Enhancing Tactile Feedback in Haptic Gloves for Immersive Virtual Reality Experiences

Justin J. Tai

Cambridge Center of International Research (CCIR)

Abstract

Haptic feedback enhances virtual reality (VR) immersion by simulating physical sensations, yet current systems are often bulky, expensive, and inaccessible. This study presents a cost-effective, minimalist haptic glove designed to replicate texture sensations through vibrations, addressing the need for accessible, realistic feedback in VR. Built with a SparkFun Thing Plus ESP32 microcontroller, vibration motors, and a ceramic vibration sensor, the glove correlates surface roughness with vibration output. Data was collected using MATLAB and an Artemis Data Logger, and virtual textures were rendered in Unity. User testing, including texture identification and reaction time trials, showed 93.2% accuracy for distinguishing textures with voltage differences above 0.29 V, though misclassifications increased at higher voltage ranges. Reaction times in VR were on average 2.5 times slower than normal, revealing the need for improved motor responsiveness and faster data processing. Compared to existing haptic gloves, this design offers lower cost, reduced size, and modularity, making it more accessible for educational and research use. However, the study is limited by a small sample size and a narrow focus on roughness, without incorporating other tactile dimensions such as temperature or compliance. Future work will expand the glove's capabilities and apply machine learning to enable adaptive, real-time texture simulation.

Keywords: Haptic, tactile, vibration, feedback, immersive.

Introduction

Virtual Reality (VR) has rapidly evolved, creating immersive environments for entertainment, education, and training. Haptic feedback, which simulates touch, friction, and weight, is crucial in enhancing user interaction—especially in applications like surgical training and robotic search-and-rescue missions. However, replicating intricate tactile sensations, particularly roughness, remains a major challenge that limits immersion.

While current haptic systems are effective, they are often bulky, relying on air pressure or piezoelectric actuators. Grounded systems may use pneumatic actuation with large reservoirs or magnetic actuation with platforms and electric coils (Adilzhan et al. 2022). This research explores a more compact, vibration-based approach to replicate roughness with a simple haptic glove. Although gloves simulating roughness already exist, they are often large and expensive, costing up to $2,500. In texture simulation, vibration motors in gloves are triggered to reflect pre-analyzed surface properties such as roughness and material type (Jiahang et al. 2024). This project aims to develop a cost-effective, minimal alternative.

These advancements can benefit astronaut and surgeon training, rehabilitation, and immersive entertainment. They may also assist in search-and-rescue robotics by enabling users to control robots with greater precision. Although haptic technology's position in VR is still unclear, there is agreement on the benefits of adding haptic feedback to training simulations, particularly for surgery (Abdenaceur et al. 2018).

This study focuses only on roughness and does not address other tactile properties like softness or elasticity. Additionally, traditional haptic studies that rely on motion parameters may not capture the full range of sensory factors (Praveena & Harsha 2025). Limitations include the use of sanding sponges, vibration motor precision, and the glove's inability to simulate force. Despite using inexpensive materials, the system offers a baseline for future work. A SparkFun ESP32 microcontroller controls the vibration motors, which replicate textures based on sanding sponge grades. Voltage values were derived from a vibration sensor and analyzed using MATLAB, OpenLog Artemis Data Logger, and an oscilloscope. The system integrates into a VR environment via Unity.

Literature Review

Haptic technology is a rapidly evolving field crucial for enhancing human-computer interaction (HCI) across various domains (Mallouk et al. 2024). Haptic technology aims to create artificial systems that can perceive and transmit the diverse information we receive when physically interacting with our environment (Claudio & Domenico 2024). This involves providing kinesthetic and tactile feedback. The goal is to provide a compelling sense of "telepresence," where a user feels physically present at a remote or virtual site (Massimo 2002).

Haptic gloves are a primary means of achieving this immersion, designed to replicate complex tactile sensations such as pressure, temperature, vibrotactile feedback, and even the elasticity of virtual objects (Mohd et al. 2024).

