A Soft Robotic Glove Providing Proprioceptive Feedback for Grip Force Regulation Training

Abstract— Inadequate regulation of grip force during tennis strokes contributes to wrist and elbow overuse injuries by elevating joint loading and reducing stroke efficiency. Existing sensing systems can quantify grip dynamics, yet most training approaches rely on visual feedback, which increases cognitive demand and limits proprioceptive learning. This work presents a soft robotic glove system integrating a six-axis load cell and pneumatic actuation to provide proprioceptive haptic feedback for grip-force regulation training. The glove delivers real-time, magnitude-specific feedback that complements natural sensation without interfering with motion execution. A user study compared haptic and visual feedback modalities during force regulation tasks. Results showed that haptic feedback produced a slower learning rate but improved retention, with an average RMSE reduction of 39% during training and performance maintained within 20% of the target force during retention. These findings demonstrate that pneumatic haptic feedback can enhance long-term motor memory consolidation and adaptability. The proposed system offers a promising framework for soft robotic training interfaces in sports performance, motor rehabilitation, and human–robot interaction.

I. Introduction

Tennis elbow is a common and serious concern among tennis players. Repetitive exposure to high forces and unnatural arm positions during strokes subjects the muscles and tendons to excessive torque, often resulting in wrist and elbow injuries such as tendinopathy and lateral epicondylitis. Approximately half of all tennis players experience such injuries, with an even higher prevalence observed among recreational players [1].

Among the key risk factors, excessive grip pressure is one of the most prevalent. During play, a tight grip stiffens the wrist, reducing its ability to absorb shock and adapt to stroke variations, which can lead to microtrauma at the tendon origin [2]. Continuous co-contraction of the forearm muscles can also disrupt the kinetic chain, making it difficult to perform smooth, natural strokes and thereby increasing the mechanical load on the forearm and the likelihood of injury. The risk becomes greater during off-center impacts below the racquet's longitudinal axis, where excessive grip pressure produces high eccentric wrist extension torques and forced wrist flexion [3]. A tight grip has also been directly linked to improper wrist flexion, a major contributing factor to lateral epicondylitis. Conversely, an overly loose grip compromises racquet stability, which may induce wrist tendinopathy and reduce overall performance. Skilled players can effectively regulate grip tightness before and after ball contact through a refined grip strategy that balances grip type, pressure, and timing.

To address the challenges associated with grip force regulation, this paper introduces a visual-haptic training system, a novel approach that integrates a soft-robotic glove as a haptic feedback device with an EMG-informed assist-as-needed (AAN) control mechanism. The soft-robotic glove provides real-time feedback on force magnitude while preserving proprioceptive awareness during performance. Grounded in the augmented feedback hypothesis, this multimodal feedback design is expected to enhance motor learning and retention efficiency beyond what can be achieved through visual feedback alone.

Although several studies have assessed grip pressure in tennis, approaches that deliver real-time feedback to players remain unexplored [4]. In practice, athletes still rely largely on subjective judgment or outcome-based coaching. Recent sensing technologies such as pressure sensors, load cells, and EMG enable a precise objective assessment of force regulation from both muscle activity and the resultant forces, which is crucial because the grip force cannot be observed directly. Visualising these data gives players external cues to detect errors and adjust technique [5], [6]. However, motor learning theory emphasizes that skill acquisition hinges on the formation of internal models that link sensory feedback to motor commands. If training relies too heavily on external information (e.g. constant visual displays), performance can degrade once those cues are withdrawn, and novices may experience cognitive overload. Consequently, it is important to complement visualization with haptic feedback that supports force regulation while preserving natural sensorimotor integration.

Despite advances in haptics, there is a gap in conveying force-magnitude information relevant to grip regulation. Many wearable and robotic systems provide spatial or temporal cues via vibration or pressure based actuators, or deliver assistance, but these signals do not replicate the proprioceptive/ kinaesthetic information people use to modulate continuous grip force. To address this, we propose using a soft-robotic glove that delivers magnitude-specific, proprioceptive haptic feedback. Robotic gloves have been increasingly employed in motor learning and rehabilitation. Various designs, including rigid exoskeletons [7], [8], robotic actuation systems [9], [10], and pneumatic gloves [11], have been developed to facilitate the training of fine motor skills such as dexterity and pinch-force control, often through visually guided interaction tasks. Exoskeleton-based systems primarily target joint kinematics but often face challenges related to fit, alignment, and user comfort. In contrast, soft pneumatic gloves have been extensively investigated for rehabilitation applications, such as providing passive repetitive assistance or facilitating mirror therapy. Even when force sensors are included [11], these systems are typically compensatory rather than designed for active force-regulation training.

