle - b \le \varepsilon + \xi_i \\ \langle \boldsymbol{w}, x_i \rangle + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \quad for\ all \quad i = 1, 2, \ldots \ldots, k \end{Bmatrix}.$$

Here, $\boldsymbol{w}$, b, and y denote the weight vector, bias, and output, respectively. C is a hyperparameter that determines the tradeoff between maximizing the margin and minimizing mistakes. ε denotes the margin. ξ_i and ξ_i^* denote the slack variables, which represent the upper and lower constraints on the system outputs, respectively. The hyperparameters in the above-mentioned formula were set to $C = 879$, $\varepsilon = 0.1205$, and $\gamma = 1.3$, referring to [19].

An average of 422.67 s of experimental data was acquired from the six participants beforehand. Responses of 70% of the randomly selected trials were used as training data, and the rest were used as test data. To compare the performance of the trials, they were evaluated using repeated ANOVA measures. The sphericity was checked using Mauchly's sphericity test, and the correction for the degrees of freedom was performed using the Greenhouse-Geisser correction. Multiple comparisons were performed using the Bonferroni method.

III. RESULTS AND DISCUSSION

A. Raw Signal Data

Fig. 4 shows the raw signal data during flexion and extension. The EMG signal of the RF was active during the extension motion and weaker during flexion. Similarly, the HM EMG signal can be confirmed during flexion, but the signal is suppressed during extension. On the other hand, there is no

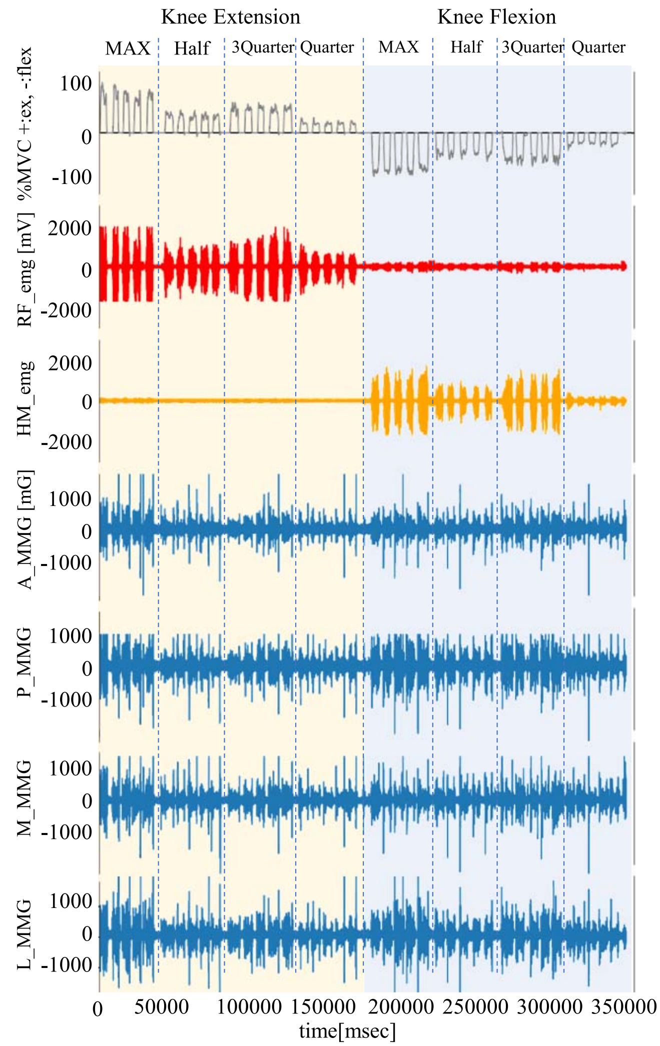

Fig. 4. Raw signal data.

observable difference between the MMG signals in the flexor and extensor muscles, because the RF and HM vibrations propagate mechanically and interfere with each other.

