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Amplifying Force-Feedback Cues for Enhancing Dexterous Skill Transfer in Virtual Environments

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Abstract— **How to teach sensorimotor skills in haptic virtual environments is a classic research question and has been investigated with different target skills and strategies. In this study, we studied how to assist users by *modulating* haptic sensations in the learning environment, presented via a force-feedback haptic device. We developed a haptic amplification method and evaluated its effectiveness on skill training with the target skill of needle felting. To this end, we initially collected the force profile data captured from an expert's job and amplified the magnitude of force to be felt clearly. Then, the augmented haptic sensations were rendered in the virtual learning environment. We assessed the usefulness of our method by conducting a user study with 24 participants performing virtual needle felting tasks involving many micro-movements. As a result, amplified force profile feedback significantly improved the novice participants' learning performance. Based on the results, we then discussed how we can provide an adequate haptic feedback method on learning tasks, especially in fields requiring precise dexterous or tool movements.**

I. INTRODUCTION

For a long time, the skills of master craftsperson are considered as "know-hows" which could be acquired after experiencing several years. How to teach such dexterous skills has been a classic research question in not only education, but also engineering fields. It includes not only instructing correct motions and actions, but more about fine details regarding skills. Thus, it is regarded that modeling and rendering sensorimotor skills involves multisensory cues and coordinating fine proprioceptive movements of body parts.

Haptic feedback, such as resistance, texture, and impact, plays a particularly important role in supporting novice learners' understanding and control in many fine motor skills. For example, in surgical training, interaction forces vary according to tissue properties, and such haptic cues can be modeled to provide haptic guidance [1]. This so-called *sensorimotor skill transfer* has been investigated in the haptics field in the recent few decades. Various target skills have been attempted, such as handwriting practice [2], [3], musical training [4], medical skill acquisition [1], [5], [6], and upper-limb motion training [7]. Those prior efforts mostly relied on the *haptic guidance* strategy [8], providing force or vibrotactile cues to guide users in the target task along with audiovisual rendering. In addition, various feedback strategies beyond traditional haptic guidance have been explored, such as *haptic disturbance* and *hybrid* approaches. These include vibrotactile error-correction [4], distracting force cues [9], and a hybrid method [10] that combines guidance and disturbance.

The perceptual characteristics of haptic sensation are also important in such experiences. Considering the limited information capability of haptic channel (maximum of a few bits, according to [11]), the most widely used strategy is providing simple error-correction mechanisms, demonstrated in training scenarios involved in sensorimotor skill-learning [1], [4], [5], [7], [10]. Such skill training systems mainly considered the user's task performance by defining error metrics such as distance or timing errors and providing error-correction feedback to let users fix them by themselves.

In this study, in contrast, we rethought the problem from a different perspective. We hypothesized that sensorimotor skill acquisition could be achieved by becoming accustomed to action-generated sensations, and that clearer, more pronounced haptic feedback can accelerate learning by reducing reliance on explicit guidance. Accordingly, we hypothesize that amplifying task-related tactile sensations improves learning outcomes, particularly in tasks requiring fine motor control. Although magnified haptic feedback has been explored in scenarios such as surgical tasks to enhance perceptual sensitivity [12], the use of such feedback as a strategy to facilitate sensorimotor skill learning still remains a research question. In this work, we focus on amplifying task-related force profiles derived from expert demonstrations to make subtle interaction cues more salient during training. We selected needle felting [13], a craft of shaping wool by repeated needle insertion, as it requires precise control of insertion depth and angle.

We initiated the study by collecting "know-how" about the skill from a few experts using a structured interview. Then, we recorded the target sensation via a 6-Degrees-of-Freedom force/torque (6DoF/FT) sensor and built force profiles that would be transferred to the novice learners. Using the measured force profiles, we generated force profile for effective force cues in the virtual environment as the cues provided during skill training. Thus, we designed and compared three types of force profiles—weakened, original, and amplified—and analyzed how each feedback type affects skill acquisition.

II. BACKGROUNDS AND RELATED WORK

A. Haptic Feedbacks for Motor Learning

Different haptic mechanisms are utilized in motor learning and skill transfer studies. Transferring virtual tactile sensations through haptic feedback can enhance realism, user

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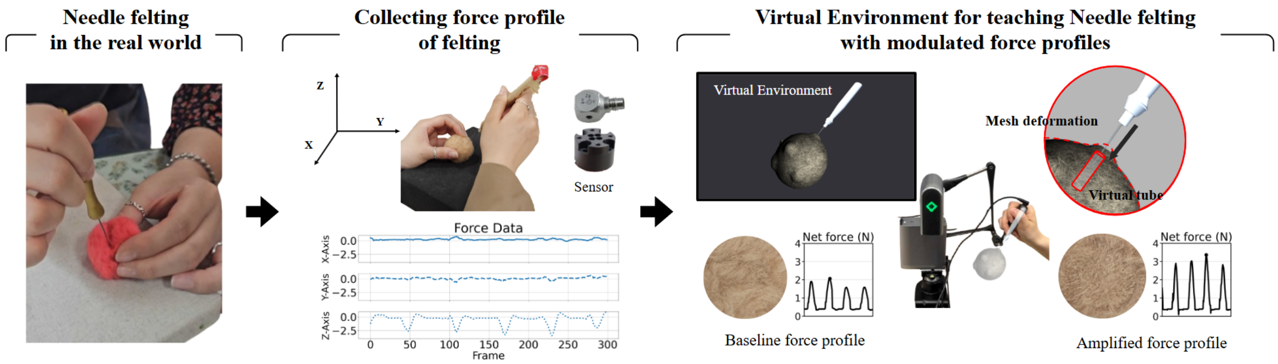


Fig. 1. Overview of the system pipeline. From left to right: (1) Real-world needle felting is performed using wool and a needle; (2) force and acceleration data are collected with a 6-axis force/torque sensor and an accelerometer; (3) based on the recorded data, a virtual felting system enables users to interact through a haptic device, rendering baseline and amplified force profiles.

immersion, and perceived virtual presence in virtual environment [14], [15]. Accordingly, various haptic mechanisms such as electrical stimulation, vibration, thermal, and force-feedback have been continuously employed in multimodal system research [16]. The most widely used one is vibrotactile stimuli, due to its simple implementation and intuitive information delivery.