For tennis, this distinction matters. Prior glove systems commonly sense fingertip forces (e.g., FSRs), which suit pinch or tripod grasps (picking up a pen or book). During tennis strokes, players employ power grips characterized by multiple contact regions and dynamic finger configurations, resulting in force distributions across the palm and along the racket handle. Fingertip measurements alone therefore underestimate whole-hand force and its distribution.

In our system, a six-axis load cell embedded in the instrumented handle measures net grip forces and moments for task execution and visualisation, while a pneumatic glove delivers haptic feedback to support active training of grip-force regulation under ecologically valid, racket-specific loading conditions. This work is aimed to introduce this visual-haptic soft robotics training system with all sensor and device calibration and characteristic. A case study was conducted to demonstrate the functional capability of the proposed system.

II. Design and calibration of the training system

We developed a prototype Tennis Racket Grip Training (TRGt) system designed to provide haptic feedback conveying force magnitude information for grip-force regulation tasks. The overall system design is shown in Fig. 1. In this setup, a six-axis force/torque sensor was integrated into the racket handle to measure grip-generated forces and torques. Compared with conventional methods that rely on pressure mats to measure grip force, the proposed approach enables a more comprehensive analysis of how human-applied forces induce kinematic changes in the racket. It also provides high–temporal-resolution force profiles and allows the acquisition of vibration data for subsequent analysis. Two Delsys Trigno sensors (EMG+IMU) are mounted over Extensor Carpi Radialis Brevis (ECRB) and Flexor Carpi Radialis (FCR) to capture muscle activity and local kinematics. The Delsys API was used to stream data from Trigno Centro sensors. The signals were resampled to 1200 Hz and processed using selected control algorithms to generate different feedback modes, including ANN haptic feedback, spring damping haptic feedback, and visual feedback. The model output was processed by the soft robotic glove controller to generate haptic feedback and by a graphical user interface (GUI) to provide visual feedback.

Fig. 2(A, B) illustrates the sensor implementation and the pneumatic control system used in the proposed setup. The load cell is embedded inside the grip and mounted to

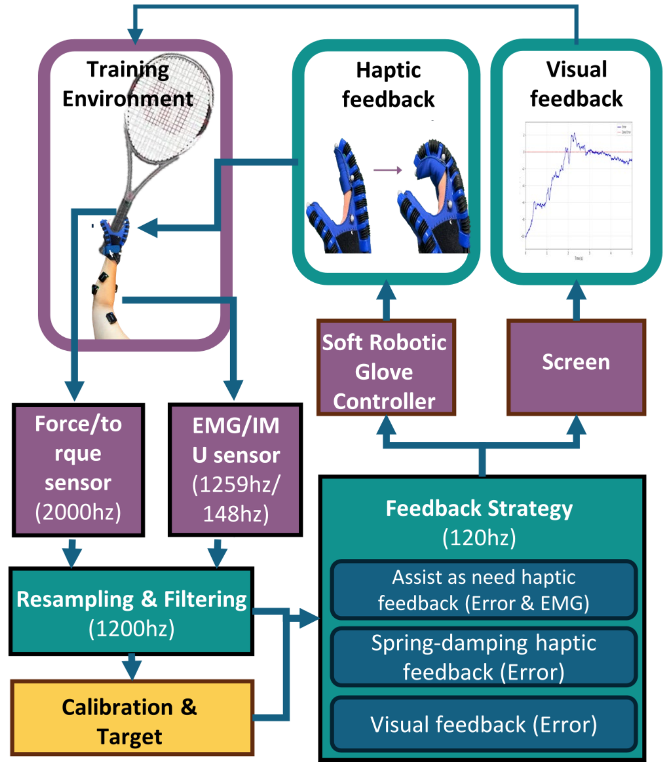

Fig. 1. Overall design of system and dataflow. A Schunk SI 125-3 six-axis load cell (Schunk, Germany) was interfaced with a Miodaq USB-6451 data acquisition device (National Instruments, USA) to record force and torque signals at a sampling rate of 2000 Hz. Surface EMG and IMU signals were acquired using a Delsys sensor system, where the EMG channels operated at 1259 Hz and the IMU channels at 148 Hz. All data streams were collected on a PC, resampled, and synchronized with a fixed delay of 30 ms to enable real-time processing. The resampled data were then processed according to the desired feedback mode, generating control commands at 120 Hz. These output signals were transmitted to both the soft robotic glove and the Unity environment to provide haptic and visual feedback, respectively.

