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Exploring the Effect of Attachment Position of Electrodes for EMG-Based Detection of Minimum Effective Load on Muscles

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Abstract— **Isokinetic training leads to rapid skeletal muscle hypertrophy, while slow-speed resistance training is effective for promoting muscle hypertrophy. It is essential to use an effective resistance load that minimizes injury risk in skeletal muscle hypertrophy interventions. Previous studies have indicated that surface electromyogram (EMG) measurements are useful for detecting the load threshold (minimum effective load). However, the attachment position of the electrodes affects the characteristics of the EMG signal readings. It remains unclear whether the system for detecting the load threshold functions correctly when the electrode attachment position shifts. The objective of this study is to explore how the attachment position of EMG electrodes affects the detection of the load threshold. We hypothesized that frequency analysis of EMG signals might be a reliable method for checking the electrode attachment position, given the alternating current nature of EMG signals. As a result, as long as the EMG electrode is placed on the muscle, slight positional shifts are not very critical for detecting the load threshold. In addition, results show that we can verify whether the electrode attachment position is appropriate for detecting the load threshold and make adjustments by examining the magnitude data of the EMG signal frequency bands.**

I. Introduction

A. Background

Loss in muscle strength is a significant issue in aging, leading to reduced independence and difficulty in performing daily activities. Physical capabilities diminish when the body is not actively engaged [1]. Assistive-based or resistance-based training has been widely studied to augment human physical capabilities [2, 3]. Notably, musculoskeletal injuries can be a severe problem because they limit daily activities. When skeletal muscle contraction is absent during complete rest after an injury, muscle size can significantly decrease. Promoting efficient muscle recovery after injury is crucial. Strong resistance loads pose a risk of injury to older adults [4], making it essential to use an effective resistance load that minimizes injury risk for skeletal muscle hypertrophy interventions.

Isokinetic training leads to prompt hypertrophy of skeletal muscles [3], and slow-speed resistance training is effective for promoting muscle-hypertrophy [5]. A larger load on the skeletal muscles induces anaerobic metabolism, leading to the production of metabolic byproducts such as lactic acid [6, 7]. Metabolic byproducts are crucial in promoting the secretion of growth hormones [8-11]. Resistance-training robotic systems [12-16] can adjust interactive force strength using robotic control technologies. However, methodology that users use to detect the appropriate resistance load for automatic adjustment tailored to each user is still immature. Developing a system that determines the minimum effective resistance load would be valuable for promoting skeletal muscle hypertrophy. Such a system should detect the load within a feasible period before training, especially considering clinical settings.

A previous study examined optimal training conditions for muscle enlargement, demonstrating the effectiveness of isokinetic resistance training with multiple sets of 8–12 repetitions at low velocity, using loads of 60%–80% of the one-repetition maximum (1RM) [17]. The 1RM is the maximum weight a person can lift in one repetition. Due to the high risk associated with measuring the 1RM directly, prediction methods using a regression model with multiple repetitions maximum or load-velocity relationships were proposed [18, 19]. However, individual differences in the effective percentage of 1RM, combined with estimation errors, can hinder accurate detection of the appropriate effective load. Therefore, a direct detection method for identifying the minimum effective load would be more advantageous.

B. Related works

Assessing lactic acid levels in the blood and expired gas is a direct method to monitor the metabolic change in the skeletal muscles [20]. However, blood sampling to assess lactic acid levels is too invasive for daily use.

Surface electromyogram (EMG) measurement is a noninvasive and relatively easy method to evaluate muscle condition. Motor units are generally recruited from fatigue-resistant to fatigue-sensitive units as the load increases [21]. The recruitment of fatigue-sensitive motor units results in the production of metabolic byproducts. Some studies have suggested that using root mean square or integrated EMG (IEMG) is useful for detecting muscle metabolic changes [22-24]. For example, the load threshold during incremental cycling exercise was defined as the intersection of two regression lines of mean IEMG values over time, showing a significant correlation with the load threshold that generates metabolic products.