Foundations of Tactile Perception

The effectiveness of haptic feedback systems is inherently tied to our understanding of human tactile perception. Tactile perception varies significantly based on factors such as nerve, location on the body, sex, and age (Emily et al. 2025). For instance:

- Age: Tactile perception generally diminishes with aging, and specifically, the detection threshold at the hand increases with age more significantly than at the elbow (Emily et al. 2025).

- Location: Hands are generally more sensitive to tactile stimuli than elbows, due to a higher density of mechanoreceptors and more superficial nerve locations (Emily et al. 2025).

- Gender: Women often exhibit better tactile spatial acuity than men (Abdenaceur et al. 2018).

Replicating this multimodal tactile perception is a significant challenge in artificial skin and haptic devices (Ye et al. 2023).

Haptic Glove Technologies and Design Evolution

Haptic gloves leverage various actuation mechanisms and sensing strategies to provide feedback:

Diverse Feedback Mechanisms: Gloves can employ force, vibrotactile, thermal, electrotactile, and skin stretch mechanisms (Aidan et al. 2022).

Wearability-Based Taxonomy: Haptic devices are categorized by wearability, moving from bulky "grounded" devices to "hand-held" and then to increasingly "wearable" devices like exoskeletons and gloves, finger-worn, and arm-worn systems (Abdenaceur et al. 2018).

Multisensory Integration for Accuracy: Combining pressure, roughness, and temperature sensing can significantly improve object recognition accuracy, reaching up to 94.9% in some multisensory tactile gloves. This addresses the limitation of single-sensing force and tactile modes, which struggle to differentiate objects with similar mechanical features but different thermal properties (Ye et al. 2023).

Low-Cost and Flexible Designs

There is a growing focus on developing compact, flexible, and affordable haptic gloves. Solutions incorporating flexible PCBs allow for scalable manufacturing (Aidan et al. 2022). Low-cost designs often utilize simpler components like servo motors for kinesthetic feedback, making immersive VR experiences more accessible (Seungchae et al. 2023).

Key Application Areas

Haptic gloves are vital for precision control in remote applications, notably in minimally invasive surgery, where haptic feedback can increase precision and reduce operation time by allowing surgeons to "feel" virtual instruments (Claudio & Domenico 2024). Additionally, haptic technology would allow for the possibility for more in depth interaction in situations unsuitable for human exposure through the use of teleoperated robotic systems (Daria & Dzmitry 2023).

Virtual Reality (VR) & Metaverse: Haptic gloves boost immersion by allowing physical interaction with virtual objects and textures. They simulate qualities like elasticity, making virtual objects feel deformable (Daria & Dzmitry 2023).

Prosthetics & Rehabilitation: Haptic feedback is crucial for improving prosthesis functionality, aiding fine motor development, and reducing prosthesis rejection (Yanisa et al. 2024).

Challenges and Future Directions

Despite significant advancements, several challenges remain in haptic glove development and integration:

Achieving Dense Hand Coverage: A "grand challenge" is densely covering the hand with tactile arrays to provide sophisticated sensory feedback comparable to human grasp (Ye et al. 2023).

Overcoming Single-Sensing Mode Limitations: Integrating multiple sensory modalities beyond just pressure or force is essential for accurately replicating the richness of human touch (Ye et al. 2023).

Hardware-Software Communication and Resource Constraints: Efficient communication between hardware and AI models, especially in resource-constrained IoT environments, is a persistent hurdle (Sibi et al. 2023). Machine learning models are being optimized for efficiency in such environments.

AI Integration for Enhanced Haptics: The proactive implementation of AI in haptics can help overcome limitations of current algorithms and devices, leading to more realistic and responsive interactions (Georgios et al. 2023). This includes applying AI for tasks like object identification, force sensation recreation, and even optimizing wireless communication in extreme environments (Praveena & Harsha 2025).