measure both the normal pressure force and the torque generated during twisting motions. Surface EMG sensors are placed on the forearm over the extensor and flexor muscle groups to monitor muscle activity related to grip force generation. The sensor placement is shown in Fig. 2(C), where one sensor detects activity in the extensor group and the other in the flexor group, the two primary muscle groups responsible for grip control. Haptic feedback is provided through the pneumatic glove Fig. 2(D), where the chamber pressure for each finger can be controlled within a range of −100 kPa to 200 kPa. The pneumatic control of the glove is achieved using a pressure regulation system that enables precise and stable control. During tennis play, various grip styles are used depending on player preference and technical requirements Fig. 2(E), which may result in different load cell responses. Thus, we compared the effect for force detecting using western grip styles and continental grip style. In continental grip style, the thenar web space of the player would face 5th bevel of the grip and have

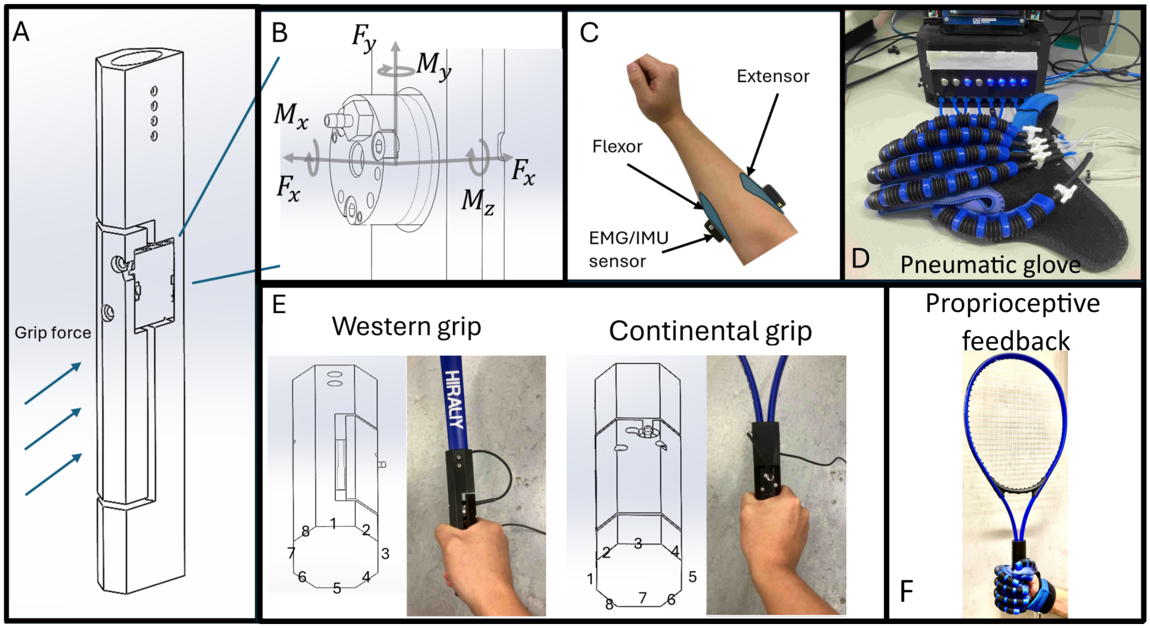

Fig. 2. Devices included in the training system. (A, B) A six-axis force/torque sensor is embedded inside a 3D-printed tennis grip, with the measuring head connected to a pad contacting only the sensor surface. (C) Surface EMG sensors are attached to both sides of the forearm, targeting the flexor and extensor muscle groups (illustrated in blue). (D) A pneumatic glove provides haptic feedback and is connected to a pressure regulator (VEAB-B, Festo, Germany). (E) The two grip styles. (F) Participant with assistant glove.

index finger on bevel 6 and 7 where the force could mainly come from the flexing of index finger and thumb. When performing the western grip, the thenar web space of player would face bevel 7. Fig. 2(F) shows the setup during training.

