Force Estimation of Five Fingers Using Infrared Optical Sensors and an IMU and its Application to Analysis of Sports Motion

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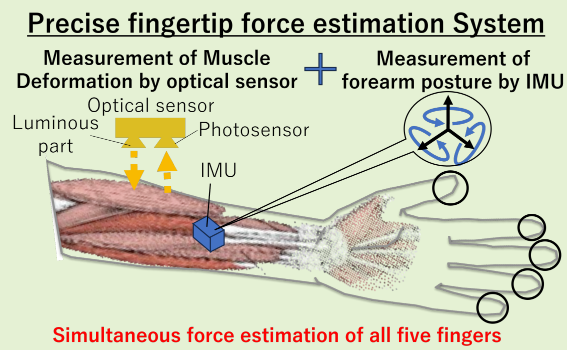
***Abstract*—Research on scientifically analyzing human movements for applications in sports and skill inheritance is actively conducted. Particularly, methods for estimating human output through the analysis of muscle deformation can be applied to static forces like grip strength. However, when focusing on finger force analysis through muscle deformation, traditional studies have only targeted a single finger, and there are no examples of simultaneously estimating the force of all five fingers. Furthermore, the most common method for acquiring muscle deformation, using electromyography (EMG), suffers from reduced accuracy due to the influence of sweat and sebum on the skin, making it challenging to analyze intense movements. Additionally, as the posture of the arm changes, the muscle configuration within the arm also changes, making finger force estimation difficult with conventional methods when there is significant arm posture variation. Therefore, this study aims to simultaneously estimate the force of all five fingers under varying arm postures by using optical sensors, which are less affected by changes in skin condition, to measure muscle deformation, and a six-axis inertial sensor (IMU) to measure the posture of the upper arm. By using the IMU to detect the posture of the upper arm, it is possible to indirectly estimate the changes in muscle configuration within the arm. In the experiments, the accuracy of finger force estimation was compared with and without the use of the IMU, focusing on sports movements, to discuss its effectiveness. Additionally, the study demonstrated how the accuracy of force estimation decreases by applying saline solution to the skin to simulate sweat. The results showed that the use of the IMU improved the accuracy of finger force estimation, and although the accuracy decreased due to sweat, force estimation remained possible. This method, which involves attaching sensors only to the upper arm, does not interfere with hand operations, suggesting its potential application for analyzing fingertip forces in various scenarios that involve the use of hands.**



***Index Terms*—Human–machine interaction (HMI), IMU, muscle deformation sensing, optical sensor, sensing methods.**

I. Introduction

A. Background

RESEARCH on technologies for measuring forces generated by the human body is an important field expected to have applications not only in sports but also in skill inheritance and medical fields [2], [3], [11]. Traditionally, studies on measuring these forces have used methods that analyze human movements with cameras [4]. However, camera-based methods face challenges in measuring static forces such as grip strength. In response to these challenges, recent years have seen extensive research into methods that measure and estimate the forces generated and exerted by the human body by directly attaching sensors to the body or using wearable devices. These new approaches aim to provide more accurate and reliable data on the forces involved in various movements and activities, overcoming the limitations of traditional camera-based methods [5]– [9]. This study focuses on methods for estimating the physical output of a human using wearable devices.

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B. Related work

Methods for estimating and measuring the force generated in the human body and the force output by the human body can be divided into four main categories, depending on the sensors and measurement methods. The first method is to attach a force or pressure sensor directly to the point where force is to be detected. Studies using this method include gait analysis by installing pressure sensors on the soles of the feet [3], [5], [10], analysis of foot pressure during running [14], a sensor that can be attached to the fingertips to measure contact force [12], and measuring punching force by installing a sensor on a boxing glove [13]. This method of directly attaching sensors to the human body or tools used by humans allows direct measurement of the force occurring at the location where the sensor is installed. However, strong applied loads to the sensors are generated when sports are performed, causing the sensor to peel off, and measurement accuracy might reduce [15]. In addition, it is also possible that the sensors installed at the measurement points may cause discomfort to people [16].

The second method is called Electromyography (EMG), which estimates the output of the human body by measuring myoelectricity using electrodes [8], [17]. Research using EMG to estimate muscle strength includes force estimation during walking [11], finger bending force estimation for quantification of climbing techniques [18], muscle strength estimation during squatting [19], and fingertip force estimation during plucking [20]. However, changes in joint angles that alter muscle length are synonymous with changes in sarcomere length, and it is known that muscle strength varies with changes in muscle length [21]. In addition, changes in muscle strength can also occur due to nerve fatigue [22]. Perspiration causes partial short-circuiting of electrodes for action potential measurement, noise in EMG measurements, and unstable measurements due to changes in impedance between electrodes and skin [23], [24] and that the human body functions like an antenna, generating noise due to fluorescent lights, electrical cords, and electronic devices [25], [26].

The third method, called force myography (FMG), estimates muscle force by measuring muscle deformation through the placement of force sensors on the skin. Studies using FMG include a study that analyzed muscle deformation during bicycle pedal turning motion [28], a study that analyzed walking motion [29], and a study that developed a sensor to perform FMG [27]. Other studies that used FMG to estimate muscle power include those that estimated the output of hand [30], [31] and ankle joint power [32]. FMG is a commonly used method for analyzing motor skills and output of the human body. However, FMG has some problems, such as the loss of measurement accuracy due to the influence of preload at the time of sensor installation, and the difficulty of accurately placing the sensor on the target muscle due to the different physique and muscle tone of each sensor wearer [33].

The fourth method uses optical sensors to measure deformation of the human body or muscle deformation for estimation of muscle force. There are studies that uses optical sensors to measure deformation of the human body to estimate muscle force by installing a sensor unit at the fingertips [34]– [36]. In these studies, fingertip force is estimated by measuring the deformation of the finger as it is deformed by the load. However, it is not possible to estimate muscle strength with the finger closed because the sensors must be placed on the side of the finger. Another study is a method of estimating muscle strength by measuring muscle deformation in the arm using optical sensors [37]. These studies used 14-channel optical sensors to estimate fingertip force. Estimating the force at the fingertip using optical sensors leaves the hand free because the sensors are installed on the arm. In addition, since the sensors do not require pre-pressure to be applied, they remain comfortable during measurement and do not interfere with human movement. Hence, optical sensors are suitable for analyzing sports movements that use the hands. However, because muscle force estimation using optical sensors is affected by changes in muscle length due to exercise, force estimation accuracy may be low when analyzing sports movements with large changes in arm posture.