In conclusion, while significant strides have been made in haptic glove technology and its applications, particularly with the integration of AI, the field is still striving for comprehensive solutions that fully replicate the complexity and nuance of human touch, especially in real-time, resource-constrained, and diverse application scenarios. Continued interdisciplinary research focusing on high-fidelity, multimodal integration, and user-centric designs remains paramount for future breakthroughs (Claudio & Domenico 2024).

Methodology

This experimental research study was aimed at creating and then evaluating the performance of a haptic glove designed to simulate roughness within a virtual environment. The research started by correlating roughness with vibration and creating a design for a haptic glove. Afterwards, volunteers were gathered and tested the glove through three distinct tests in order to gauge effectiveness of replication of roughness, reaction time while using the glove, and sensory feedback of the glove.

Participants

A total of 20 volunteers participated in the study. To better understand how user characteristics might influence sensory response and interaction with the haptic glove, participants were stratified by age, gender, and dominant hand. These categories were chosen for their potential impact on tactile perception, reaction time, and motor coordination (Emily et al. 2025).

Participant demographics

- **Ages 20–39:**
    - Male: 1 participant
    - Female: 1 participant
- **Ages 40–59:**
    - Male: 3 participants
    - Female: 8 participants
- **Ages 60 and older:**
    - Male: 4 participants

    - Female: 3 participants
- **Right-handed:** 17 participants
- **Left-handed:** 3 participants

Sampling method. Participants were selected through contact via a flier that was distributed to local community centers and neighborhoods.

Variables

Table 1.

Voltage Reading Chart

Average Voltage (V) Reading from Vibration Sensor					
Sand Sponge	Grade 60	Grade 80	Grade 120	Grade 220	Table Surface
Voltage (V)	0.91	0.57	0.43	0.29	0.21

The first variable measured was voltage, corresponding to sand sponge grade. A ceramic vibration sensor was scraped over four sponge grades, generating voltage readings sent to the ESP32 microcontroller (Table 1).

Other variables included reaction time, quantitative sensory feedback, and accuracy which were gathered from their respective tests.

Tests

Each participant was given one of two glove configurations, fitted to either the right or left hand based on their dominant side. These stratified categories will be used in the analysis of the three main tests.

Each results section will include breakdowns by age group and gender where applicable, to highlight any trends or differences that may inform future glove development and testing protocols.

Texture Identification Test

Objective. The objective of this test is to ensure that users can differentiate between different textures based on haptic feedback alone. This test was chosen to ensure the glove could accurately replicate different levels of roughness

Method. Volunteers will be asked to interact with virtual textures using a glove. Afterwards, they'll be given a list of sand sponge values and will be asked to identify each one.

Evaluation. The accuracy of texture identification and the percentage of correct answers will be evaluated and compiled

Quantitative Sensory Feedback Test

Objective. The objective of this test is to measure the sensitivity and precision of the haptic glove by conveying different textures. This test was chosen to ensure the ratio of roughness remained consistent when using the glove.

Method. The users will be asked to interact with virtual textures. However, they will already know the grade of sand sponge they're interacting with. Instead, they will be asked to use a numerical scale from 1 to 10 to rate the intensity and roughness of the vibration they felt.

Evaluation. The ratio of the user ratings will be compared with the ratio of the voltages of the textures to assess how well the haptic glove simulates them.

Reaction Time Test

Objective. Determine how quickly volunteers can react to a change in texture. This test was chosen to see the limitations of the glove and the possible delay within the glove, primarily due to its low-cost components. It was used to test reaction time and how much it differed from normal reaction time.