Other studies have indicated that IEMG increases nonlinearly with resistance load during leg extension exercises [25, 26]. Additionally, using linear approximation to detect real-time deviations from the initially approximated line, which indicates the effective load, is challenging. Our previous study found that logarithmic regression is effective to

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detect the minimum effective load [27]. The IEMG–load relationship could be expressed by logarithmic functions whose gradient approaches zero, based on the idea that the rate of increase in measured EMG magnitude might decrease as the load increases, due to the motor recruitment pattern shifting from superficial to deeper muscles. The increase rate of IEMG with increasing load would rise sharply due to a change in the logarithmic function type when fatigue-sensitive motor units start to be recruited in addition to fatigue-resistant motor units at the threshold.

Attachment position of electrodes affects the characteristics of reading of EMG signals [28, 29]. Action potential is fired in innervation zone of muscle fiber and bilaterally propagated along the muscle fibers. The more distance between the EMG electrode position and muscle belly, the more difficult it might be to read EMG signals. If the attachment position of the EMG electrode is deviated from the innervation zone, whether the system of detecting the load threshold [27] can estimate the recruitment pattern of muscle fibers from IEMG-load mapping is unclear.

C. Objective

In this study, the objective is to explore how the attachment position of EMG electrodes affects the detection of the load threshold (minimum effective load). Attaching properly sensors to the target areas requires the knowledge of muscles. Since users are assumed to lack sufficient knowledge about the placement of sensors, it can be difficult for them to attach the sensors correctly by themselves. To address this issue and enable use in a home environment, it is essential to have a system that can guide users without specialized knowledge to the correct placement of the sensors. Therefore, we aim to explore the methodology and the feature of EMG to check whether the attachment position of the EMG electrode is appropriate or not before load-IEMG plotting.

We hypothesized that frequency analysis of EMG signals might be a strong tool to check the attachment position of the EMG electrode considering the nature of alternating current of EMG. In this study, we investigated the differences in detection rates and the magnitude of the EMG signals due to the electrode attachment positions by arranging multiple EMG sensors along the longitudinal axis when the preliminary isokinetic movement was conducted.

II. METHOD

A. Principal of load threshold detection

The EMG magnitude is related to the number of activated muscle fibers. As the load increases, the rate of increase in IEMG tends to decrease due to the motor recruitment pattern, which progresses from superficial to deeper muscle fibers. To model this relationship, we applied a logarithmic function with a gradient that approaches zero, reflecting the decreasing rate of IEMG increase with higher loads.

The load threshold was detected based on the deviation degree from the logarithm functions. First, the logarithmic function was derived using the load-IEMG plots after two plots were recorded. Next, the fitting error between the measured IEMG and the logarithm curve was calculated.

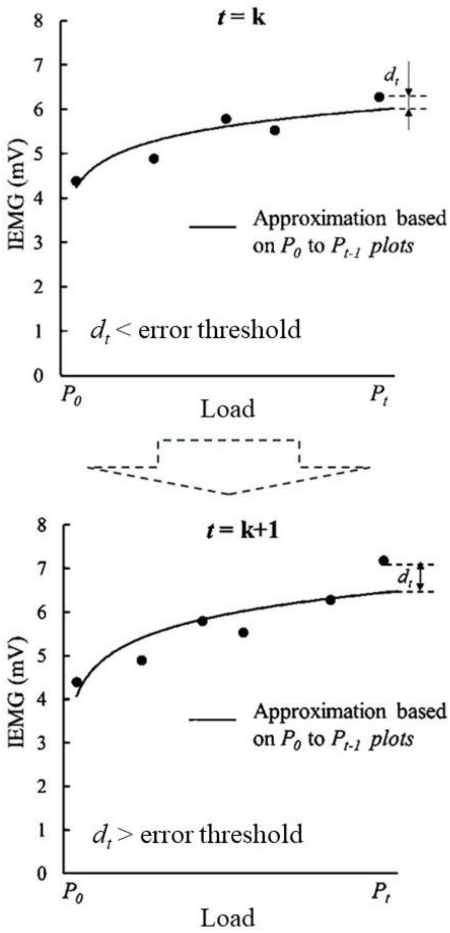

Figure 1. The pricipal of Detection of the load threshold by monitoring the distance d_t between the current plot and the logarithm curve [27].

Because the logarithmic function type changed when the load was higher than the load threshold, the plot deviated from the first logarithm function in condition where the load is higher than the threshold.