C. Research Objectives

In this study, it is verified whether fingertip force estimation is possible even when playing sports with large arm movements using optical sensors and IMU. It is known that combining methods such as EMG and FMG with IMU improves accuracy in gesture estimation [38]– [40]. These studies show that the use of arm posture data measured by IMU is effective, and it is assumed that the use of IMU together with muscle deformation sensors will improve the accuracy of force estimation. Fingertip strength was chosen as the target of estimation in this study because fingertip strength and hand strength have been analyzed by many researchers [12], [18], [20], [30], [31], [34]– [37]. In addition, optical sensors were selected as muscle deformation sensors for the following reasons.

1) The optical sensors are worn on the arm, so it does not interfere with hand-related sports activities.
2) Optical sensors do not require pre-pressurization and remain comfortable when installed.
3) Proven fingertip force estimation in static conditions.
4) The optical sensing method is resistant to perspiration.
5) Optical sensors are inexpensive.

In the experiment, the fingertip force is estimated from the index finger to the thumb, respectively, and compared with and without the IMU. In addition, the case where a saline solution is applied to the skin, assuming perspiration during sports will be examined.

II. SYSTEM

The system developed in this study uses optical sensors to acquire the deformation of muscles and estimate the magnitude of the force generated at the fingertips during sports activities. To measure finger movement, the deformation of the forearm muscles, which correlates with finger movement, is acquired using infrared optical sensors. Infrared optical sensors are commonly used for musculoskeletal monitoring [41]– [45] because near-infrared light is strongly scattered when passing through biological tissue [46], allowing the reflected light to contain information from relatively deeper muscle layers. However, measuring muscle deformation alone is insufficient for accurately estimating forces generated by the human body. This limitation arises because muscle tension changes nonlinearly with muscle length [21], and the geometric arrangement of the skeleton and muscles shifts with body posture, altering the direction of force generation by muscles relative to the body.

To address this, a six-axis inertial sensor (IMU) is utilized to measure forearm posture, aiming to build a fingertip force estimation model that accounts for the influence of arm posture. The IMU, which detects changes in rotation, orientation, and axial velocity, is equipped with three translational axes and three rotational axes, forming a six-axis configuration. In this study, the IMU measures the three-dimensional rotation angles of the arm and outputs data in quaternion format to prevent gimbal lock. Consequently, the IMU can provide angle information about the forearm, enabling the estimation of muscle length and internal muscle arrangement changes corresponding to variations in forearm posture.

In this study, a band-type sensor called FirstVR [51], equipped with 14-channel infrared optical sensors and IMU was used as a sensor worn on the forearm. An explanation of FirstVR is shown in Figure 1. FirstVR has previously been used as a sensor to measure muscle deformation in the forearm and has successfully estimated fingertip force using only the optical sensor in conditions where the forearm posture does not change [37]. The single-channel infrared optical sensor on the FirstVR consist of one infrared optical emitter and one receiver. This optical sensor detects the intensity of reflected infrared light at the receiver when the infrared emitted from the emitter is reflected by the skin or biological tissue. Consequently, when skeletal muscles or skin deform, the readings of each optical sensor channel on the FirstVR change. Therefore, the FirstVR can measure deformations in the arm's muscles and skin. The reflected light at the receiver is recorded as 8-bit data, with infrared intensity values ranging from 0 to 255. The IMU on FirstVR outputs data in the form of quaternions of three-dimensional rotations, which represent the posture of the forearm. The arm's reference position is set with the arm positioned in front of the body, perpendicular to the line connecting both shoulders, with the palm facing upward, as shown in the image of step 1 in Figure 4. The quaternion is output as a four-dimensional float data type. The data detected by FirstVR is transmitted to the PC via Bluetooth Low Energy.

Infrared optical sensors and IMU values do not directly represent muscle status. Since hemoglobin and myoglobin absorb near-infrared light [47], [48], the reflection of near-infrared light is influenced by the oxygenation activity of muscles involved in deformation and changes in the reflectance caused by skin deformation [49], leading to complex variations in near-infrared reflectance. As a result, the measurement values from the optical sensors also exhibit complex behavior depending on the state of the muscles. Additionally, muscle output is nonlinear in relation to muscle length [21]. Furthermore, muscle fibers are not always aligned parallel to the muscle; during muscle contraction, muscle bundles spread radially [50], leading to a nonlinear relationship between muscle tension and muscle deformation. Therefore, the relationship between the optical sensor readings of the FirstVR and muscle deformation is expected to be nonlinear, as is the relationship between muscle deformation and fingertip force. To overcome these challenges, the present study employs SVR, a method capable of learning nonlinear models and estimating continuous values, as used in previous research [37], to estimate fingertip force.

An explanation of FirstVR is shown in Figure 1. In this study, Support Vector Regression (SVR) is used to determine the correlation between fingertip force and FirstVR data. The input data for the SVR are the 14-channel infrared optical sensors and the 4-dimensional data of the quaternion output from

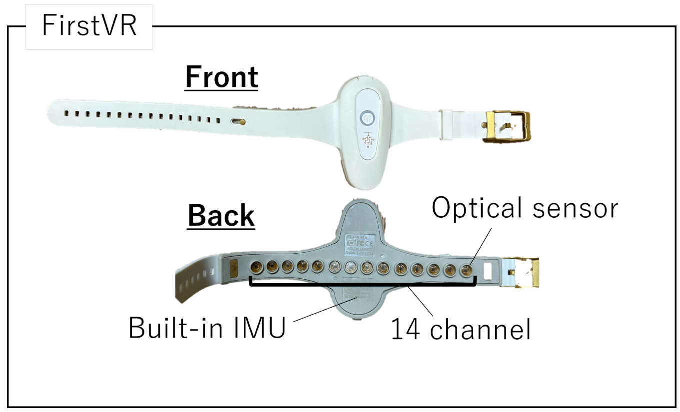

Fig. 1. Device explanation of FirstVR.