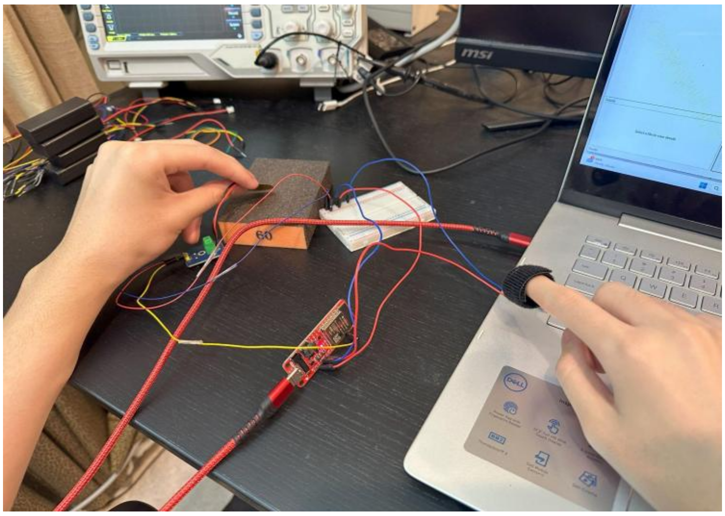
Method. After measuring the volunteer's normal visual reaction speed, use a VR simulation that will randomly send out a vibration. The cube will also start to vibrate within the VR setting. The volunteer will then be asked to press a button, stopping a stopwatch that will measure how fast their reaction time in VR was.

Evaluation. Compare the reaction time of the vibration with the normal reaction times of the volunteers.

Procedure

Figure 1.

Voltage Testing Setup



The procedure began by connecting an ESP32 microcontroller to a laptop running MATLAB and attaching a ceramic vibration sensor as shown in figure 1. Initial tests confirmed the sensor could accurately detect tactile feedback and transmit analog signals to MATLAB. Four sanding sponge grades (60, 80, 120, 220) were used to correlate surface roughness with voltage output.

The ESP32 data was then used to drive a vibration motor, replicating the tactile feedback in real time. After correlating roughness with voltage, a Unity project was created in order to prepare for testing. Using an accelerometer, a box was created in Unity's virtual space that could be rotated from side to side and from front to back in order to create a rudimentary sense of virtual motion for testing. A program was written to change the power of the vibration motor based on the angle that the hand had rotated, in order to test whether or not the volunteers would be able to feel the difference in the vibrations and how accurate the difference they felt was.

Figure 2A.