Fig. 1 explains the overflow of the detection method of the plot deviating from the first logarithm curve [27]. To detect plots that deviate from the first logarithm curve, the probability that the current plot belongs to the logarithm curve approximated with 1st to the current measured plots is calculated with the standard deviation between the 1st point to previous measured plots and the approximated curves. The threshold of the error Te is calculated as:

$$Te = Ke\sqrt{\frac{\sum_{i=1}^{t-1}(I_i-(A_s\ln(Pi-P_0)+I_{P0}))^2}{t-1}}, \quad (1)$$

where A_s is a constant of the logarithm when the load is lower than the load threshold, I is IEMG, P is load, t denotes the current plot number of the measured data, and Ke is a constant. P_0 and I_{P0} are load and IEMG when the load is the smallest measured value, respectively. The value of Ke was determined based on methodology of finding outlier by considering normal distribution. If a plot deviated from the regression logarithm curve, this deviation can be observed

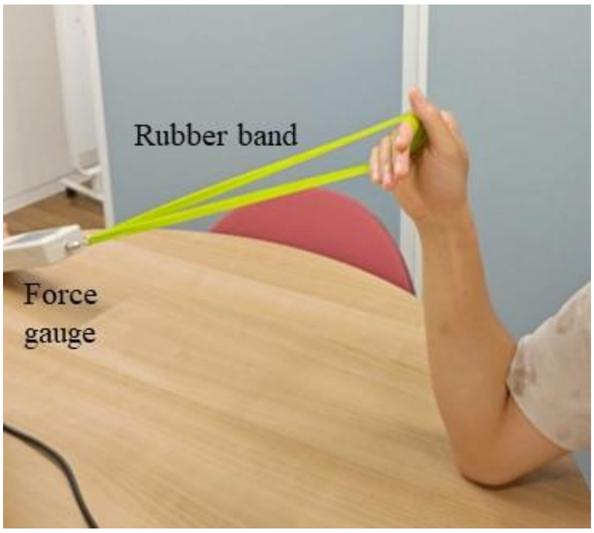

Figure 2. The experimental landscape during flexion-extension trials with 8-load conditions.

with Ke and the distance between the plot and the regression curve. The standard deviation between the measured IEMG and IEMG of the logarithm curve which is calculated using 1st to the previous plots. We selected 10% probability (Ke is 1.64) as the threshold to detect the deviation plot from the first logarithm curve (i.e., if the probability was less than 10%, the plot was regarded as that of the load threshold). This value was set to allow for a relatively large fitting error considering small number of samples for fitting.

B Experimental procedure

We hired seven young adults (four men and three women; mean age was approximately 24 years, standard deviation of age was approximately 5 years, mean weight was approximately 58 kg, standard deviation of weight was approximately 8 kg, mean eight was approximately 1.64 m, standard deviation of height was approximately 0.08 m). We explained the informed consent to the participants, including the fact that they have the right to stop the experiment at any time according to their requests. Our experimental protocol was approved by the Ethics Review Committee on Human Research of Waseda University (2024-271).

In this experiment, the participants performed an arm flexion exercise. They sat on a chair and followed the below instructions.

1) Sit deep in the chair and keep your right elbow on the table.
2) Flex your arm from 0 to 90 degrees over 5 seconds.
3) After holding the 90-degree position for 0.5 seconds, extend your arm from 90 to 0 degrees over 5 seconds.

The interval of trials was set 30 s if the participants did not request anything. The movement speed was not strictly constant, allowing for some variation in speed under the experimental conditions.

Fig. 3 shows the attachment position of EMGs. The EMG of the biceps muscle was measured using an EMG amplifier (SX230-1000, Biometrics Ltd., Newport, UK). Three EMG sensors was attached along the longitudinal axis of a right upper arm. The main EMG electrode was attached to a belly of biceps. The 2nd EMG electrode was attached 3 cm closer to the elbow than the main EMG electrode. The 3rd EMG electrode was attached 3 cm closer to the shoulder than the main EMG electrode. The analog I/O board (AIO-163202FX-USB, Contec, Osaka, Japan) was connected to the main controller (Windows) via a USB interface. The sampling frequency of data recording was approximately 30 Hz.