Vibrotactile cues, which are utilized in various domains such as sports [17], [18], musical instrument [4], and driving [19], are often used to deliver guidance cues indicating the next actions or error-correction cues to help learners notice their mistakes. In drum practice, vibration-based haptic feedback delivers signals to guide playing positions and striking strengths [20]. It is also used in pitch adjustment systems like HapTune, where vibrotactile feedback conveys pitch errors to the user through vibrations on the upper and lower arms [4]. Additionally, providing different textual information through vibration encoding also helped trainees to understand the circumstance [6].

The most classic and intuitive mechanism is force-feedback devices, which enables users to feel the physical properties of virtual objects in a simulated environment through a robotic device [21]. The simulation of part assembly tasks [22], 3D graphics manipulation [22], and rubber engraving arts [23] has utilized the stylus of the desktop haptic devices. Moreover, direct force-feedback cues were used to provide guidance force to the trainees, which is beneficial for tasks requiring precise manipulation and path guidance. Such guidance feedback has been utilized in surgical skill training, and has been shown to aid user's task precision [1]. In handwriting practice, corrective force-feedback is applied when deviating from the path [2]. In VR medical simulators, resistance is simulated during soft tissue penetration [5]. Not only desktop haptic devices, but robotic devices are also deployed in learning. In haptic guidance in welding training scenarios, the robot's haptic guidance improves force control and accuracy [24].

B. Strategies for Haptic Skill Transfer

Skill trainings using visuo-haptic interfaces with the basic *record-and-play* strategy has been studied in early stage [25]. Despite real-world training remaining the most effective method, simulator-based training has proven to positively impact real-world performance [26]. Integrating haptic feedback into audiovisual systems can play a crucial role [27], especially in training precise hand control, such as invasive techniques in surgery [28].

As mentioned in Section I, the classic, typical strategy for skill transfer through haptic force-feedback would be *haptic guidance*, and most studies adopted this to help the users. Haptic guidance may be effective in short-term learning, but its tendency to increase learner dependency may hinder its success as a long-term training method [29]. In contrast, *haptic disturbance*, which distracts or disturbs the users while the training, has been proposed as an alternative [9]. As described by Seidler et al. [30], providing errors helps the trainee's concentration on the task and yields a better performance ultimately. Hybrid approaches, mixing up both haptic guidance and perturbations, have been evaluated and have shown their effectiveness in learning, with scenarios of virtual steering task [10]. Collaboration between two trainees is another strategy for conducting a complex task, demonstrated in [31]. For experts, simply noticing the error is effective, given that those seasoned users know how to correct their errors.

A method so-called error amplification, which emphasizes the errors from the trainee, showed its effectiveness in training scenarios with learners [28], [32], [33]. In addition, recent studies have explored predictive guidance methods based on deep learning technologies [1], [34] as well as adaptive feedback mechanisms that adjust according to the user's performance [35]. Those methods share the idea that adjusting task difficulty—through disturbance or error-based feedback rather than simple guidance—can be more effective for motor learning and skill transfer.

C. Modeling of Motor Skills

Prior to the advent of various haptic feedback strategies, the earliest approach was a record-and-play approach that could imitate expert movements [25]. Capturing, modeling, and transferring human skills to robots is the most basic approach to motor skill transfer. Learners can use it as a simulator to get a sensory transfer of experts' know-how. For example, a leader-follow scheme utilizing a robotic platform

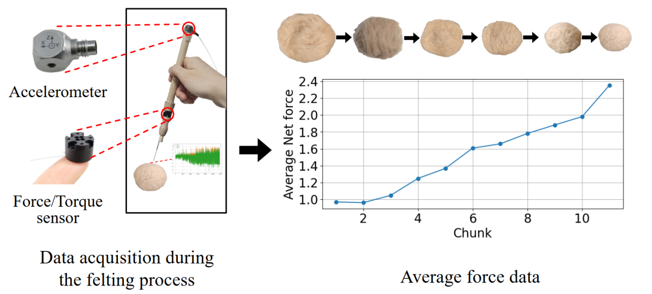


Fig. 2. (Left) The setup for measurement. (Right) The measured net force in needle felting process between data chunks.

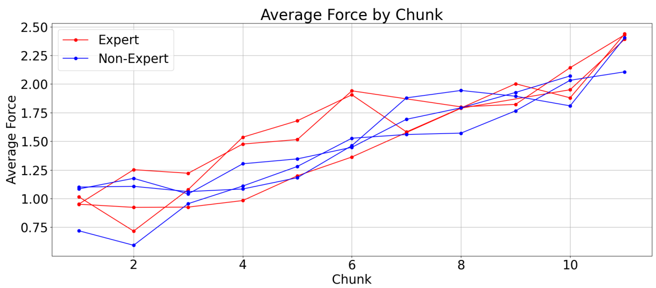


Fig. 3. Average net force in each chunk (10,000 frames).

enables haptic communication, which can be used to convey dance moves [36] or intuitive writing skills [37]. Endo et al. [38] proposed the finger skill-transfer method by modelling the trainer's finger force and position trajectory. Such modeling and rendering is not merely happened between human. For example, robot Learning from Demonstration (RLfD) is an common and effective method for human-robot skill transfer [39].