A. Calibration and characteristic

1) Characteristic of EMG: In this study, a force–torque sensor was implemented inside the grip, and a characterization of this newly integrated sensing method was conducted. The characteristics of the sensor measurements were compared with EMG data to validate the system's performance. Therefore, a calibration procedure and analysis of EMG activity were performed. First, participants were asked to perform their maximum voluntary contractions (MVC) for the flexor and extensor muscles separately, repeating each contraction three times. The EMG signals were recorded and subsequently converted into root mean square (RMS) values using the following equation:

$$\mathrm{RMS}\{x\} = \sqrt{\mathrm{MA}_T(|\mathrm{BP}\{x\}|^2)} \tag{1}$$

where MA_T represents the mean average over the time period T, and BP denotes the bandpass filter (20–450 Hz) applied by the Delsys sensor. The RMS values obtained during the MVC periods were averaged and saved as $MVC_{extensor}$ and MVC_{flexor}, respectively. For each participant, the RMS values during the experiment were normalized using these reference values and expressed as a percentage of MVC ($\%MVC$). Fig. 3 illustrates the relationship between the RMS amplitude

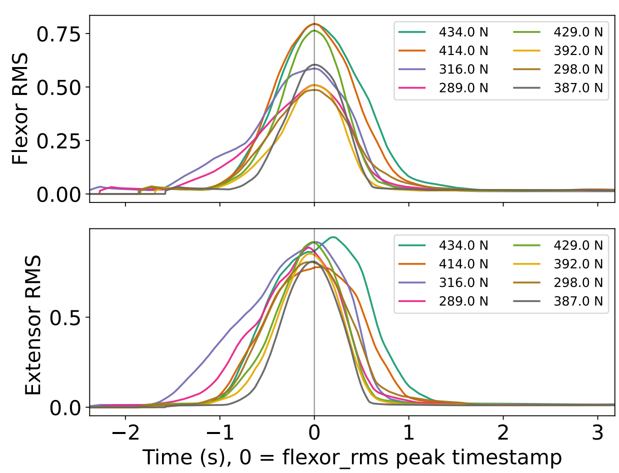

Fig. 3. RMS of extensor and flexor during the maximum grip force measurement

change during the maximum grip force measurement test.

A regression analysis was conducted using RMS_{max} to estimate the force that generated. The equation for the regression is set as:

$$F_{estimate} = a * RMS_{flexor} + b * CCI + c \tag{2}$$

The flexor muscle group is primarily responsible for generating force during a power grip, whereas the extensor muscle group contributes mainly to stabilization [12]. The co-contraction index (CCI), where c denotes a constant, quantifies the simultaneous activation of agonist and antagonist muscle pairs. Increased co-contraction