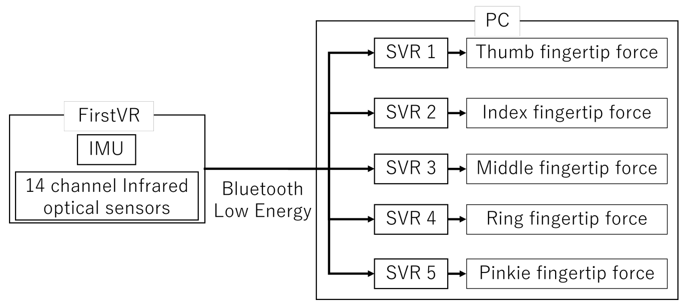

Fig. 2. Fingertip force estimation system in this study.

the IMU, a total of 18 variables. SVR has high regressivity by using acceptable errors and kernel function transformations of the input data, and it is adaptable to complex data structures for a small number of input variables (18 in this study) [52]. Therefore, SVR is suitable for regression modeling of complex models such as muscle deformation with a small number of input data, as in this case. The regression equation $f(x)$ for SVR is as follows.

$$f(\boldsymbol{x}) = \boldsymbol{w}^{\boldsymbol{T}}\phi(\boldsymbol{x}) + \boldsymbol{b}. \tag{1}$$

$\boldsymbol{x}$ is a vector of input data (18 in total, consisting of infrared optical sensor measurements transmitted and IMU data from FirstVR), $\boldsymbol{\phi}$ is a kernel function, $\boldsymbol{w}$ is a vector of weight parameters, and $\boldsymbol{b}$ is a bias parameter. The Radial Basis Function is implemented as a kernel function as follows in order to handle nonlinear data.

$$\boldsymbol{\phi}(\boldsymbol{x}) = exp(-\gamma||\boldsymbol{x} - \boldsymbol{x'}||^2). \tag{2}$$

$\boldsymbol{x'}$ is the mean value of the input training data and γ is a Gaussian function. The objective function $L(w)$ is expressed by the following equation.

$$L(\boldsymbol{w}) = \frac{1}{2}||\boldsymbol{w}||^2 + C\sum_{i=1}^{N} max(0, |y_i - f(x_i)| - \epsilon) \tag{3}$$

To learn the parameters $\boldsymbol{w}$ and $\boldsymbol{b}$, minimize the objective function involving C. ϵ represents the tolerance and penalty for errors. N is the total number of vectors, i is the sample number, and y_i is the target value. $L(\boldsymbol{w})$ is minimized based on Lagrange multipliers with slack variables [53].

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III. EXPERIMENT

A. Subjects

There were 6 subjects (2 females and 4 males) with a mean age of 33.3 (23-40) years. Participants were selected with a minimum of two males and two females to account for differences in experimental results based on gender. Additionally, to avoid potential interference of subcutaneous fat with muscle deformation measurements using optical sensors, only healthy adults with an average body type were chosen. While this study focuses on the analysis of sports movements, prior experience in sports was not a selection criterion for participants. All participants were informed of the experiment and their consent was obtained before the experiment was conducted. Instructions were also provided on how to interrupt the experiment so that participants could stop the experiment at any time. However, the purpose of the experiment was not explained. This experiment was approved by The Japanese Society for Wellbeing Science and Assistive Technology (ID:22-13).

B. Purpose of experiment

The purpose of this study is to estimate the force generated at the fingertips during sports activities by using optical sensors and IMU. Therefore, the following two items should be verified.

1) To estimate fingertip strength when performing sports movements.
2) To estimate fingertip strength in sweaty conditions.

In the experiment on the estimation of fingertip forces during sports movements, it was confirmed that data on fingertip force estimation during movements in which the arm posture changes significantly. Through this experiment, the effect of IMU on estimation accuracy can be confirmed. In addition, since humans perspire during exercise, it is necessary to verify the measurement of force estimation in sweating conditions to analyze sports movements. Therefore, the difference in fingertip force estimation with 0.5 % concentration of saline [54] applied to the skin, simulating sweat, and having nothing applied to the skin, respectively is discussed.

C. Experiment Device and Methods

Figure 3 shows the experiment device. The experiment device consisted of a glove for measuring fingertip force, a data acquisition platform for measuring data from the glove, a PC, a FirstVR, and a Bluetooth module. A pressure sensor (FRS402, Interlink Electronics Inc.) was mounted on the fingertips of the glove to enable measurement of the force generated at the tip of each finger. This sensor has a property where its resistance changes when force is applied, and in the experiment, a voltage divider circuit is used to convert force into an analog voltage signal. This voltage is then converted to digital data by an Arduino UNO (Arduino S.R.L.) based data acquisition platform, with an A/D conversion maximum frequency of 9.6 kHz. The resolution of the pressure sensor for converting data into force is 1 gf, rounding to the nearest tenth. Additionally, the force data obtained from the sensor is transmitted to a PC via serial communication. The data from the FirstVR's optical sensors and IMU were transmitted to the PC through a Bluetooth module (UB500, TP-Link).

In this experiment, it is essential to acquire fingertip force values and muscle deformation data in sync as closely as possible. Therefore, once the PC receives data from FirstVR, it sends an acquisition command to the data acquisition platform for the force information, and the PC then receives the fingertip force data. Using this method, the delay between FirstVR data and force data is kept below 200 µs. Since the data acquisition frequency of FirstVR is 40 Hz, the entire experimental setup also acquires data at 40 Hz.

The experiment was performed according to the following procedure, as shown in Figure 4.

1) Attach the FirstVR and the glove to the subjects on the left arm and the left hand.
2) Record the FirstVR and fingertip force data while playing sports.
3) Integrate the data of all subjects.
4) Split the integrated data into training data and test data.
5) Perform training (SVR) using the training data.
6) Estimates fingertip force using test data with the trained SVR and compares it to the measured fingertip force.

In this study, fingertip force was estimated in kendo, baseball, and golf swinging as sports activities in which the arm posture changes significantly. An overview of each practice swing movement is shown in Figure 5. In this study, data were collected across a variety of arm postures to evaluate whether fingertip force can be estimated by combining forearm muscle deformation with IMU data, regardless of arm posture. To achieve this, three movements were selected: kendo swings, which involve moving the arm above shoulder height; baseball swings, which involve arm movement around shoulder height; and golf swings, which involve moving the arm below shoulder height. These three movements also involve significant forearm motion, allowing for the collection of data across various arm postures. During data acquisition, subjects performed each of the three types of movements once for 45 seconds. In each trial, at least 10 swings were performed. Additionally, a minimum 3-minute break was taken after each movement, which was extended as needed until the participant declared they felt no fatigue.

For data integration, any data where the FirstVR values were negative despite not being expected to be, data with empty fields in the FirstVR readings, or cases where fingertip data could not be acquired due to errors were deemed invalid and excluded from the dataset.All other data points were included in the integrated dataset. The total number of data points was approximately 32,000. In this study, parameter tuning was performed using k-fold cross-validation.