III. System Design and Implementation

Here, we focused on modulating the environmental feedback—the force profile of the resistance force during felting—instead of applying an error amplification method. We selected the needle felting as the target task. To design and implement the system, we conducted interviews with three female felting experts from the local community, each possessing a minimum of three years of professional experience. Through these interviews, we collected foundational knowledge and general insights regarding the felting process, common errors made by novices, and appropriate task designs for instructional purposes. Then, by reflecting the comments and basic know-how, we developed a needle felting simulation system using a desktop haptic device, presented in Fig. 5. We hypothesized that scenarios involved with fine motor skills, with subtle sensations, would benefit from our approach, which makes the sensation clear and distinct. To provide the amplified sensation to the users, we first collected the force profile using sensors and data acquisition devices (DAQ), and preprocessed the data to generate the amplified profile.

A. Data Acquisition

We gathered the force data to be used in our haptic feedback system in virtual environment via the setup de-

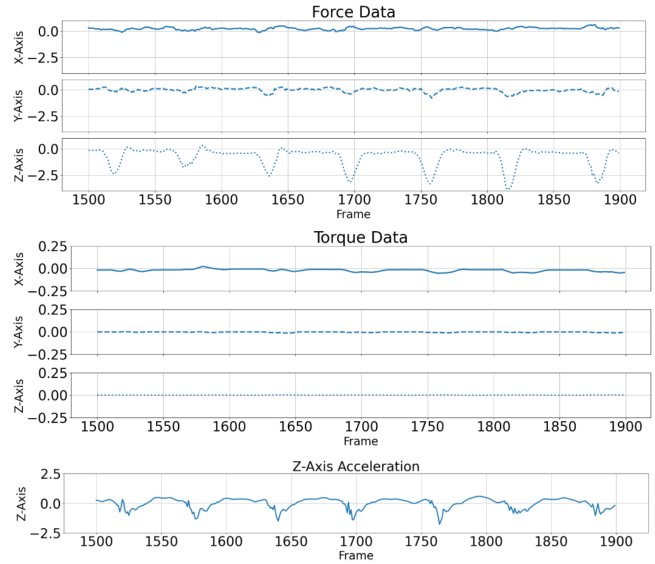


Fig. 4. X, Y, and Z-axis Force and torque profiles and acceleration data extracted from Chunk 1, recorded during needle felting. Z-axis force is the most significant component due to vertical motion of the needle in felting.

picted in the left panel of Fig. 2. An accelerometer (Kistler 8794A)[1] was attached to the tip of the needle, and a six-axis force/torque sensor (6DoF Mini, Aiden Robotics)[2] was placed between the needle and its handle. To observe whether overall force patterns were consistent regardless of felting experience, we measured force data from an expert needle felter (E1) and a non-expert (one of the authors).

To minimize material-induced variability, both participants used the same type of wool and needle, as the degree of felt densification may differ depending on the characteristics of both the wool and the needle [40]. They performed felting on three spherical wool objects (5 cm in diameter, 33 g in weight) until the diameter was reduced to approximately 3.5 cm (Fig. 2, right-top). The trend of material's resistive force was collected throughout the felting process performed at a consistent tempo of 100 bpm. The force data along the x, y, and z axes were collected at a sampling rate of 100 Hz. Across all six wool objects, we verified the consistency of the force data throughout the felting process (Fig. 3).

The accelerometer data, the 6-DoF FT sensor data, and the torque data were collected throughout the felting process, showing consistent patterns (Fig. 4). Torque varied negligibly across trials, consistent with the expert's note that needle felting typically involves straight in–out motion without twisting. Therefore, we considered the torque component to be negligible in the learning context and excluded torque data from the profile modeling. As a result, we utilized force data derived from the averaged profiles shown in Fig. 2 for our implementation.

B. Modeling Force Profile on Haptic Device

As seen in Fig. 2, the resistive force of wool increased as the felting was repeated (material gets compressed). The

[1] www.kistler.com
[2] www.aidinrobotics.co.kr

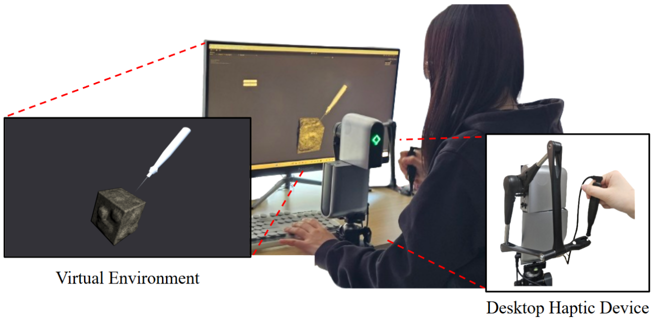


Fig. 5. Experimental setup

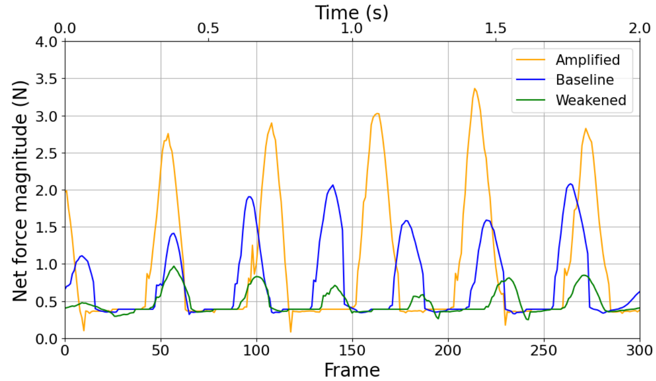


Fig. 6. Net force magnitude recorded during the preliminary study under three force profile conditions (weakened, baseline, and amplified). The signals reflect the rendered force during participants' self-paced interactions.

resistive force was modeled as the stiffness value of the virtual object. The stiffness coefficient K was derived from the force–depth data obtained from expert trials. N is implemented as small random white noise to emulate the micro-texture of uniformly felted wool. This approach ensured that the force profile provided realistic feedback, effectively simulating the unique characteristics of wool fibers. The term $B\mathbf{v}$ denotes a velocity-dependent resistive force during the felting process, where $\mathbf{v}$ is the tool velocity. The gravity compensation factor G is a constant term added to counteract the perceived weight of the device.