Fig. 2 shows the experimental landscape of flexion and extension trials. The participants conducted flexion-extension trials with 8-load conditions. The maximum force during one-trial was recorded. If the data recording or task performance was failed, they conducted the trial again. There were 5 types (hardness) of rubber band. The rubber band was connected to a force gauge (HP-500, Baoshishan, Liaoning Sheng, China). First, softer to harder rubber band with the same distance between the participants and the force gauge. In addition, the participants conducted trials under three more load conditions with different distance the participant and the force gauge. The experiment was conducted in two sets for each condition, totaling 16 trials.

C. Data analysis

The maximum force measured by the force gauge during one-trial flexion-extension movement was used as the index of the load. IEMG was derived from 100 samples of absolute values of EMG signals. The absolute values of EMG signals were smoothed with the moving average using a five-sample window. The maximum value of the IEMG was used as the index of the IEMG. These hyper-parameters were determined heuristically. Therefore, the maximum force and the maximum value of the IEMG were plotted and regressed. Data containing large IEMG values even during rest periods were considered to indicate a problem with the circuit during that trial and were excluded from the analysis.

The effect of the attachment positions of the EMG electrodes on the ability to detect the load threshold was analyzed. In addition, the effects of the magnitude of the EMG signals in the lower-frequency bands (0.1-0.3 Hz) on

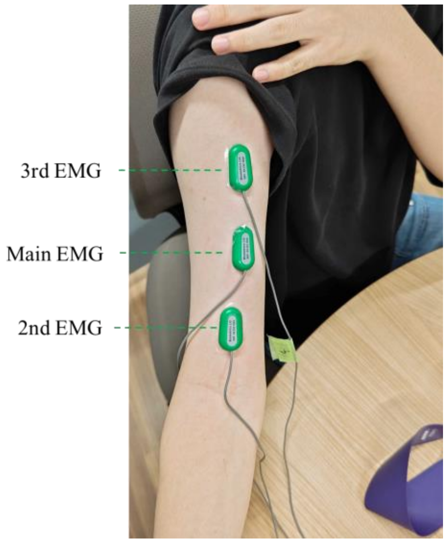

Figure 3. Attament position of the EMG electrodes. Three EMG sensors were attached along the longitudinal axis of a right upper arm.

the ability to detect the load threshold was analyzed. This frequency bands were associated to the target movement velocity. The data obtained from a single movement under the first trial with light load condition (approximately 20 kg) was subjected to a fast Fourier transform (FFT). The magnitude of the EMG signals for each frequency band were derived.

III. Experimental Result

Fig. 4 shows an example of the measured data plots and logarithmic approximation curves for each trial of the elbow flexion-extension exercise. The plots represent the maximum measured IEMG corresponding to the maximum resistance loads. The orange line represents the logarithmic approximation curve for loads below the load threshold, while the blue line represents the logarithmic approximation curve for loads above the load threshold. The load threshold was determined by the method of [27].

Fig. 5 shows the number of the detected load threshold for each EMG electrode position. The deviated plot could be detected for 7 of 7 samples when the main EMG data were analyzed. The deviated plot could be detected for 6 of 7 samples when the EMG electrode attached 3 cm closer to the elbow than the main EMG electrode. The deviated plot could be detected for 5 of 7 samples when the EMG electrode attached 3 cm closer to the shoulder than the main EMG electrode.

Fig. 6 shows average of the magnitude in the 0.1-0.3 Hz bands for each EMG electrode position. Shapiro-Wilk test revealed that the data were normally distributed. An analysis of variance (ANOVA) was conducted to determine whether there were statistically significant differences between the groups. The results indicated a significant effect. The statistical significance level was set at $p<0.05$. For further exploration of these differences, post-hoc tests were performed using Tukey's HSD, which revealed that all data groups were different significantly.

Fig. 7 analyzed the effect of the mean magnitude in 0.1-0.3 Hz bands on the detection ability of the load threshold. Except outliers of magnitude values, the lower magnitude (less than 1.40) did not have the ability to detect the load threshold.