For k-fold cross-validation, commonly used values for k are 5 or 10 [67]- [69]. In methods utilizing support vector machines (SVMs), which employ a calculation process similar to the SVR used in this study, $k = 5$ or $k = 10$ is often recommended [69]. Generally, k values and computational cost have a trade-off relationship [68], so it is preferable to set k as small as possible. Additionally, results for $k = 5$ and $k = 10$ often show little difference [70], and the same trend was

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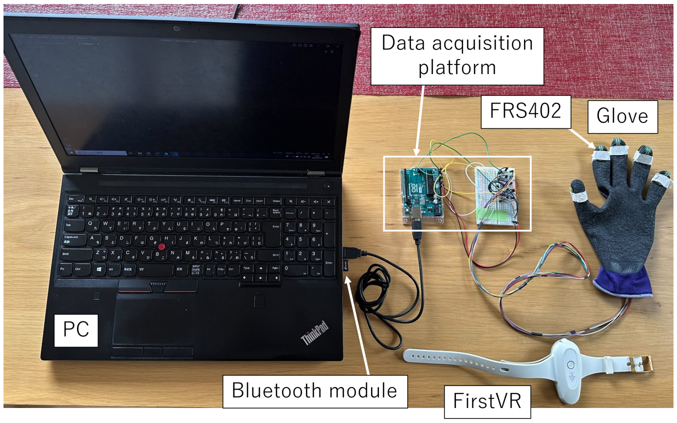

Fig. 3. Experiment device diagram.

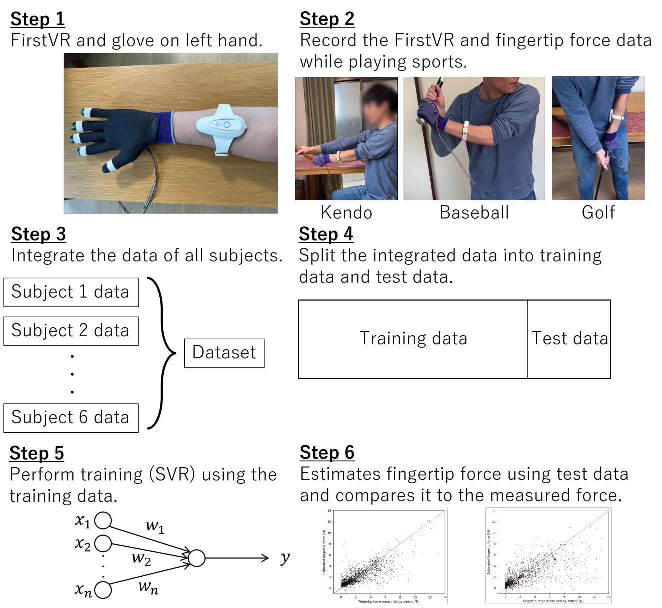

Fig. 4. Experimental procedure.

confirmed in this study. Therefore, this study adopted $k = 5$, utilizing 5-fold cross-validation.

D. Fingertip force estimation during sports movements

In addition to investigating the possibility of estimating fingertip force during sports activities using muscle deformation measured by optical sensors and arm posture data by IMU, the estimation accuracy was checked both with and without the IMU data. SVR was trained using training data from both cases of using only optical sensors and using both optical sensors and IMU, and its regression accuracy was verified.

Figure 6 shows the relationship between the fingertip force measured by the pressure sensor during sports and the estimated fingertip force. The red dotted lines in Figure 6 show that the estimated fingertip force is consistent with the measured values. To verify the regression accuracy, the correlation coefficient, coefficient of determination (R^2), and root mean square error (RMSE) were derived. The RMSE is calculated as follows, where N is the total number of samples, F is the measured fingertip force, and $\widehat{F}$ is the estimated value.

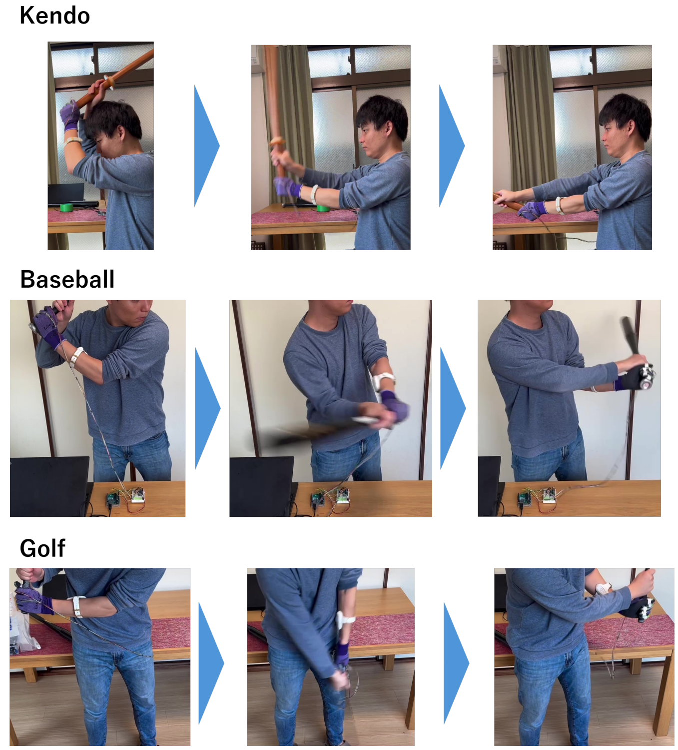

Fig. 5. Practice swing movements in kendo, baseball, and golf.

These results are shown separately for each finger in Table I (with IMU) and Table II (without IMU).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=0}^{N-1}(F_i - \widehat{F}_i)^2} \tag{4}$$

To verify the validity of the correlation coefficients, a statistical test was conducted under the null hypothesis that the correlation coefficient is zero. As a result, the p-values for all correlation coefficients shown in the tables were $p < 0.001$. The experimental results for those using the IMU and optical sensors as input data showed that the coefficients of determination for the measured and estimated force values exceeded 0.5 except for the index finger. The index finger, which had the lowest coefficient of determination, also exceeded 0.49. On the other hand, without IMU, the coefficient of determination was below 0.5 except for the middle finger. In addition, for all fingers, the coefficient of determination was larger and the RMSE was smaller when the IMU was used as input data. Additionally, the correlation coefficients for each finger were examined to determine whether there was a significant difference between cases with and without IMU data. The data with and without IMU were trained using the same dataset, differing only in the utilization of IMU data. Since the ground truth data for fingertip forces was identical, Williams' Test, a commonly used method for testing differences in dependent correlation coefficients, was applied to assess the significance of the differences. The results showed $p < 0.001$ for all fingers, indicating a significant difference in the correlation coefficients between the cases with and without IMU data.