Here, we modeled the force components as follows, where Δx denotes the penetration depth of the tool into the virtual wool material. The force profile was formulated as follows:

$$\mathbf{F}_{\text{total}} = \mathbf{K}\Delta\mathbf{x} - B\mathbf{v} + \mathbf{G} + \mathbf{N} \quad (1)$$

C. Learning Environment with Modulated Haptic Rendering

Given that the effect of torque/twist was minimal, 3-DoF force rendering was considered sufficient. Thus, we used a 3-DoF desktop haptic device (Inverse3, Haply Robotics[3]) controlled via a PC for rendering force. The virtual environment was implemented using the Unity 3D (2022.3.7f11) engine (see Fig. 1 (3)).

In this environment, an invisible "virtual tube" was rendered to simulate real-world needle felting tasks. The virtual tube is generated based on the needle's insertion angle at the moment it pierces the wool, ensuring that subsequent felting actions can only be performed along that angle. When the needle contacts the tube boundary, the system detects it as an angular error. The wool object was rendered in a virtual environment, which is 360-degrees rotatable in all directions using the keyboard arrow keys. We specifically care about the insertion direction, as the wool fibers are compressed along the direction in which the needle is driven, to reflect that the quality of felting depends on maintaining the insertion angle consistent. To simulate this effect, our system incorporated mesh deformation of the virtual wool object based on the needle's angle of entry. The virtual wool deformed when a virtual needle (mapped to the device stylus) pierced the object, and its deformation parameters were modeled based on measurements. The simulated environment was evaluated by an expert in needle felting and confirmed the task realism is sufficiently similar to the real-world one.

[3]www.haply.co

D. Initial Validation of Force Profile Modulation

To confirm whether ordinary users' performance is affected by modulated (amplified or weakened) force profiles, we conducted a preliminary study. A total of eight participants (5 females, 3 males, average age 23.8 years) were recruited, all of whom reported no sensory impairments or prior experience in artistic training. Three force profiles were tested: amplified twice, baseline (as-is), and weakened to 50% (see Fig. 6). We selected these levels to keep the manipulation simple while ensuring clear differences between conditions. Participants first completed a 3-minute familiarization session. Each force profile condition was then provided in each of the sessions, which lasts a maximum of 5 minutes. During each force profile condition, participants were asked to perform felting virtual wool to have a specific shape. The task performance was defined as the geometric similarity, the shape difference (distance) between the participant's outcome and the reference shape, scaled in a 0-100 scale.

The task performance was compared in Fig. 7. The amplified force profile showed a generally faster performance rate, but in the later stage, it crossed the baseline and reached a similar level of completeness. In contrast, the weakened force profile showed lower performance throughout the entire duration. Given that the as-is condition would be the baseline in the main experiment, we only compared the amplified and weakened profiles.

We also collected subjective ratings via a post-experimental survey that asks about the modulated profiles, including ease of use, ease of learning, and satisfaction in the usability evaluation tool (USE) [41] questionnaire. The average USE score for the weakened force profile was 6.47 ($SD = 0.53$), while the amplified force profile scored 6.36 ($SD = 0.56$). Considering the overall task performance results, the amplified force profile was adopted for the main experiment.

IV. User Study

The experiment was approved by the Institutional Review Board of the authors' institution (IRB No. HYUIRB-202412-024-1).

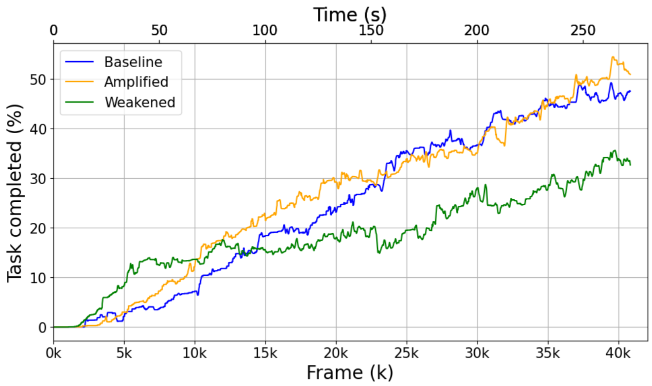


Fig. 7. Performance score average of baseline, amplified, and weakened force profiles.

A. Participants

We recruited a total of 24 participants for the study (12 females, 12 males, 19-27 years old, $M = 22.58$). All participants were considered beginners; they did not have any needle felting experience or only one or two times of experience. The participants were divided into two groups: the Baseline Group (n = 12) and the Amplified Group (n = 12). Written informed consent was obtained from all participants, and each participant received compensation equivalent to approximately 12 USD in local currency for their participation.

B. Setup and Procedure

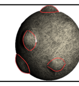
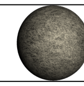
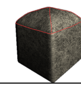
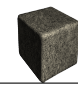
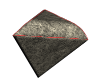
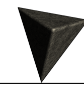
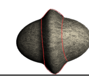
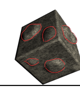
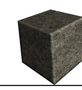
According to the expert we interviewed, a simple felting task in which novices transform a soft spherical wool object into a firm cube can typically be completed within 30 minutes to 1 hour. However, in this study, we did not include the full process of creating a shape from start to finish due to time constraints and concerns about participant fatigue. Although observing the complete transformation would have been ideal for evaluating learning progress, it would have required considerable time and could have placed a burden on participants. Thus, we decided to provide partial tasks of felting after consultation with the experts.