Side-view of glove

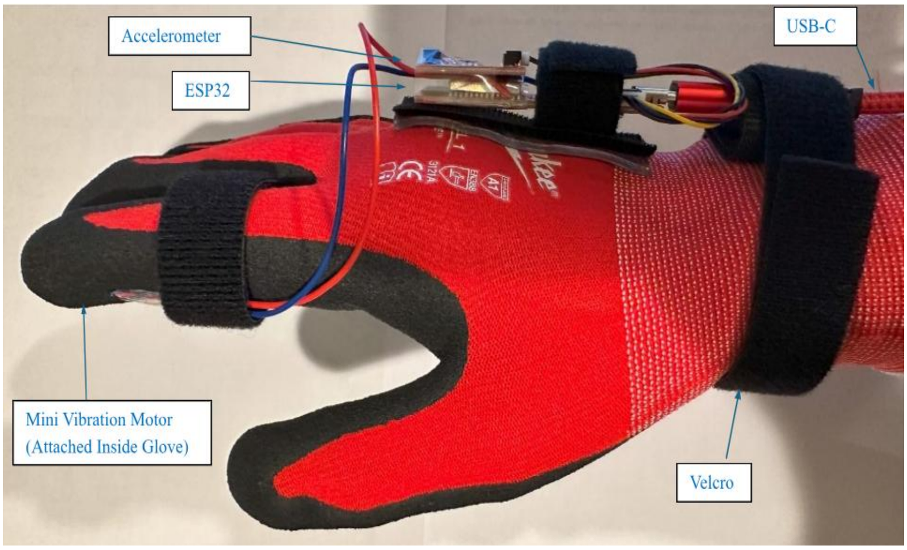
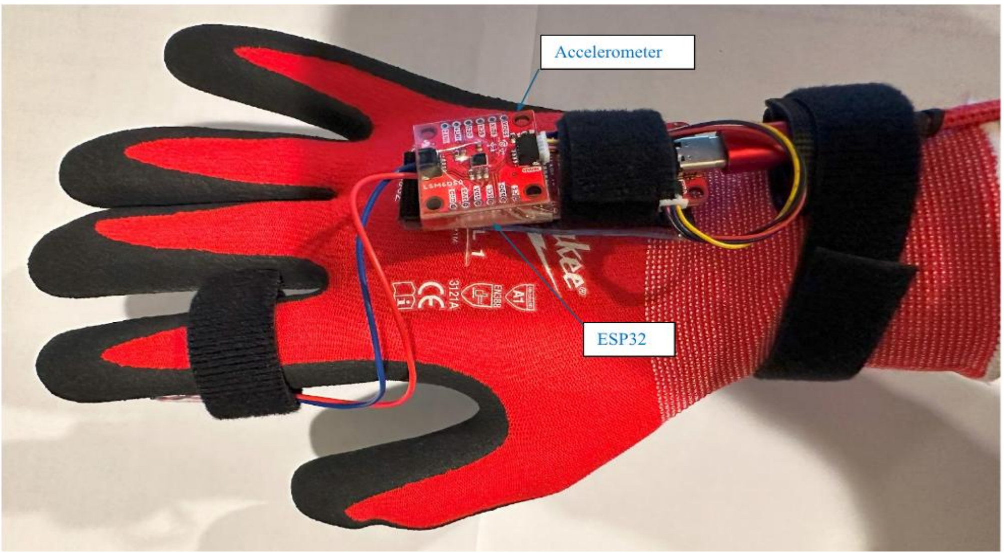


Figure 2B.