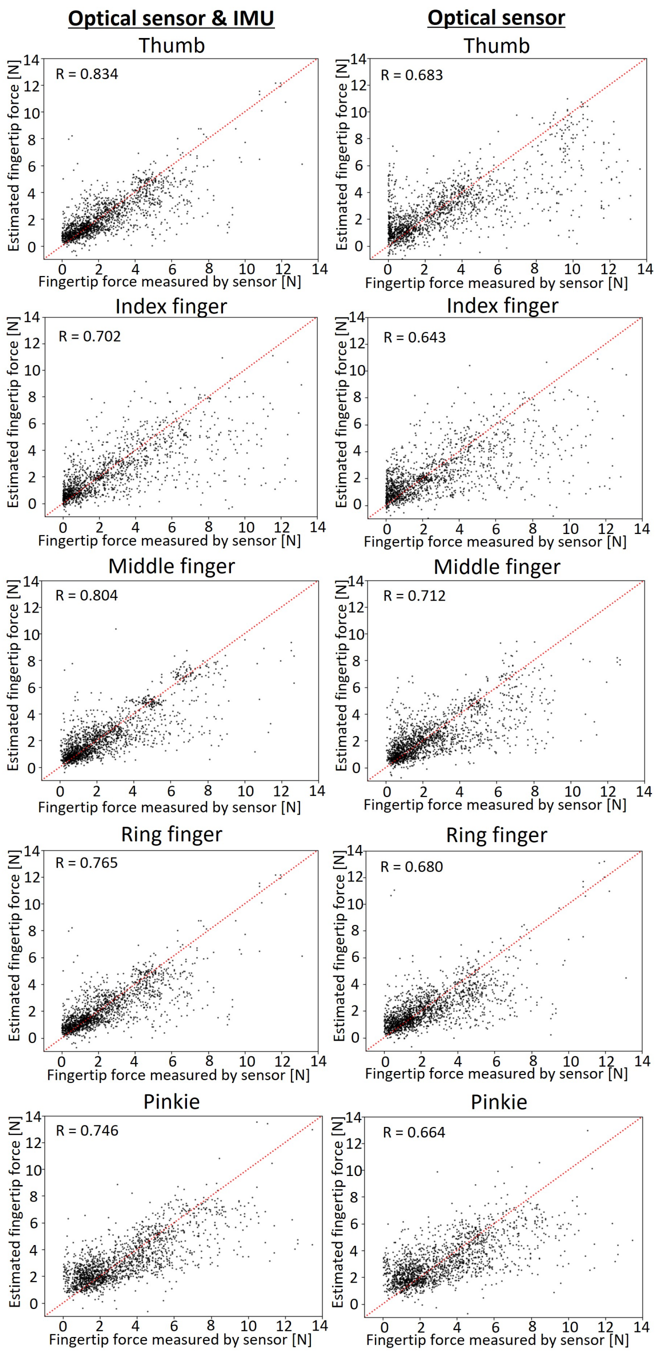

Fig. 6. Relationship between estimated fingertip force and measured values.

E. Fingertip force estimation when sweat is on the skin surface

The accuracy of fingertip force estimation by measuring muscle deformation with an optical sensor when sweat is present on the skin is verified. In this experiment, fingertip force estimation was performed both with and without using the IMU. However, when the subject is in a state of sweating, muscle fatigue occurs, which places a burden on the subject. Therefore, a 0.5% saline solution was applied to the subject's skin to measure the data. The saline solution was applied before the FirstVR was applied, and the application area was the entire circumference of the arm where the FirstVR was applied. Therefore, the optical sensors measured muscle deformation through the saline solution.

Figure 7 shows the relationship between the fingertip force measured by the pressure sensors during sports and the estimated fingertip force with sweat on the skin. The red dotted lines in Figure 7 show that measured values are consistent with measured values, as in Figure 6. In addition, the correlation coefficient, R^2, and RMSE are shown separately for each finger in Table III (with IMU) and Table IV (without IMU). To verify the validity of the correlation coefficients, a statistical test was conducted under the null hypothesis that the correlation coefficient is zero. As a result, the p-values for all correlation coefficients shown in the tables were $p < 0.001$. Even with sweat on the skin, fingertip force estimation using the IMU resulted in larger coefficients of determination and smaller RMSE for all fingers.

TABLE I
RESULTS ON FINGERTIP FORCE ESTIMATION USING OPTICAL SENSORS AND IMU.

Finger	Thumb	Index	Middle	Ring	Pinkie
Correlation coefficient	0.834	0.702	0.804	0.765	0.746
R^2	0.695	0.492	0.646	0.586	0.557
RMSE [N]	1.70	1.95	1.34	1.28	1.56

TABLE II
RESULTS ON FINGERTIP FORCE ESTIMATION USING ONLY OPTICAL SENSORS.

Finger	Thumb	Index	Middle	Ring	Pinkie
Correlation coefficient	0.683	0.643	0.712	0.680	0.664
R^2	0.467	0.414	0.507	0.462	0.440
RMSE [N]	2.25	2.10	1.59	1.47	1.75

IV. DISCUSSION

A. The Force estimation for each finger

To ensure a comparison free from external disturbances, this discussion focuses on experimental results obtained under conditions without the influence of sweat. Additionally, the thumb is discussed separately from the other four fingers, as it has independent flexor muscles. The index, middle, ring, and pinkie fingers are flexed primarily by the flexor digitorum superficialis (FDS) and the flexor digitorum profundus

TABLE III
RESULTS ON FINGERTIP FORCE ESTIMATION USING OPTICAL SENSORS AND IMU WITH SWEAT ON THE SKIN.

Finger	Thumb	Index	Middle	Ring	Pinkie
Correlation coefficient	0.778	0.631	0.732	0.577	0.646
R^2	0.606	0.400	0.537	0.333	0.417
RMSE [N]	1.43	1.74	1.54	1.36	1.61

TABLE IV
RESULTS ON FINGERTIP FORCE ESTIMATION USING ONLY OPTICAL SENSORS WITH SWEAT ON THE SKIN.

Finger	Thumb	Index	Middle	Ring	Pinkie
Correlation coefficient	0.664	0.568	0.587	0.521	0.631
R^2	0.441	0.323	0.344	0.271	0.398
RMSE [N]	1.69	1.85	1.83	1.80	1.74