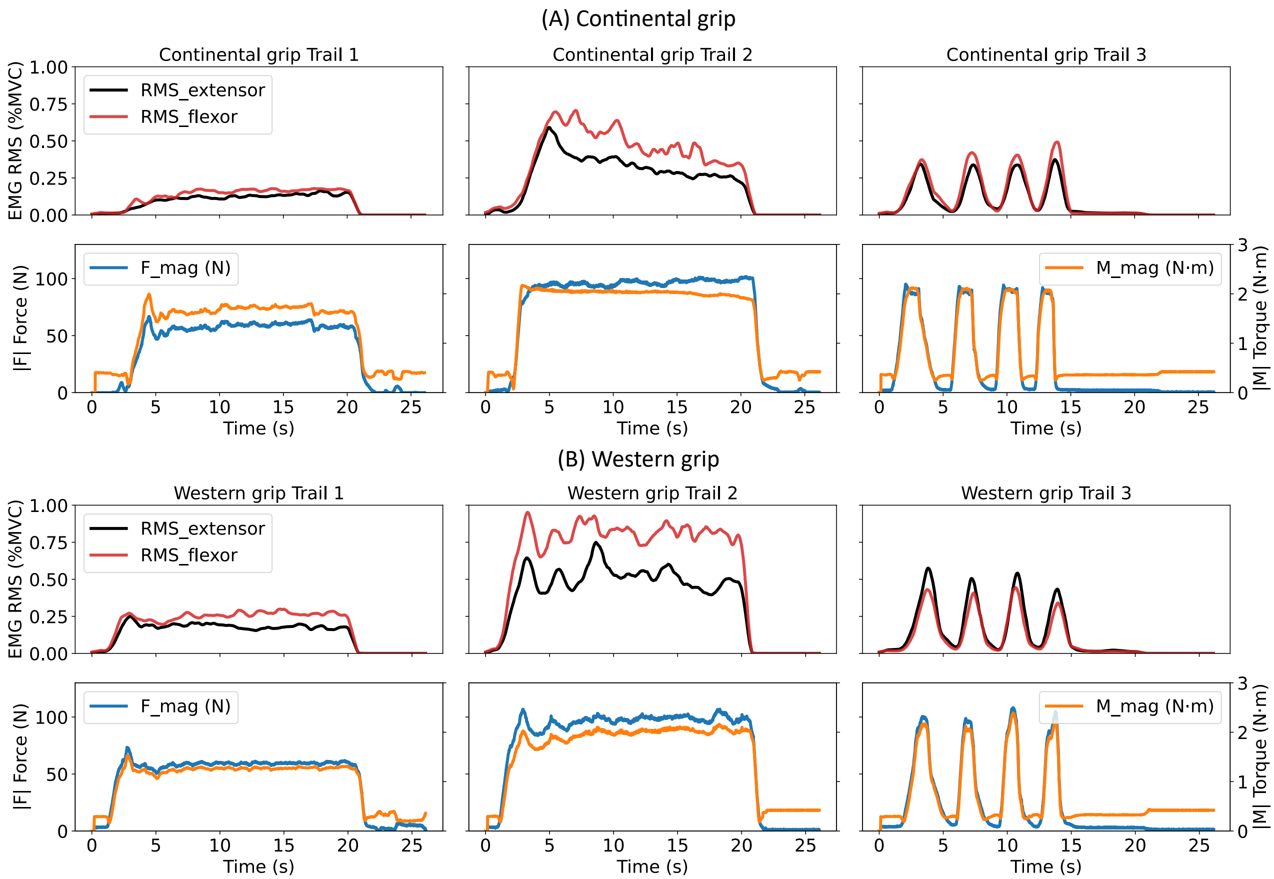

Fig. 4. Comparison between continental (A) and western (B) grip styles. In Trials 1 and 2, participants were instructed to regulate the resultant force magnitude ($|F|$) to 60 N and 100 N under visual guidance. The blue line represents the measured force output, while the orange line indicates the corresponding moment generated during the task. In Trial 3, participants repetitively varied their grip from minimal to maximal force.

enhances joint stiffness without necessarily increasing the net output force, as both muscle groups exhibit elevated activity. The CCI is calculated using the equation proposed by Falconer and Winter:

$$CCI = \frac{2 * RMS_{low}}{RMS_{low} + RMS_{high}} \tag{3}$$

A least square optimization is used to calculate coefficient a, b and c. With regression model the RMS trail have been used to predict the force generated in the whole trail. The regression RMSE is 22.24 with R2 equals to 0.89.

2) Characteristic of force torque sensor: To investigate the relationship between force output and muscle activity, a comparative analysis was performed across different grip styles. Each participant was instructed to produce target resultant force magnitudes ($|F|$) of 60 N and 100 N, as well as to perform trials involving transitions from a relaxed state to a maximal power grip. The corresponding force profiles are shown in Fig. 4. In both subplots A and B, the blue line represents the target normal force ($|F|$), and the orange line denotes the resultant moment magnitude ($|M|$). The upper panels of each trial illustrate the RMS variations in muscle activity, which generally correspond to changes in force output. The average directions of the resultant force and moment vectors across trials are summarized in Table I.

TABLE I
Direction vectors of force (F) and moment (M) for two grip styles under 60 N and 100 N load conditions.