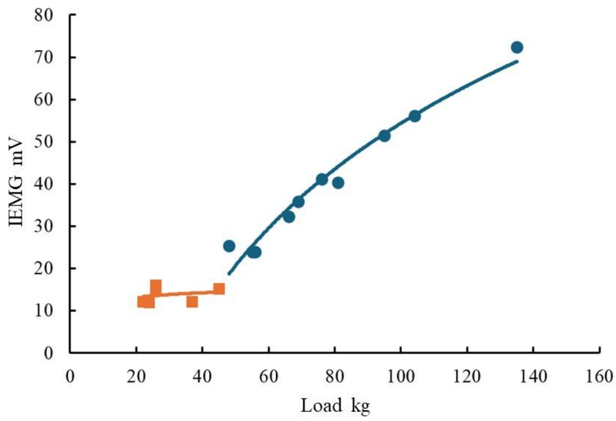

Figure 4. An example result of the rleationship of the maximum load and the maximum measured IEMG. Orange and blue cruves represent the logarithm approximation curves below and above load thresholds, respectively.

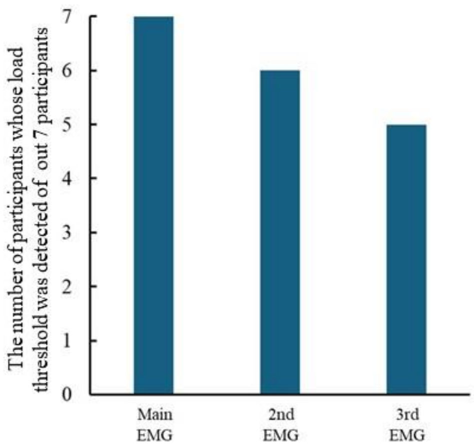

Figure 5. The number of paticipants whose load threshold was detected for each EMG electrode position. The main EMG electrode was attached to a belly of biceps. The 2nd EMG electrode was attached 3 cm closer to the elbow than the main EMG electrode. The 3rd EMG electrode was attached 3 cm closer to the shoulder than the main EMG electrode.

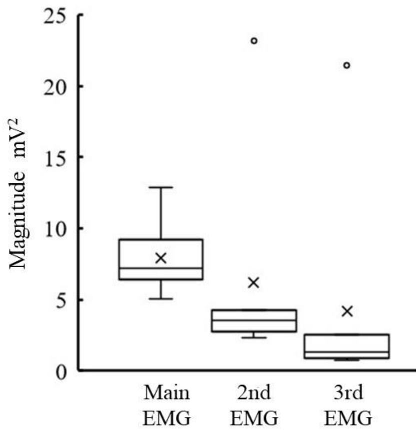

Figure 6. Average of the magnitude in the 0.1-0.3 Hz band obtained by Fourier transform for each EMG singals. The main EMG electrode was attached to a belly of biceps. The 2nd EMG electrode was attached 3 cm closer to the elbow than the main EMG electrode. The 3rd EMG electrode was attached 3 cm closer to the shoulder than the main EMG electrode. All data are significantly different for each other.

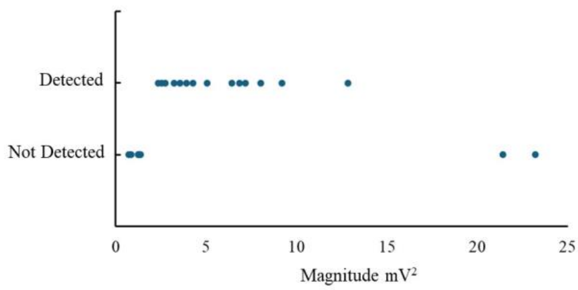

Figure 7. The results of detection of the load threshold corresponding to the average of the magnitude in the 0.1-0.3 Hz band obtained by Fourier transform.

IV. DISCUSSION

In this study, the effect of the electrode attachment position was investigated. As shown in Fig. 5, the electrode attachment position affected the detection rate of the load threshold. The results indicated that the ability to detect the load threshold decreases if the electrode attachment points deviate from the muscle belly. In particular, electrodes attached closer to the shoulder, specifically the upper part of the biceps muscle, had the lowest ability to detect the load threshold. This result aligns with the anatomical fact that the volume of the biceps muscle is smaller on the proximal side than on the distal side [30]. As long as the EMG electrode is placed on the muscle, slight positional shifts are not very critical for detecting the load threshold.