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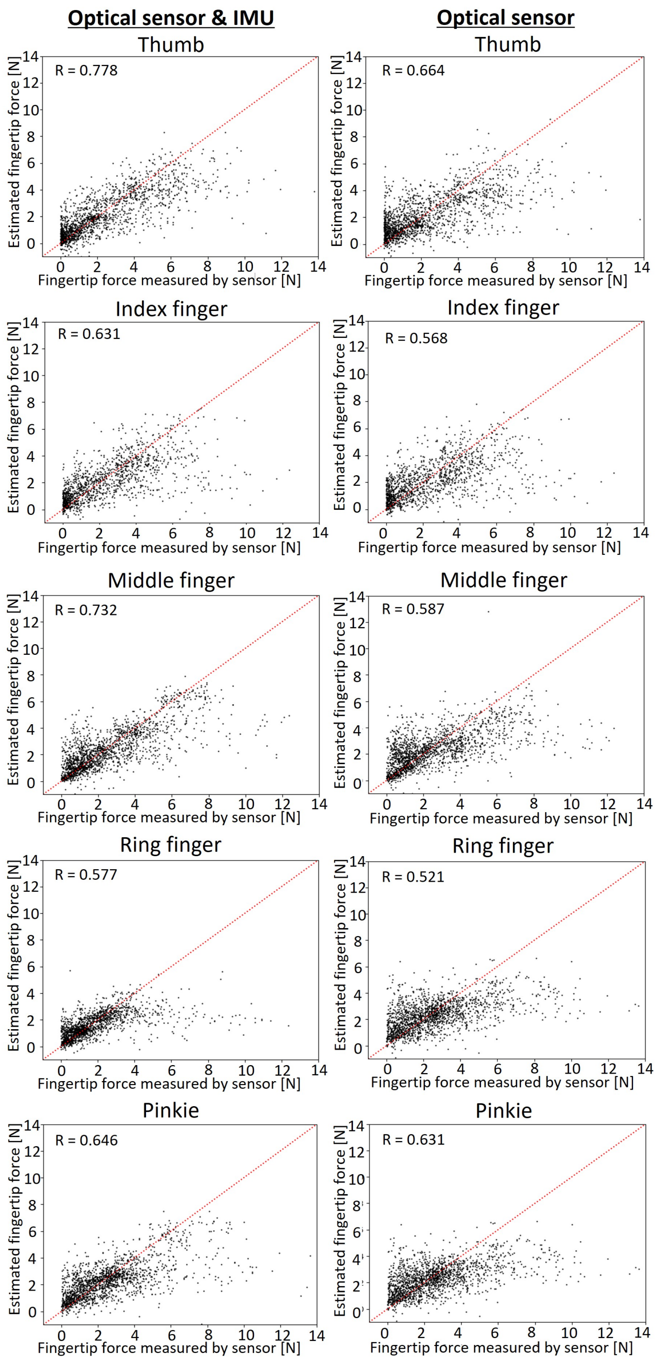

Fig. 7. Relationship between estimated fingertip force and measured values with sweat on the skin.

(FDP). However, the flexion of these fingers is not entirely independent [57]. While FDS and FDP are not completely synchronized, it is known that specific muscle bundles primarily control the movement of each finger [58]. Figure 8, based on the study by Franziska et al. [58], illustrates the arrangement of these muscle bundles responsible for finger movement alongside the placement of the FirstVR optical sensors. This Figure is a cross-sectional diagram of the forearm, with labels indicating the muscles involved in finger flexion. The optical sensors measure muscle deformation, capturing information from both superficial and deeper layers. However, due to their reliance on reflected light, they are likely more sensitive to the properties of superficial layers. Based on Figure 8, it can be inferred that the optical sensors ch1 and ch2 correspond to the pinkie finger, ch2, ch3, ch5, and ch6 correspond to the ring finger, ch6, ch7, ch8, and ch9 correspond to the middle finger, and ch9, ch10, and ch11 correspond to the index finger. Additionally, the relative positions of muscles vary across the channels of the optical sensors. As a result, the muscle deformation data recorded by each channel likely represent a composite of deformations from multiple muscles, each contributing with varying weights. By calculating the relationship between differences in information from adjacent sensors and the forces of each finger, it becomes possible to extract deformation data specific to the flexion of individual fingers. This approach enables accurate estimation of individual finger forces, even in the context of complex, multi-muscle movements. However, individual differences, such as variations in arm thickness and muscle development, may introduce discrepancies, potentially reducing the accuracy of fingertip force estimation.

When comparing the correlation coefficients for the index, middle, ring, and pinkie fingers using IMU and optical sensors, it is observed that the correlation coefficients follow the order: middle finger > ring finger > pinkie finger > index finger (Table I). From Figure 8, The muscle bundle that moves the index finger is located further away from the epidermis than the muscle bundles that move the other fingers among the major muscle bundles for finger bending. Since the acquisition of muscle deformation in this study is performed by optical sensors, it is considered that more information about superficial muscle deformation is captured compared to deep muscle deformation. Therefore, it is challenging to accurately capture muscle deformation located farther from the epidermis, resulting in the index finger having the lowest correlation coefficient among all fingers. On the other hand, the muscle bundles that move the middle and ring fingers are particularly located near the epidermis, resulting in a more accurate measurement of muscle deformation and a higher correlation coefficient. The muscle bundle that moves a pinkie finger is also located near the epidermis. However, Franziska et al. mention that some subjects may not show clear activation of the pinkie finger muscle bundle, and the pinkie finger is less independent than the other fingers [58]. Hence, the relationship between muscle deformation and pinkie finger force estimation is lower than for the middle and ring fingers, presumably resulting in a lower correlation coefficient for the pinkie finger than for the middle and ring fingers. Thus, the estimation accuracy of fingertip force estimation using optical sensors for muscle deformation measurement and IMU is considered to be higher in the order of middle finger > ring finger > pinkie finger > index finger.

B. Improvement in Grip Force Estimation Accuracy Using IMU

First, the differences between the cases with and without IMU are discussed. Comparing the RMSE, an index to evaluate the error between measured and estimated values, for

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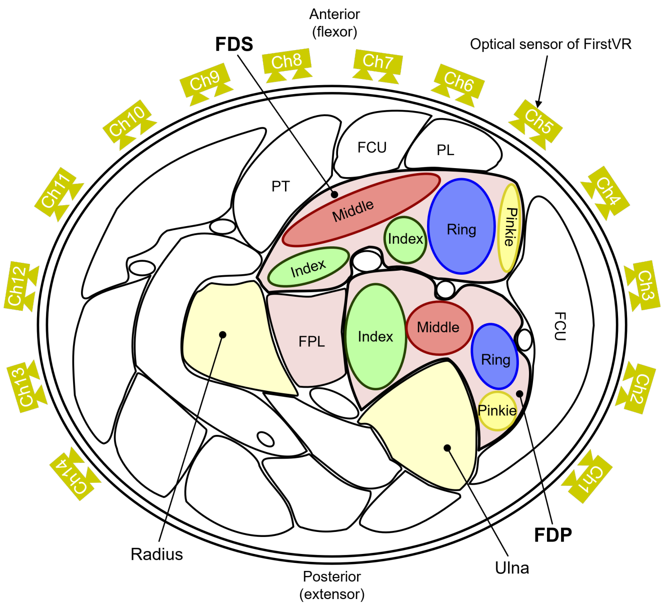

Fig. 8. The arrangement of muscle bundles controlling the flexion of each finger and the placement of the optical sensors are based on F. L. Hodde et al., 2019 [58].

each finger using Table I–IV, the RMSE was smaller for the model with IMU, both with and without the effect of sweat. Additionally, the correlation coefficients with and without the use of the IMU showed $p < 0.001$, indicating a significant difference. Furthermore, the coefficient of determination, a measure of the accuracy of the prediction model, was higher using the IMU regardless of the effect of sweat, as was the RMSE. The comparison of these two indices shows that the regression model with IMU has smaller errors and higher regression accuracy than the model without IMU.