Condition	Force (F)	Moment (M)
Continental		
60N	$[0.066, -0.282, -0.932]$	$[0.536, -0.002, 0.435]$
100N	$[0.075, -0.351, -0.921]$	$[0.551, 0.096, 0.412]$
Western		
60N	$[-0.071, -0.275, -0.949]$	$[0.598, 0.237, 0.281]$
100N	$[-0.014, -0.332, -0.928]$	$[0.501, 0.301, 0.255]$

From Fig. 4, it can be observed that achieving the target $|F|$ values required moments of comparable magnitude across grip styles. During the 60 N target trials, the average torque was 1.8 Nm for the continental grip and 1.5 Nm for the western grip. When the target force increased to 100 N, the average peak torque for both grip styles was approximately 2 Nm. Across all trials, the RMS torque of the continental grip remained lower than that of the western grip. Additionally, EMG data

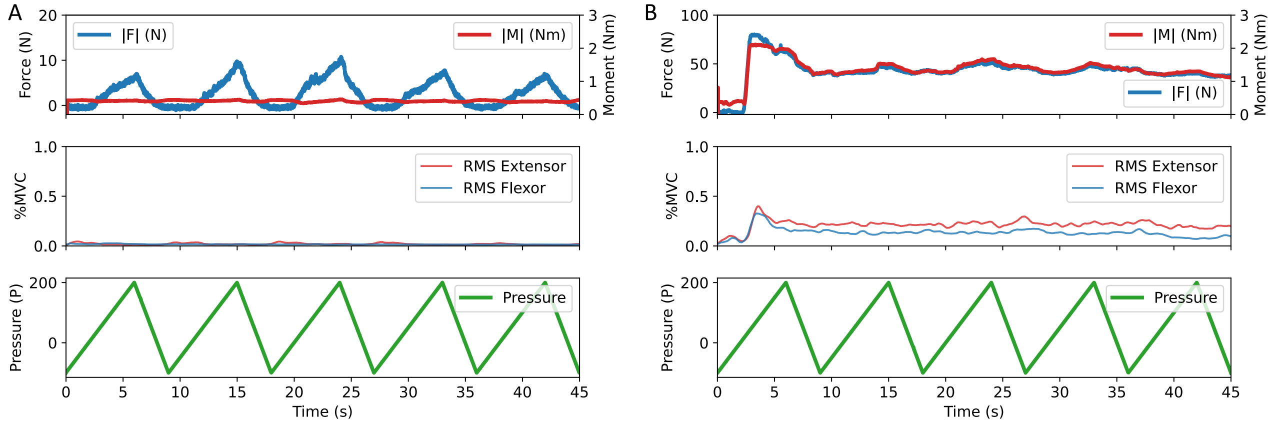

Fig. 5. Calibration of the pressure–force coefficient. (A) Participants maintained a relaxed grip while wearing the pneumatic glove. The top panel shows the force and torque variations detected by the sensor, the middle panel illustrates muscle activity that remaining near zero during relaxation. The bottom panel displays the cyclic pressure changes. (B) Participants performed a tight grip while the glove pressure was repeatedly varied between –100 kPa and 200 kPa. The middle panel indicates increased muscle activation corresponding to the pressure modulation

indicated greater flexor muscle activation when using the western grip compared to the continental grip, suggesting higher muscular effort associated with this configuration.

As shown in Table I, the magnitude of $|F|$ was similar for both grip types, but the torque vector $|M|$ exhibited a major difference in direction between the two grips.

3) Characteristic of pneumatic glove: Building upon the previous calibration results, the relationship between EMG activity and the measured force and torque was clearly established. In this section, we evaluate how variations in glove chamber pressure influence the corresponding force sensor readings. The calibration was conducted under two grip conditions: a relaxed grip and a tight grip. During both procedures, the pressure within the glove chambers was cyclically varied between −100 kPa and 200 kPa, as illustrated in the pressure–force diagram in Fig.5.

In the relaxed-grip calibration Fig.5(A), when the chamber pressure was below 0 kPa, the hand was extended and did not contact the handle, resulting in no measurable force output. Once the pressure exceeded 0 kPa, a distinct increase in grip force was observed, while no substantial change in RMS muscle activity was detected. The average maximum force recorded under this relaxed condition was approximately 15 N. The coefficient describing the relationship between chamber pressure and force generation during this phase was determined as $C_{increase} = 0.075$, $F = P * C_{increase}, 200 > P > 0$.