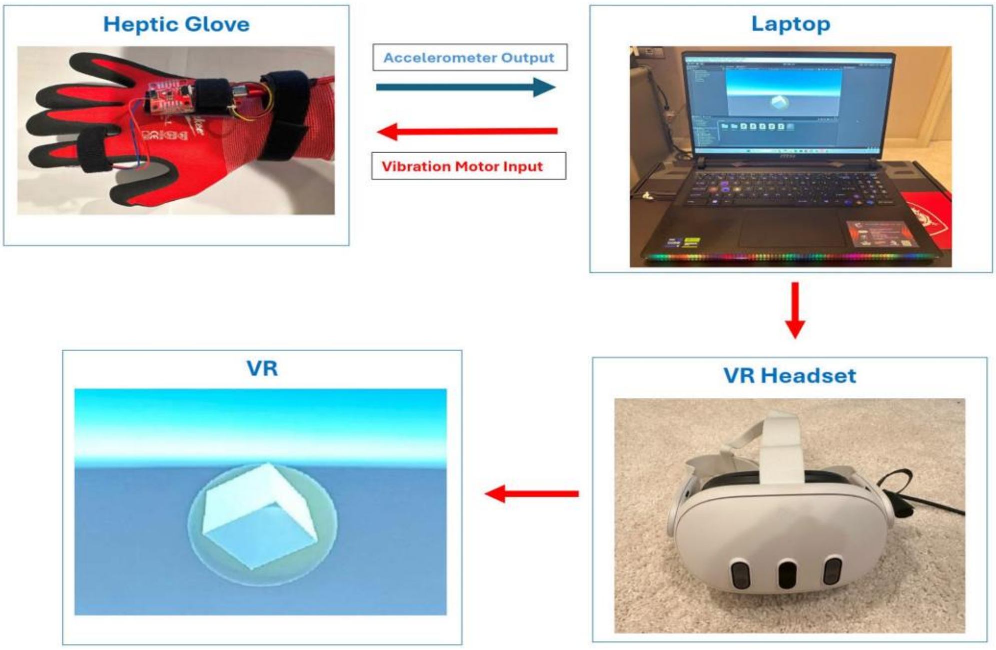
Top-view of glove



A pair of haptic gloves was developed as shown in figure 2, each capable of controlling a virtual object and detecting changes in vibration feedback. A vibration motor was installed on the inner side of the index finger of each glove, with wiring routed through a small hole in the fabric. The cable, ESP32 microcontroller, and accelerometer were secured to the glove using tape and Velcro. The same process was repeated for the second glove. The Oculus Quest headset was connected to Unity using Quest Link. After verifying that the gloves maintained full functionality within the VR environment, testing commenced.

Figure 3.

Flowchart of Data transfer



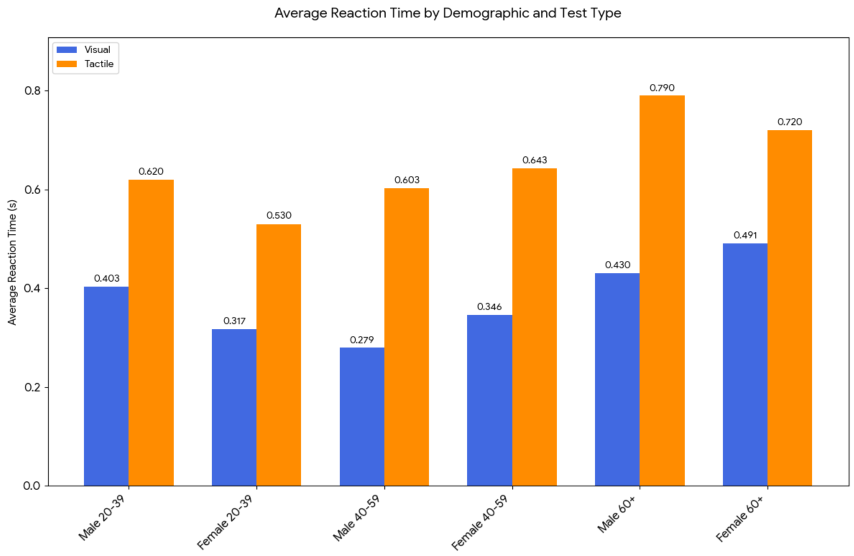
As shown in figure three, the accelerometer attached to the back of the glove was transferred to unity via a USB-C cable. Using Meta Quest Link, the data was transferred to the Meta Quest 3 headset which displayed a VR environment for the user. Additionally, depending on the reading of the accelerometer, a specified vibration motor input was sent to the glove.

Results

Reaction Time Test

Figure 4.

The results of the Reaction Time Test.



Furthermore, charts were used in all three tests to help visualize and analyze the data. In this chart showing the results of the reaction time test, the blue bars represent each volunteer's baseline visual reaction time measured through the Human Benchmark test. The red bars represent their reaction time when wearing the haptic gloves and responding to tactile feedback. For the VR test, reaction time was measured using a unity program that would measure the time difference between the start of the vibration and the time a button was pressed.