We expect that this situation is the reason for the lack of conventional methods using multiple channels. However, although the vibration propagates mechanically, it decays with distance, resulting in a slight change in the mechanomyogram depending on the sensor position. If this change can be correlated with torque using regression analysis, highly accurate torque estimation by multi-channel MMG will be possible.

B. Regression Results

Table II shows the coefficients of determination (R^2) and mean squared error (MSE) for each trial's training and testing data. The SVR with the EMG RMS as a feature (Trial 1) had a coefficient of determination R^2 of 0.84 for both training and testing. The SVR with the RMS and PTP features of the mechanomyogram (Trial 2) had an average R^2 of 0.46 for training and 0.44 for testing. On the other hand, the results of multiple regression analysis using the RMS of multi-channel mechanomyograms as features (Trial 3) showed an average R^2

TABLE II
COEFFICIENT OF DETERMINATION AND MSE OF EACH TRIAL

Trial			*Training* *Average*	*Training* *SD*	*Testing* *Average*	*Testing* *SD*
Trial 1	*sEMG*	R^2	0.84	0.06	0.84	0.06
	SVR	*MSE*	16.30	3.61	16.29	3.65
Traial 2	*MMG SVR*	R^2	0.46	0.13	0.44	0.14
	RMS&PTP	*MSE*	23.50	2.34	23.73	2.44
Traial 3	*4ch*	R^2	0.58	0.10	0.58	0.11
	Multi Reg	*MSE*	26.51	2.81	26.57	2.77
Traial 4	*A-P 2ch*	R^2	0.69	0.08	0.69	0.08
	SVR	*MSE*	23.06	4.07	23.15	3.99
Trial 5	*M-L 2ch*	R^2	0.33	0.07	0.33	0.08
	SVR	*MSE*	34.07	2.71	34.08	2.82
Traial 6	*4ch*	R^2	0.91	0.03	0.91	0.03
	SVR	*MSE*	11.70	1.97	11.97	1.96

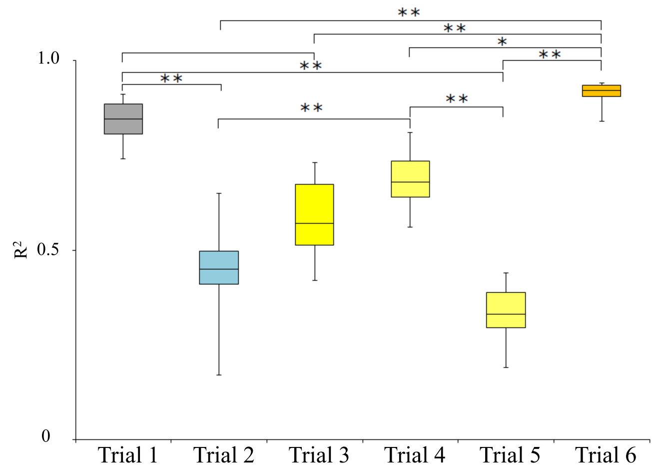

Fig. 5. Multiple comparisons between trials.

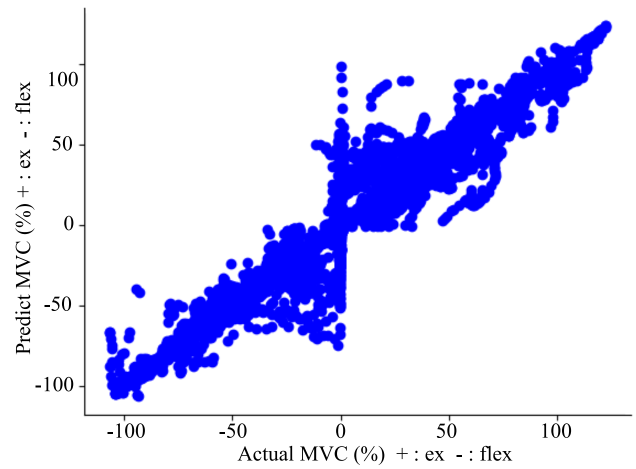

Fig. 6. Scatter plot of estimated and measured torque.