In tight grip condition, the force $|F|$ change, pressure change and RMS change is shown in Fig.5(B). However, when voluntary contraction is conducted, it's difficult to distinguish the force change generate by glove and the force change caused by muscle control vibration. The regression model built in last section is used to estimate the force that generate with muscle, with the subtraction is the estimated force change caused by pressure change

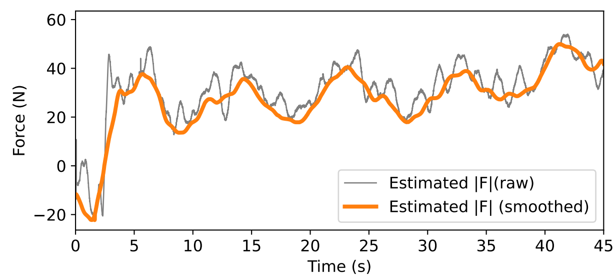

Fig. 6. Illustration of the difference between EMG-predicted force and measured force during cyclic pressure changes in the glove. Under the tight-grip condition, a regression model was applied to estimate voluntary force output from EMG signals, enabling separation of force variations induced by voluntary motion from those caused by glove pressure fluctuations.

of pneumatic glove. The decrease of force is calculated with following equation with $C_{decrease} = 0.13$, $F = P * C_{decrease}, 0 > P > -100$.

B. Feedback Design

Both visual and haptic feedback were employed in this study to guide participants during the training tasks. To provide intuitive feedback based on the collected sensor data, the following representation methods and control functions were implemented.

Visual Feedback: Force feedback was visualised as a real-time line graph displayed using python plotting GUI with a refresh rate of 20 Hz. The target (desired) force was represented by a stationary horizontal line, while the measured force was plotted dynamically in real time, allowing participants to continuously monitor their grip performance. A tolerance band of $\pm 2.5\%$ around the target force was also displayed to indicate the acceptable range of force error.

Haptic Feedback: The haptic guidance followed an ANN principle, providing corrective feedback only when the participant's performance deviated from the target. The direction of the feedback force was set opposite to the error direction, in contrast to error-augmentation methods that amplify deviations. The desired feedback force was determined using both the force error and the rate of change of the EMG signal, which reflects the participant's voluntary muscle activity. The base control law for the feedback force was defined as:

$$F_{d_{\text{error}}} = -K(e)e - B\frac{de}{dt}, \tag{4}$$

where $K(e)$ is the stiffness gain and B is the damping coefficient. An adaptive modulation factor $\gamma \in [0, 1]$ was introduced to scale the feedback according to voluntary EMG activity:

$$F_d = \gamma \times F_{d_{\text{error}}}, \tag{5}$$

where γ reflects whether the EMG change corresponds to a corrective (appropriate) or erroneous (opposite) effort. This adaptive scaling allows the system to reduce haptic assistance when the participant is voluntarily correcting the error, thereby promoting motor learning. A guidance-free zone of $\pm 2.5\%$ around the target force was implemented to ensure that participants could still perform voluntary corrections without continuous haptic intervention.

III. Case Study

A. Experiment protocol

The first task in the case study involved a force regulation experiment, in which a target pressure was predefined and participants were instructed to modulate their grip accordingly. The task consisted of three stages: (1) relaxation with the control system deactivated, (2) relaxation with the control system activated, and (3) active contraction with the control system activated. The assistive force range of the pneumatic glove was between –20 N and 15 N; therefore, the target force was randomly set around 10 N within this range.

The second part of the case study involved force regionalization training under different feedback conditions, divided into training and retention phases. During each training trial, participants held the racket with wrist support and adjusted their grip force in response to auditory and visual cues indicating the target force. Feedback was triggered when the force error exceeded 2.5% of the target. Each trial lasted 10 seconds, followed by a 10-second rest and a non-feedback test. After six training trials, participants rested for 2 minutes before completing the retention test, during which only terminal feedback was provided. After the retention phase, the target force was randomly changed to a new value between 20 and 100 N.

B. Result

The results of the first task are presented in Fig. 7, and the outcomes of the force regulation training with haptic feedback are shown in Fig. 8. In this trial, the