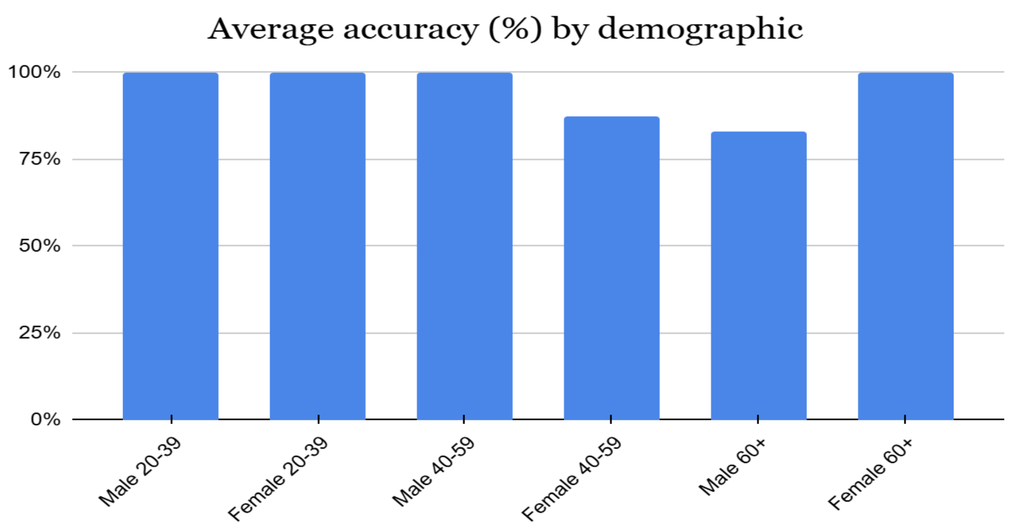
To analyze the data, this study first calculated the average reaction times for both conditions. The average visual reaction time was 0.376 seconds, while the average tactile (vibration) reaction time in VR was 0.672 seconds.In line with prior research, which indicates that mean visual reaction times are generally 180-200 milliseconds and reaction time to touch being intermediate at 155 milliseconds (Robert 2013), this study converted visual reaction times into estimated tactile reaction times using the factor derived from prior research. This yielded an average estimated tactile reaction time of 0.308 seconds.Compared to the observed VR tactile reaction time of 0.672 seconds, this shows an increase of approximately 0.364 seconds. To better understand how age and gender may have influenced the results, the study grouped volunteers into stratified categories. However, although reaction times varied from group to group the difference in reaction time stayed similar, suggesting that gender and age had little effect on the difference.

This stratified data can help reveal whether older participants or one gender experienced greater delays when responding to tactile stimuli in VR. Across all groups, the observed increase in reaction time suggests that current haptic glove feedback may not yet match the speed of natural tactile perception. Potential causes include hardware limitations such as motor strength, feedback resolution, and communication latency between the glove and the VR system. These findings suggest that for more accurate texture replication, future versions of haptic gloves may require more sensitive actuators and faster data transmission.

Texture Identification/Accuracy Test

Figure 5.

The results of the Texture Identification Test.



For the Texture Identification Test, three vibration levels were generated based on the roughness of grade 60, 120, and 220 sand sponges. Volunteers were asked to feel these vibrations and match each to its corresponding virtual texture in a VR setting. To explore whether age or gender affected performance, participants were divided into stratified groups as shown above; however there wasn't much discrepancy among the age groups and genders. As shown in figure 5, eighteen of the twenty initial volunteers achieved 100% accuracy in matching, while two volunteers had an accuracy of 66%. The overall average accuracy across these twenty volunteers was 93.2%.