To match the scope of the experiment, the full felting process was divided into five subtasks, each assigned to a separate session. As shown in Table I, the experiment involved six tasks in total. The appropriateness of task difficulty and assignment was reviewed and confirmed by the expert. Task 1 is the most typical and frequent scenario in felting and was used in the familiarization session to help participants become accustomed to the system and practice rotating the object using the keyboard. Tasks 2, 3, and 4 were used in the training sessions and were randomly assigned with balanced difficulty levels. Task 5 and Task 6 were selected to be moderately difficult and used as the immediate and delayed retention tasks.

The apparatus was the same as that used in the initial validation study (Sec.III-D). Participants sat down in front of a desktop computer and Haply haptic device placed in front of the monitor (Fig. 5). In the virtual environment, the stylus

TABLE I

FELTING TASKS IN EACH EXPERIMENTAL SESSION.

Task	Initial Shape	Target Shape	Description
Task 1			(Most frequent)—removing bumps with vertical stabs.
Task 2			(Easy)—flattening the cube's top surface by stabbing straight down.
Task 3			(Difficult)—sharpening the tetrahedron's top edge with precise control.
Task 4			(Moderate)—smoothing the oval surface using curved vertical strokes.
Task 5–6			(Moderate)—refining a rough cube by targeting bumpy and flat areas.

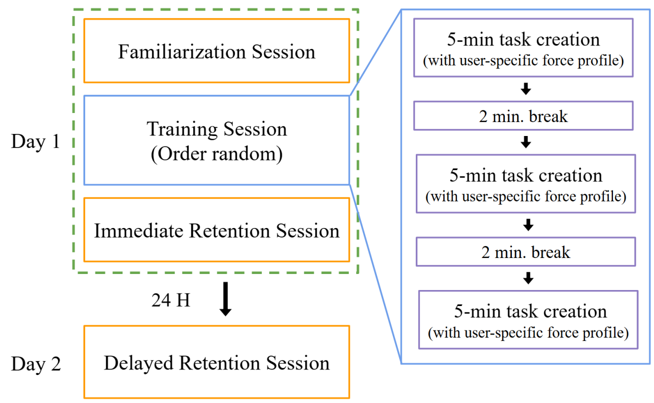


Fig. 8. The procedure of the user study.

of Haply was mapped to a virtual needle, and participants performed felting in the virtual space using the setup.

The flow of the experimental sessions is illustrated in Fig. 8. The familiarization session lasted for 3 minutes, and each of the other tasks was conducted for 5 minutes. A minimum break of 2 minutes was provided between sessions, and the main session lasted approximately 1 hour. The familiarization and training session were performed using the force profile assigned to each group (i.e., the Baseline Group and the Amplified Group). In contrast, both Retention tasks (immediate and delayed) were conducted using the same non-amplified (baseline) force profile for all participants, ensuring consistency in retention evaluation. The delayed retention test was conducted 24 to 48 hours after the initial session, following the recommendation of a review article [42].

C. Data Collection and Analysis

We defined a normalized performance measure as the progress score. Given that (1) both objects are topologically identical and (2) the vertices of the target object are always being pushed by the needle, the moving direction of each vertex is the intended pressing direction in the task. Thus,

TABLE II
STATISTICAL TEST RESULTS ON TRAINING PHASE (1–5) AND RETENTION PHASE (5–6) BY FORCE-FEEDBACK CONDITIONS.

Group	Training Phase (1–5)		Retention Phase (5–6)	
	Statistics	p-value	Statistics	p-value
Baseline Group	$F(4, 44) = 3.893$	0.009^{**}	$t(11) = 0.775,$	0.455
Amplified Group	$F(4, 44) = 1.245$	0.306	$t(11) = -0.138$	0.893

we utilized the absolute magnitude of movement due to the felting. We compared the coordinates of each vertex $k = (x_k, y_k, z_k)$, in the initial ($PI_k = (x_{ki}, y_{ki}, z_{ki})$, the target ($PT_k = (x_{kt}, y_{kt}, z_{kt})$), and the resultant meshes ($PR_k = (x_{kr}, y_{kr}, z_{kr})$). For each vertex, we calculated the distance between the same vertices on each mesh, $|VP_r - VP_i|$, and divided by $|VP_t - VP_i|$ to get normalized progress to calculate the score of a single vertex. For example, if a vertex lies exactly halfway between the initial and the target positions, the score would be 50 (i.e., 50%).

Then, we averaged the scores of all vertices in the mesh to derive each participant's raw progress score. Task-wise normalization was performed by mapping the highest raw score in each task to 100 and scaling the others accordingly.

A more intuitive interpretation is: the scaled progress score of the resultant object was "how far" each vertex has been pushed, by measuring the distance of each vertex of the target. Additionally, to detect whether the participants' moving directions (needle angles) during insertion and ejection were correct or not, we set a cylindrical virtual tube around the correct and counted the number of collisions. After completing all experiments, participants were surveyed using Raw-TLX [43] and System Usability Scale (SUS) [44] to evaluate the system. In addition, a few open-ended questions were included to collect qualitative feedback regarding perceived realism of the virtual interaction.

V. RESULTS

A. Task Performance

The task performance score was normalized to a 0-100 scale, using the highest score within each task set to 100, to compare across tasks and the between-groups' relative performance. The Amplified Group achieved higher average scores than the Baseline Group across all tasks compared to the base force profile (Fig. 9). We first confirmed normality by Shapiro–Wilk tests, then conducted pairwise t-test to determine whether the differences in scores by force profile for each task. The results indicated that the amplified feedback induced a significant improvement in users' performance, especially in familiarization and retention sessions (task 1, 5, and 6, $p = 0.011$, $p = 0.015$, $p = 0.006$, respectively). In Tasks 2, 3, and 4, which are in-training sessions with different difficulty levels, the Amplified Group showed better results but was statistically insignificant ($p = 0.054$, $p = 0.107$, $p = 0.429$, respectively).