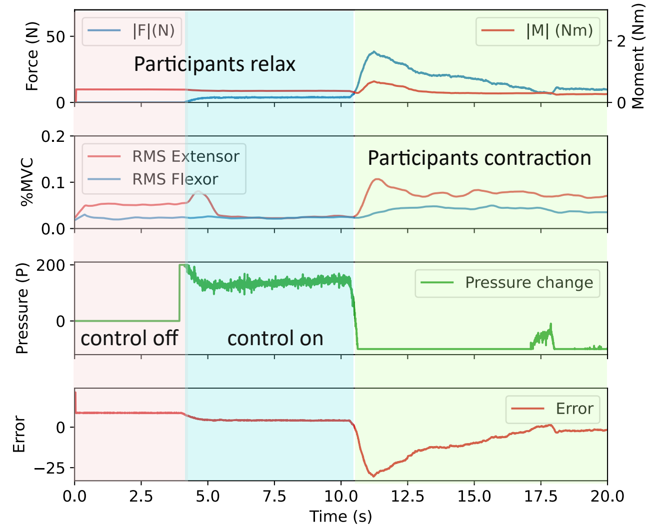

Fig. 7. Force regulation task with glove assistance. The top panel illustrates changes in the resultant force magnitude ($|F|$) measured by the force/torque sensor during the glove-assisted regulation task. The second panel shows corresponding muscle activity, highlighting the phases of relaxation and gripping. The third panel presents the chamber pressure profile, which was modulated to compensate for force error. An overshoot near the end of the trial corresponds with the trend observed in the error data shown in the bottom panel.

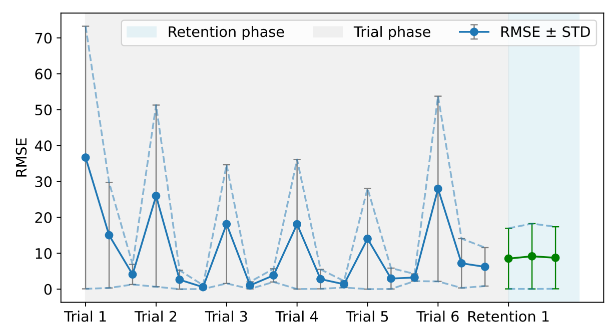

Fig. 8. Training and retention results from the force regulation experiment with haptic feedback. Each trial consisted of baseline, training, and non-feedback sessions. Performance across trials was quantified using RMSE, with standard deviations indicated. Retention tests were performed after the training phase without feedback.

target force was set to 40 N. The root mean square error (RMSE) during the baseline, training, and non-feedback trials was analyzed, yielding an overall average error of 20% of the target force.. The mean reduction in RMSE from baseline to training trials was 39% of the target force., while the reduction between training and non-feedback trials was 3% of the target force.. During the retention trials, the mean RMSE was 20% of the target force.

The results of the force regulation training with visual feedback are presented in Fig. 9. In this trial, the target force was set to 50 N. The overall average error across all trials was 19.9% of target force. The mean reduction in RMSE from baseline to training trials was 36.6% of

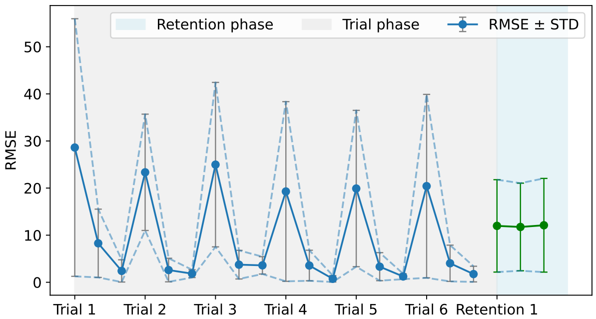

Fig. 9. Training and retention results from the force regulation experiment with visual feedback. Each trial included baseline, training, and non-feedback phases. Retention tests were conducted after training without feedback.

the target force., which was greater than that observed in the haptic feedback group. The reduction between training and non-feedback trials averaged 4.3% of the target force., while the mean RMSE during retention trials was 23.6% of the target force .

The findings of this study demonstrate the feasibility of using a soft robotic glove as a haptic feedback modality for force regulation training. In particular, the retention outcomes from both visual and haptic feedback conditions support the initial hypothesis: visual feedback facilitates faster learning, whereas haptic feedback yields superior retention. These preliminary results lay the groundwork for future large-scale studies involving multiple participants to further evaluate learning efficiency and long-term retention in force regulation training. One major limitation of the current system is the limited force output of the glove, which could be improved through enhanced actuator and glove design. Another limitation lies in the absence of surface force sensing on the grip, which would enable more accurate estimation and prediction of applied forces.

IV. Conclusion

This study demonstrates how a haptic–visual feedback system can be used in motor learning researches. By varying feedback across modalities, we observed how differences in error representation caused changes in learning process. While this work focused on behavioural outcomes, the collected EMG data offers potential for future studies on motor command modelling and understanding how different error presentations influence sensorimotor processing in the brain.

ACKNOWLEDGMENT

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