The maximum grip strength is known to vary depending on the angles of the elbow and wrist [55]. This is primarily because the flexor digitorum superficialis (FDS) and flexor digitorum profundus (FDP), which are responsible for finger flexion, connect the finger bones to the humerus, radius, and ulna. As a result, flexion, extension, pronation, and supination of the elbow and wrist alter the muscle length and configuration, leading to nonlinear changes in muscle output as the muscle length varies [21]. Additionally, changes in muscle length cause nonlinear variations in muscle deformation, making it difficult for optical sensors to distinguish between deformation caused by muscle tension and those resulting from changes in posture.

Using an IMU to measure the posture of the human body facilitates the estimation of muscle configuration and length. Muscle length, which significantly impacts muscle deformation, is geometrically determined by musculoskeletal models [56]. By utilizing the IMU to measure the three-dimensional angles of the forearm, it becomes possible to obtain a more accurate understanding of the geometric state of muscles like the FDS and FDP, thereby accounting for the nonlinear patterns of muscle deformation. By integrating posture data from the IMU with muscle deformation data obtained via optical sensors, it is possible to differentiate between posture-induced deformation and muscle-tension-induced deformation. This integration ultimately enhances the accuracy of fingertip force estimation under dynamic and diverse posture conditions.

Additionally, the configuration of forearm muscles changes with pronation and supination of the forearm. Figure 8 illustrates the relationship between the arrangement of muscle bundles responsible for flexing each finger and the optical sensors. During pronation or supination, it is expected that the muscle configuration rotates and shifts according to the forearm's posture. Consequently, the optical sensor channels corresponding to each finger are likely to change. Since the IMU measures the forearm's posture, it can capture pronation and supination movements. Therefore, by adjusting the referenced optical sensor channels based on the IMU data, it is possible to achieve more accurate fingertip force estimations for each finger.

The correlation coefficient of the thumb was not as high as that of the other fingers when the IMU was not used (Table I), but the correlation coefficient was the highest when the IMU was used for estimation (Table II). The muscle deformation measurement using the optical sensors in this study is not effective at measuring muscle deformation at a position far from the epidermis. The flexor pollicis longus muscle (FPL), which flexes the thumb, is located farther from the epidermis than the FDS and the FDP, which flex the other four fingers. Hence, force estimation at the fingertip of the thumb by muscle deformation is considered more difficult than for other fingers. Nevertheless, the highest correlation coefficient was obtained by using the IMU because the FDS and FDP muscle deformations due to arm posture were partially canceled by combining the IMU data, and the FPL muscle deformations were estimated more accurately from the arm surface muscle deformations than when the IMU was not used. The above results suggest that the IMU can be used to construct a model that takes into account changes in muscle deformation when the arm posture changes, and that the use of the IMU can improve the accuracy of motion estimation in general.

C. The impact of sweat on grip strength estimation using optical sensors

To begin, this discussion examines the differences in the impact of 0.5 % saline solution and sweat on optical sensor measurements. Sweat plays a crucial role in regulating body temperature during activities such as exercise and is essentially a filtrate of plasma. Its primary component is water, with trace amounts of substances such as sodium, chloride, potassium, and lactate [60]. During exercise, the concentration of sodium chloride increases, reaching up to approximately 0.4 % by weight [61]. Generally, an increase in solute concentration in water results in a higher refractive index. However, even in a 1.0 % saline solution, the refractive index differs from that of pure water by only about 0.3 %, which is negligible [62]. While sweat contains components other than sodium chloride, their concentrations are minimal [61] and do not significantly influence the refractive index compared to water. Thus, 0.5 % saline solution is considered a suitable substitute for real sweat, with a negligible impact on experimental results.

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When comparing the coefficients of determination for each finger, it was found that the coefficients were smaller when sweat was present on the skin compared to when it was not. On the other hand, no trend was observed in RMSE. The coefficient of determination is one indicator of the regression performance of SVR, and the fact that the coefficient of determination is reduced by sweat means that sweat has a negative effect on the measurement of muscle deformation and fingertip force estimation by the optical sensors. The data from the optical sensors of one channel when a subject was swinging a baseball bat with and without sweat, and the results of the Fourier transform of the two data are shown in Figure 9. The two optical sensors in Figure 9 are the same channel. Baseball swinging is a cyclic exercise, indicating that cyclic muscle deformation data is acquired by the optical sensors when there is no sweat. On the other hand, when sweat was present on the skin, there was little periodicity in the data. The Fourier transform results show that the spectral intensity was small when sweat was present. The cause of this phenomenon was that some of the infrared optical used by the optical sensors were diffusely reflected by sweat on the skin surface, reducing the accuracy of the muscle deformation measurement. Therefore, it is assumed that the accuracy of the fingertip force estimation decreased because the data that should have been acquired could not be acquired partially due to sweat.

D. Analysis of HGC Applicability and Dataset Bias

Hand Grip Control (HGC), which represents grip control ability, is typically evaluated at 30–70 % of the Maximum Voluntary Contraction (MVC), the maximum force a muscle can exert [55], [63], [64]. This evaluation range is adopted for several reasons. First, assessments using maximum MVC output pose risks of excessive stress on muscles and tendons, making such tests challenging to conduct safely for participants. Additionally, maintaining conditions near the upper limit of MVC can increase intramuscular pressure, restricting blood flow and reducing oxygen supply, thereby compromising the endurance and stability of muscle tension [63], [65] , [66]. It has been reported that grip forces exceeding 50 % of MVC lead to oxygen levels in the muscle reaching a lower limit with no further changes [63]. Even at 10 % MVC, prolonged exertion can adversely affect muscle strength [65]. These factors indicate that higher MVC levels significantly impact grip endurance.

An examination of the dataset reveals that individual fingertip force maxima range between 10N and 15N, with over 90 % of the data being below 6N. This suggests that most of the collected data corresponds to forces below 50–60 % of MVC. This trend can be attributed to sports swinging motions, where maximum grip force is not continuously applied, and the majority of the movement involves lightly gripping the object. From the perspective of HGC practicality, the predominance of data below approximately 50 % of MVC is natural, and its impact on the applicability of this study is minimal.