To observe learning effects within groups, we additionally conducted session-wise statistical analyses for the training phase (Tasks 1–5) and the retention phase (Tasks 5–6)

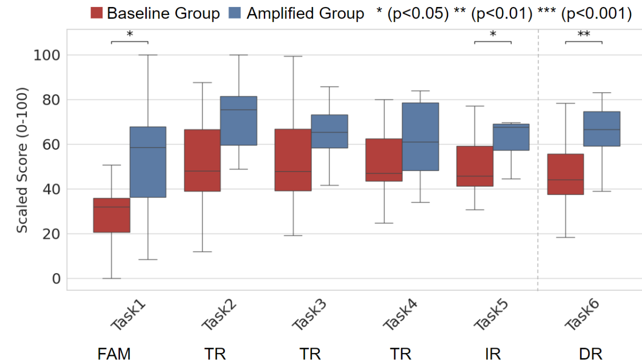


Fig. 9. Task performance scores (normalized) for the Baseline Group and Amplified Group. Asterisk: Statistical significance observed by t-test.

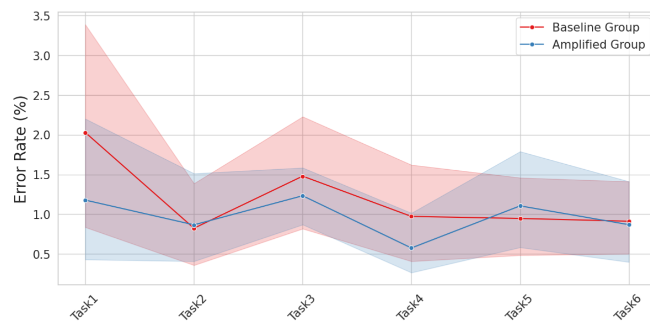


Fig. 10. Error rates across tasks by group.

(Table II). Since normality assumptions were satisfied in both groups, a two-way repeated measures ANOVA was performed for the training phase, and a paired t-test was conducted for the retention phase. Results showed that during the training phase, the baseline group exhibited significant differences ($p = 0.009$), while the amplified group did not ($p = 0.306$). In contrast, no significant differences were found for either group during the retention phase. Post-hoc analysis using paired t-tests with Bonferroni corrections was conducted for the Baseline group's training phase, and effect sizes were assessed via Cohen's d. The analysis revealed that only the comparison between Task 1 and Task 4 remained statistically significant after Bonferroni correction ($p = 0.043$, $d = -1.034$).

Given that maintaining needle angles during insertion and ejection is important, we counted the number of trials in which participants failed to maintain the proper angle. That was done by detecting collisions between the virtual needle and a cylindrical virtual tube around the trajectory. The error rate was the proportion of collisions and was used as an indicator to evaluate whether users maintained the correct needle angle with each insertion. The amplified force profile showed generally lower error rates than that of baseline (Fig. 10), though not statistically significant.

B. Usability Surveys

The SUS scores showed an average of 79.58 ($SD = 16.02$) for the Baseline group and 77.71 ($SD = 15.32$) for the amplified group. The Shapiro–Wilk test confirmed normality for both groups. An independent samples t-test revealed no significant difference between the two groups ($p = 0.772$). The average TLX score was 3.17 ($SD = 1.04$) for the Baseline group and 3.08 ($SD = 0.86$) for the amplified group. As groups satisfied normality, an independent samples t-test showed no significant difference between them ($p = 0.833$). These results suggest that there were no significant differences in usability or perceived workload between the baseline and amplified groups. In addition to the quantitative results, qualitative feedback supported perceived realism; e.g., participants reported that it "feels similar to real felting" (P1) and "like doing actual felting" (P24).

VI. Discussions

The study results demonstrated that amplified force profile induced a better learning performance in dexterous skill training with fine details. Specifically, statistical significance was observed in pairwise comparisons of the familiarization stage (Task 1) and retention phase (Tasks 5 and 6). The tasks in the study were to find the correct depth and angle for needle insertion and ejection using haptic sensations. The effect of amplification were clear, given that these tasks particularly require precise and delicate movements.

The presence of a distinct force cue likely helped participants better identify and reach the exact insertion points on the object with higher spatial accuracy through force amplification. Such an amplification provides clearer sensations induced by the participant's interactions. These clearer sensations may have helped participants better recognize the outcomes of their actions, enabling them to take subsequent steps with greater confidence. In contrast, Tasks 2, 3, and 4 involved felting across relatively wide target areas, where the amplified cues are less effective, since precise localization is not necessary.

Moreover, comparing Task 5 and Task 6—both performed under the same non-amplified force profile—demonstrated that the Amplified Group still outperformed the Baseline Group in Task 6. It means the force profile experienced during training had a long-lasting effect, suggesting that precisely tuned force-feedback not only enhances immediate performance but also supports skill retention. These findings suggest that an amplified force profile can enhance task performance during the learning process and help users acquire skills more easily and effectively. The findings can be applied in many scenarios, including arts, crafting, and precision industries. Modeling such skills and then amplifying them would be a straightforward workflow. Further applications in other domains involving dexterous skills that require fine, object-centered manipulation—such as embroidery or sculpting-where precise tactile interaction with a target material is essential—would be desirable.

The significance observed in the group-wise statistical test (Table II) could be attributed to familiarization difficulty. Following Bonferroni correction, only the comparison between task 1 and task 4 remained statistically significant in the training phase ($p = 0.043$, $d = -1.034$). For a short familiarization in task 1, with limited exposure time, it might be considered too difficult with baseline force profile. However, the significance was not observed with the amplified force profile. It could be interpreted that amplified force profile allows quick familiarization, resulting in statistical insignificance in session-wise comparison in the amplified force group. In contrast, baseline force profile requires a relatively longer familiarization.