As shown in Fig. 6, the relationship between the attachment position and signal magnitude in the lower frequency bands was analyzed. The differences in attachment positions significantly affected the magnitude of the EMG signals. Fig. 7 indicates that the magnitude of the EMG signals in the lower frequency bands is important for detecting the load threshold. When the magnitude was lower than 1.40, the ability to detect the load threshold was lost. On the other hand, when the magnitudes were higher than 20 mV^2, failures in detecting the load threshold occurred. The two samples with magnitudes higher than 20 mV^2 might be abnormal outliers. We assume that strong noise during measurement prevented the extraction of EMG features. While it is crucial to find a position where the signal can be measured above a certain level, values can become excessively large due to factors such as GND settings or cable conditions. In these cases, the values tended to be high across all frequency bands. Except for these outliers, lower magnitudes did not have the ability to detect the load threshold. Noticeably, the threshold of the magnitude depends on the load amount of the preliminary movement checking the EMG signals.

Since EMG signals are alternating current, they include several frequency components. The frequency content of EMG signals changes when the load on the muscles or the fatigue state of the muscle changes [31]. Specifically, fatigue characteristics appear in the 15-45 Hz frequency band of EMG signals during isometric contractions. In this study, we selected frequency bands to detect components related to movement during isokinetic contraction. The 0.1-0.3 Hz band was associated with the flexion-extension movement. As a result, the magnitude of the frequency bands related to the preliminary movement was correlated with whether the load threshold was detected. We suggest that the target frequency bands should be selected appropriately according to the conditions of the preliminary movement. There is a tendency for electrodes attached to the upper part of the biceps muscle to have larger magnitudes across a wider range of frequencies. We assume that an inappropriate electrode attachment position increases the noise content. Consequently, we can verify whether the electrode attachment position is appropriate and make adjustments by checking the magnitude data of the EMG signal frequency bands, which helps users attach sensors and monitor the load appropriately.

There are several limitations in this work. Automatic determination of the target frequency bands and the threshold of the magnitude for automatic checking of the electrode attachment position has not been considered yet. In future work, we would develop the system automatically adjusting the target frequency bands and the threshold of the magnitudes of the EMG signals for checking the attachment position by feedbacking the velocity of the movement and the load.

The regression procedure is easily affected by noise or fluctuation of the values. Due to the lack of precision in the velocity of the flexion-extension movements among trials, the IEMG values tended to fluctuate. The current system did not consider the movement speed. In future work, we would expand the model considering the effect of speed into the model as well. Especially, the power of muscles considering both velocity and load would be a key factor in determination of effective minimum load.

The exploration of range of the EMG electrode locations was limited in this study. In addition, the density of the EMG electrode attachment was not considered. High-density EMG electrode array has been studied to estimate muscle fatigue and pain [32-34]. These EMG channels enable wide-range measurement of EMG signals and analysis of the difference of signals between channels in close proximity. Applying our methodology to such a high-density EMG electrode array would enable automatic extract the important EMG signals to be used and detection of the load threshold for muscle hypertrophy.

The EMG reading values are affected by the effect of sweating or fatigue. This study did not consider the adjustment method of detecting the load threshold corresponding to the sweat or fatigue states. In future work, we would develop the system compensating to the temporal change due the sweating or fatigue states.

V. CONCLUSION

The methodology of slow-system resistance training as a isokinetic training for rapid and efficient skeletal muscle hypertrophy has been investigated. This study explores a methodology using signal magnitude of the EMG to verify the appropriateness of the EMG electrode attachment position before load-IEMG plotting. It is crucial to apply an effective resistance load minimizing injury risk in skeletal muscle hypertrophy interventions. Previous studies have shown that EMG-based systems are useful for detecting the load threshold (minimum effective load). However, concerns exist that the electrode attachment position may affect the characteristics of EMG signal readings. It remains unclear whether the load threshold detection system remains effective if the electrode attachment position shifts.

We proposed that frequency analysis of EMG signals could be an effective method for evaluating electrode attachment positions, considering the alternating current characteristics of EMG signals. The experiment suggests that as long as the electrode is placed on the muscle, small positional adjustments are unlikely to significantly impact load threshold detection. Therefore, the suitability of the electrode attachment can be assessed and fine-tuned by analyzing the magnitude of specific frequency bands in the EMG signals.

In the future, we aim to develop a system that automatically adjusts target frequency bands and magnitude thresholds for verifying electrode attachment position by incorporating feedback on movement velocity and load. Additionally, muscle power, considering both velocity and load, will be a key factor in determining the effective minimum load. We also plan to develop a system that compensates for temporal changes due to sweating or fatigue.

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