of 0.58 for both training and testing, which is not a sufficient estimate; However, regression of the multichannel signal with SVR (Trials 4, 5, and 6) yielded 0.69 for training and 0.68 for testing in the A-P 2-channel (A-P 2ch) and 0.33 for both training and testing in the M-L 2-channel (M-L 2ch). The MMG signals closer to the targeted muscle group performed better. The 4-channel (4ch) mechanomyogram integrating A-P and M-L showed an average R^2 of 0.91 for both training and test. These results suggest that the M-L MMG signal contains information that complements the A-P MMG signal.

The coefficient of determination R^2 of Trial 2 was significantly lower ($p = 0.01$) than that of Trial 1. In a previous study [19], the muscle torque generated during electrical stimulation was estimated using the RMS and PTP features of MMG, and a coefficient of determination R^2 of 0.94 was obtained for the training subset and 0.89 for the testing subset. We similarly performed SVR processing with the RMS and PTP features of MMG in Trial 2, but the coefficient of determination R^2 was much lower at 0.46 and 0.44 when no electrical stimulation was performed. These facts show the limitations of conventional MMG methods. The result of Trial 3 shows better performance than Trial 2 by introducing multiple MMG channels, while its coefficient of determination R^2 is still significantly lower than that of Trial 1.

The MMG signal contains the acceleration of the vibration caused by the contraction of each muscle, but it also contains the superimposed acceleration caused by the motion of the limbs. The former is the main contributor to torque estimation, while the latter is the source of error. M-L 2ch is not suitable for estimating muscle contraction by itself because it contains more components of acceleration caused by limb motion than A-P 2ch, but by incorporating it into multiple regression analysis, it has the effect of contributing to the compensation of errors caused by limb motion.

SVR based on 2 and 4ch MMG (Trials 4, 6) showed better performance than other MMG methods, and 4 ch MMG (Trial 6) R^2 did not differ significantly from that of EMG (Trial 1) (Fig. 5). This result shows that using multiple channels is effective in improving muscle torque estimation based on MMG. It also shows that MMG with multiple channels can estimate bidirectional motions (extension and flexion) with performance comparable to that of EMG.

Two channels, one for the leading muscle and the other for the antagonist muscle, are commonly measured with EMG to estimate bidirectional muscle force in flexion-extension. The comparison between Trial 2 and Trial 4 shows that two channels are required for bidirectional torque estimation in MMG as well. Although the raw data in Fig. 4 show no significant difference between the results of the lead and antagonist muscles, the results of Trial 4 show that the SVR estimates muscle torque from the small difference in the lead and antagonist muscles. The difference between Trials 4 and 6 is the use of the internal and external MMG signals, which do not occur directly above the main movement muscle during flexion and extension. The higher performance of Trial 6 suggests that the internal and external MMG signals contain the necessary information for knee flexion-extension motion estimation.

C. Dependency on Exercise Intensity

Fig. 6 shows a scatter plot of the estimated and measured torques obtained from the test subset in Trial 6. The x-axis

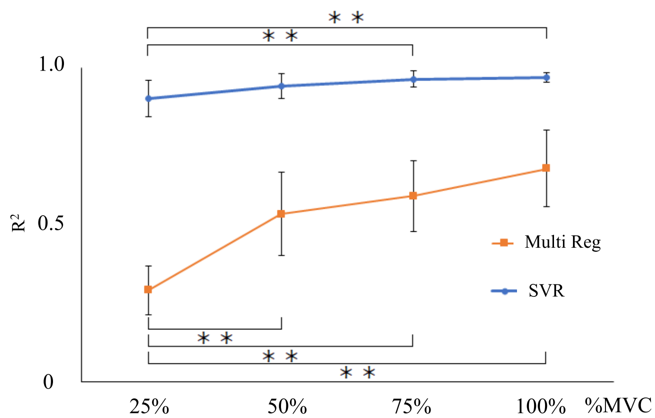

Fig. 7. Dependency on exercise intensity.

denotes the torque measured by the force sensor, and the y-axis denotes the torque estimated by SVR using the four-channel MMG. The positive and negative values represent extension and bending movements, respectively. When the exercise intensity is significant, the estimated and measured values have a linear relationship. However, the estimated values vary around a measured torque of 0, and this trend can be observed up to approximately ±50%. It can be inferred that the estimation accuracy declines when the exercise intensity is low.