However, the bias in the dataset may have influenced the learning outcomes. Specifically, as data above 6N accounts for less than 10 % of the total, the insufficient training data for higher force levels might have limited the regression accuracy. Nonetheless, as previously mentioned, collecting data near the upper limits of MVC is challenging. Therefore, studies focusing on fingertip force estimation at outputs near MVC would require experimental setups distinct from those aimed at evaluating sports-related movements, as in this study.

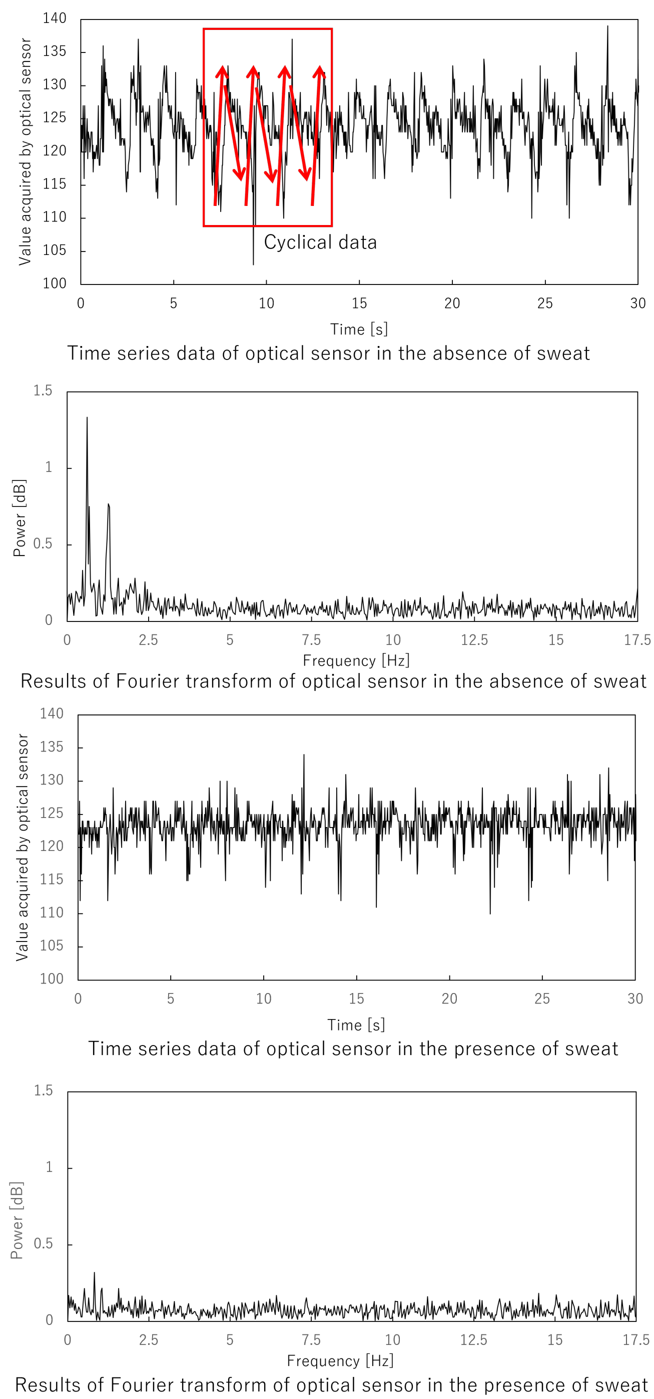

Fig. 9. Optical sensor data with and without sweat and Fourier transform results.

E. Impact of Experimental Conditions on Force Estimation

In this study, participants were selected regardless of their previous experience with the target sports. In addition, the objects used for the swinging motions, the bat, the golf club, and the wooden sword, each featured different gripping methods. As a result, inconsistencies in data collection may arise due to the variability in swing stability and grip techniques, potentially leading to reduced force estimation accuracy. Furthermore, differences in the shape and weight of the swinging objects could influence muscle deformation patterns, adding complexity to the analysis.

On the other hand, this study successfully collected and analyzed data under a wide range of conditions, enabling the development of a highly versatile force estimation model capable of adapting to diverse scenarios. Such an approach is expected to serve as foundational data for motion analysis across various situations. Moving forward, more detailed analyses targeting specific motions and grip techniques, combined with the integration of refined models, are anticipated to further enhance estimation accuracy.

F. Limitations of This Study

The first limitation is related to device constraints. The study utilized FirstVR, a device integrating muscle deformation sensors and an IMU. While this device is convenient and easy to use, it is limited to measuring only the posture of the forearm. To more accurately capture changes in muscle length and arrangement caused by body posture variations, it would be necessary to measure the posture of the upper arm and wrist as well. However, increasing the number of measurement points may lead to a more complex and less user-friendly system. Balancing ease of use with high-accuracy estimation will require careful consideration and innovation in future research.

The second limitation concerns the estimation of forces near the MVC. Near MVC levels, data collection is challenging, and muscle output tends to be unstable. Consequently, the current method, which does not rely on prior data, may not account for the effects of muscle fatigue, potentially limiting its applicability for estimating forces near MVC. To address this, approaches that incorporate past force estimation data to model fatigue-induced reductions in muscle output could be considered to enhance estimation accuracy near MVC levels.

V. Conclusion and Future Work

In this study, a FirstVR equipped with infrared optical sensors and an IMU was used to estimate fingertip force during movements involving significant changes in arm posture and the application of a saline solution, simulating sweat during sports activities. The results showed experimentally that the accuracy of fingertip force estimation was increased by using an IMU to measure arm posture and optical sensors to measure muscle deformation. In addition, the possibility that the accuracy of the estimation was increased by using the IMU to indirectly measure changes in muscle length due to arm posture, suggests that the use of the IMU may be generally effective in estimating human body output using sensors that measure muscle deformation. Furthermore, it was demonstrated that some finger forces can be estimated when sweat adheres to the skin, although the diffuse reflection of optics from the sensors due to sweat reduces the accuracy of the estimation.

Future work is described. In this study, muscle deformation was measured by wrapping a band around the arm, but it may be more accurate to measure muscle deformation by placing the sensors at an angle to the arm, as in the UnlimitedHand [59]. Therefore, it will be confirmed whether the accuracy can be improved by using sensor arrangements that measure muscle deformation more precisely. In addition to sports, the social implementations of this study will be promoted by applying it to the analysis of craftsmen's movements, such as knife handling during cooking and hand usage by craftsmen, as well as to rehabilitation.

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