Lastly, we mention that we had a limited sample size for this study, including only 12 participants per condition. To generalize and strengthen the findings, it is necessary to conduct a longitudinal study with a larger number of participants using a 6-DoF force profile device. Also, further studies are needed to understand whether the improved performance came from enhanced angle control or cognitive and perceptual factors.

VII. Conclusion and Future Work

In this study, we explored how to provide better haptic cues to enhance users' dexterous skill learning performance in a virtual environment. Specifically, we proposed a method that amplifies the force profile (sensation) for haptic dexterous skill transfer and evaluated its effectiveness via a user study with a target scenario of needle felting. We collected the force profile during the needle felting task and generated its amplified profile, which was implemented in a haptic-based skill training system. The results indicated that the group trained with amplified profiles showed significantly better task performance, suggesting the effectiveness of our method, especially on target tasks with fine and subtle movements. Our future work includes a longitudinal study with a larger number of participants and generalized tasks, as well as a comparison between our approach and existing methods to explore better strategies for skill transfer.

References

[1] P. Fekri, J. Dargahi, and M. Zadeh, "Deep learning-based haptic guidance for surgical skills transfer," *Frontiers in Robotics and AI*, vol. 7, 2021.

[2] A. Teranishi, G. Korres, W. Park, and M. Eid, "Combining full and partial haptic guidance improves handwriting skills development," *IEEE Transactions on Haptics*, vol. 11, no. 4, pp. 509–517, 2018.

[3] W. Park, V. Babushkin, S. Tahir, and M. Eid, "Haptic guidance to support handwriting for children with cognitive and fine motor delays," *IEEE Transactions on Haptics*, vol. 14, no. 3, pp. 626–634, 2021.

[4] Y. Yoo and S. Choi, "A longitudinal study of haptic pitch correction guidance for string instrument players," in *2017 IEEE World Haptics Conference (WHC)*. IEEE, 2017, pp. 177–182.

[5] L. H. Sallaberry, R. Tori, and F. L. Nunes, "Automatic performance assessment in virtual reality medical simulators: A model based on procedure trajectories and machine learning," *Expert Systems with Applications*, vol. 238, p. 122201, 2024.

[6] C. Gießer, J. Schmitt, E. Löwenstein, C. Weber, V. Braun, and R. Brück, "Skillslab+—a new way to teach practical medical skills in an augmented reality application with haptic feedback," *IEEE Transactions on Learning Technologies*, vol. 17, pp. 2034–2047, 2024.

[7] H. Muramatsu, Y. Itaguchi, C. Yamada, H. Yoshizawa, and S. Katsura, "Direct comparisons of upper-limb motor learning performance among three types of haptic guidance with non-assisted condition in spiral drawing task," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 32, pp. 2545–2552, 2024.

[8] B. Forsyth and K. Maclean, "Predictive haptic guidance: Intelligent user assistance for the control of dynamic tasks," *IEEE Transactions on Visualization and Computer Graphics*, vol. 12, no. 1, pp. 103–113, 2006.

[9] J. Lee and S. Choi, "Effects of haptic guidance and disturbance on motor learning: Potential advantage of haptic disturbance," in *2010 IEEE Haptics Symposium*, 2010, pp. 335–342.

[10] H. Lee and S. Choi, "Combining haptic guidance and haptic disturbance: an initial study of hybrid haptic assistance for virtual steering task," in *2014 IEEE Haptics Symposium (HAPTICS)*. IEEE, 2014, pp. 159–165.

[11] H. Z. Tan, S. Choi, F. W. Y. Lau, and F. Abnousi, "Methodology for maximizing information transmission of haptic devices: A survey," *Proceedings of the IEEE*, vol. 108, no. 6, pp. 945–965, 2020.

[12] L. Meli, C. Pacchierotti, and D. Prattichizzo, "Experimental evaluation of magnified haptic feedback for robot-assisted needle insertion and palpation," *The International Journal of Medical Robotics and Computer Assisted Surgery*, vol. 13, no. 4, p. e1809, 2017.

[13] L. Bohm, "Mechanism of felting of wool fibres," *Nature*, vol. 155, no. 3940, pp. 547–548, May 1945.

[14] E.-L. Sallnäs, "Haptic feedback increases perceived social presence," in *Haptics: Generating and Perceiving Tangible Sensations*, A. M. L. Kappers, J. B. F. van Erp, W. M. Bergmann Tiest, and F. C. T. van der Helm, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2010, pp. 178–185.

[15] T.-H. Yang, J. R. Kim, H. Jin, H. Gil, and J. Koo, "Recent advances and opportunities of active materials for haptic technologies in virtual and augmented reality (adv. funct. mater. 39/2021)," *Advanced Functional Materials*, vol. 31, 09 2021.

[16] C. Pacchierotti, S. Sinclair, M. Solazzi, A. Frisoli, V. Hayward, and D. Prattichizzo, "Wearable haptic systems for the fingertip and the hand: Taxonomy, review, and perspectives," *IEEE Transactions on Haptics*, vol. 10, no. 4, pp. 580–600, 2017.

[17] K. Jung, S. Kim, S. Oh, and S. H. Yoon, "Hapmotion: motion-to-tactile framework with wearable haptic devices for immersive VR performance experience," *Virtual Reality*, vol. 28, no. 1, Jan. 2024.

[18] J. Hoffard, X. Zhang, E. Wu, T. Nakamura, and H. Koike, "SkiSim: A comprehensive study on full body motion capture and real-time feedback in VR ski training," in *Proceedings of the Augmented Humans International Conference 2022*, ser. AHs '22. New York, NY, USA: Association for Computing Machinery, 2022, p. 131–141.

[19] S. Jung, C. Li, R. McKee, M. C. Whitton, and R. W. Lindeman, "Floor-vibration VR: Mitigating cybersickness using whole-body tactile stimuli in highly realistic vehicle driving experiences," *IEEE Transactions on Visualization and Computer Graphics*, vol. 27, no. 5, pp. 2669–2680, 2021.