In a previous study, a sharp increase in MMG-RMS was observed after 40% MVC, and the increasing trend flattened out and even decreased after 80-100% MVC [20]–[22]. The results of the current study showed that low exercise intensity affected the torque estimates and high exercise intensity had less effect.

Fig. 7 show the results of multiple regression analysis and SVR analysis for each of the flexion-extension torques (%MVC) in Trial 6. In both the multiple regression analysis and SVR results, the coefficient of determination R^2 tended to improve as exercise intensity increased. Although the multiple regression analysis did not provide a sufficient R^2, SVR confirmed that a higher R^2 could be maintained even in situations with low exercise intensity.

Unlike the case of discriminating and classifying movements from MMG signals reported in the literature [19], when regressing muscle activity quantitatively from MMG signals, muscle activity intensity is also a factor that has a significant influence on the regression. In particular, when the intensity was more than 75% of the maximum voluntary contraction, the results obtained from the MMG signals were comparable to those obtained from sEMG.

IV. Conclusion

In this study, we proposed a regression analysis method to estimate the torque of the knee joint during voluntary movement, using MMG signals. The proposed method differs from conventional methods because it integrates MMG sensor responses from four locations (anterior/ posterior: just above the main operating muscle, and medial/lateral: middle of the anterior and posterior), and focuses on the acceleration response characteristics, which change slightly depending on the location of the MMG sensor. To demonstrate the effectiveness of this method, we conducted a test to estimate the torque at each of the four levels for the knee joint flexion and extension motion tasks in both directions. Continuous muscle torque was estimated from nine levels of exercise intensity at rest and during the four levels of flexion and extension. The RMS of the obtained signals was processed using a low-pass filter, and regression was performed.

For comparison, sEMG was also measured simultaneously. As a baseline method, we also validated the conventional method of measuring MMG with a single sensor.

The method of measuring the MMG signal with four channels resulted in a coefficient of determination R^2 of 0.91 and an MSE of 11.70 during training and 11.97 during testing. On the other hand, the results of sEMG showed that the coefficient of determination R^2 was 0.84 and the MSE was 16.30 and 16.29 during training and testing, respectively. The results of the conventional MMG method were much lower, with coefficient of determination R^2 of 0.46 and 0.44 and MSE of 23.50 and 23.73 during training and testing. The two-channel estimation with more MMG sensors for the anterior protruding and antagonist muscles improved the performance over the previous method, and the four-channel estimation with more sensors for the medial and lateral muscles further improved the performance. These results suggest that the estimation performance of the proposed method is better than that of sEMG. We also evaluated the performance of the proposed method at different exercise intensities to investigate the difference in the noise of the MMG signal depending on the exercise intensity. The results show that the coefficient of determination R^2 improves with the increase of exercise intensity and the estimation accuracy improves.

In addition, the performance results of MMG shown in Fig. 5 was better than those of sEMG. These results suggest that the MMG may be superior to the sEMG when multiple channels are used. Furthermore, MMG is simpler and less susceptible to sweating than EMG. Therefore, MMG may be fully utilized for prosthetic leg and hand manipulation and HMI technology in the future. The evaluation of torque estimation in this paper was limited in static situations. When this technology is applied to active prosthetics, dynamic torque estimation during walking is necessary. Therefore, the estimation of dynamic torque in situations where there is interference with the environment remains as future works.

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