[20] I. Lee and S. Choi, "Vibrotactile guidance for drumming learning: Method and perceptual assessment," in *2014 IEEE Haptics Symposium (HAPTICS)*. IEEE, 2014, pp. 147–152.

[21] K. Salisbury, F. Conti, and F. Barbagli, "Haptic rendering: introductory concepts," *IEEE Computer Graphics and Applications*, vol. 24, no. 2, pp. 24–32, 2004.

[22] B. M. Howard and J. M. Vance, "Desktop haptic virtual assembly using physically based modelling," *Virtual Reality*, vol. 11, no. 4, p. 207–215, Oct. 2007.

[23] J. Park, D. Kwak, J. Lim, T. Lee, S.-g. Kim, and Y. Yoo, "To guide or to disturb - how to teach dexterous skills using AI?" in *Proceedings of the 30th International Conference on Intelligent User Interfaces*, ser. IUI '25. New York, NY, USA: Association for Computing Machinery, 2025, p. 1458–1469.

[24] Y. Ye, P. Xia, F. Xu, and J. Du, "Enhance kinesthetic experience in perceptual learning for welding motor skill acquisition with virtual reality and robot-based haptic guidance," *IEEE Transactions on Haptics*, 2024.

[25] Y. Yokokohji, R. Hollis, T. Kanade, K. Henmi, and T. Yoshikawa, "Toward machine mediated training of motor skills. Skill transfer from human to human via virtual environment," in *Proceedings 5th IEEE International Workshop on Robot and Human Communication. RO-MAN'96 TSUKUBA*, 1996, pp. 32–37.

[26] F. Richlan, M. Weiß, P. Kastner, and J. Braid, "Virtual training, real effects: a narrative review on sports performance enhancement through interventions in virtual reality," *Frontiers in Psychology*, vol. 14, p. 1240790, 2023.

[27] F. Danieau, A. Lecuyer, P. Guillotel, J. Fleureau, N. Mollet, and M. Christie, "Enhancing audiovisual experience with haptic feedback: A survey on HAV," *IEEE Transactions on Haptics*, vol. 6, no. 2, pp. 193–205, 2013.

[28] M.-H. Milot, L. Marchal-Crespo, C. S. Green, S. C. Cramer, and D. J. Reinkensmeyer, "Comparison of error-amplification and haptic-guidance training techniques for learning of a timing-based motor task by healthy individuals," *Experimental brain research*, vol. 201, pp. 119–131, 2010.

[29] R. A. Schmidt, "Frequent augmented feedback can degrade learning: Evidence and interpretations," in *Tutorials in motor neuroscience*. Springer, 1991, pp. 59–75.

[30] R. D. Seidler, Y. Kwak, B. W. Fling, and J. A. Bernard, "Neurocognitive mechanisms of error-based motor learning," in *Progress in Motor Control: Neural, Computational and Dynamic Approaches*. Springer, 2013, pp. 39–60.

[31] E. J. A. Mireles, J. Zenzeri, V. Squeri, P. Morasso, and D. De Santis, "Skill learning and skill transfer mediated by cooperative haptic interaction," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 7, pp. 832–843, 2017.

[32] C. Milanese, G. Facci, P. Cesari, and C. Zancanaro, "Amplification of error: A rapidly effective method for motor performance improvement," *The Sport Psychologist*, vol. 22, no. 2, pp. 164–174, 2008.

[33] N. Shirzad and H. F. M. Van der Loos, "Error amplification to promote motor learning and motivation in therapy robotics," in *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2012, pp. 3907–3910.

[34] H.-S. Moon and J. Seo, "Optimal action-based or user prediction-based haptic guidance: Can you do even better?" in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, ser. CHI '21. New York, NY, USA: Association for Computing Machinery, 2021.

[35] D. Rowland, B. Davis, T. Higgins, and A. M. Fey, "Enhancing user performance by adaptively changing haptic feedback cues in a Fitts's law task," *IEEE Transactions on Haptics*, vol. 17, no. 1, pp. 92–99, 2024.

[36] H. M. Camarillo-Abad, J. A. Sánchez, and O. Starostenko, "An environment for motor skill transfer based on wearable haptic communication," *Personal and Ubiquitous Computing*, vol. 25, no. 2, pp. 411–435, 2021.

[37] C. Yang, P. Liang, A. Ajoudani, Z. Li, and A. Bicchi, "Development of a robotic teaching interface for human to human skill transfer," in *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2016, pp. 710–716.

[38] T. Endo and H. Kawasaki, "A fine motor skill training system using multi-fingered haptic interface robot," *International Journal of Human-Computer Studies*, vol. 84, pp. 41–50, 2015.

[39] K. Kronander and A. Billard, "Learning compliant manipulation through kinesthetic and tactile human-robot interaction," *IEEE Transactions on Haptics*, vol. 7, no. 3, pp. 367–380, 2014.

[40] B. Aktas, M. Mäkelä, and T.-K. Laamanen, "Material connections in craft making: The case of felting," in *Design Research Society International Conference*. Design Research Society, 2020, pp. 2326–2343.

[41] A. M. Lund, "Measuring usability with the USE questionnaire," *Usability Interface*, vol. 8, no. 2, pp. 3–6, 2001.

[42] S. S. Kantak and C. J. Winstein, "Learning–performance distinction and memory processes for motor skills: A focused review and perspective," *Behavioural Brain Research*, vol. 228, no. 1, pp. 219–231, 2012.

[43] S. G. Hart, "NASA-task load index (NASA-TLX); 20 years later," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 50, no. 9, pp. 904–908, 2006.

[44] J. Brooke *et al.*, "SUS: A quick and dirty usability scale," *Usability evaluation in industry*, vol. 189, no. 194, pp. 4–7, 1996.