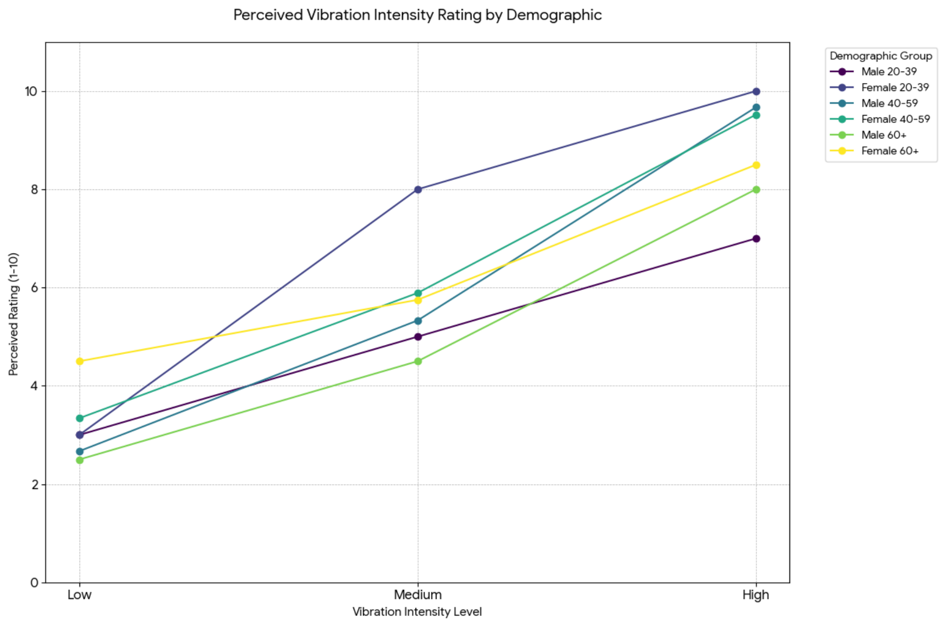
The current data suggests that users can accurately distinguish between textures when the difference in roughness is equivalent to or greater than that of 220, 120, and 60-grade sand sponges. These differences correspond to voltage changes greater than approximately 0.29 V. However, finer distinctions—such as between textures with voltage differences less than 0.29 V—may not be as reliably detected, potentially reducing identification accuracy.

To improve performance in these finer ranges, further testing with smaller roughness intervals is recommended. If a limit is found where users can no longer distinguish textures, the solution may involve using more sensitive vibration motors or increasing the resolution of the feedback system. Despite these limitations, the results so far demonstrate that haptic gloves are capable of delivering accurate and perceivable differences in texture when the voltage differences are sufficiently large.

Quantitative Feedback Test

Figure 6.

The results of the Quantitative Feedback Test.



Each triplet of dots on the chart represents one volunteer's response. After completing the Texture Identification Test and being informed of the relative strength of each vibration, participants were asked to rate all three vibrations on a scale from 1 to 10.

To analyze the results, the average ranking of the all three settings were calculated. These ratings were then compared to the actual voltage ratios. The highest voltage level was more than twice the medium setting, while the medium setting had about 50% more voltage than the lowest. As shown in figure 6, the comparison of voltage to rating was relatively consistent at lower levels: the average low-to-medium rating ratio was 3.21:5.57, which aligns closely with the expected 50% voltage increase. However, the medium-to-high ratio of 5.57:8.98 was lower than anticipated, suggesting either a limitation in participants' ability to distinguish higher-intensity vibrations or a hardware constraint in the glove's vibration motor.

However, while the scale provided a general sense of perceived intensity, the 1–10 rating system may not have been sensitive enough to capture subtle differences, and inter-participant variability in tactile perception likely contributed to inconsistencies in medium and high-range evaluations.

Discussion

The results of this study underscore the potential and challenges in developing a haptic feedback system for virtual reality (VR) applications. The use of the ESP32 microcontroller, similar to other microcontrollers like Teensy used for voltage readings, data processing, and motor control in haptic gloves (Yanisa et al. 2024), in conjunction with MATLAB and the Artemis Data Logger, demonstrated the ability to capture and process analog signals from a vibration sensor. Despite achieving functional data collection and vibration feedback, the measurements revealed discrepancies.

The integration of Unity software allowed for the creation of a virtual hand, enhancing the realism of haptic feedback in VR environments. Unity Engine is widely used for visualizing virtual hands and objects, and for controlling haptic gloves to simulate elastic effects (Mohd et al. 2024). This technology aims to make virtual experiences feel life-like, allowing users to interact with virtual objects as if they were real.

Constraints

The discrepancies can be attributed to inherent limitations, as sensors used in haptic devices are known to be affected by narrow bandwidth, signal noise, and instability (Praveena & Harsha 2025). Issues such as unstable hand tracking, inaccurate position data (Seungchae et al. 2023), and variability in stimulus application (timing, force, location) can lead to inconsistencies. Physical components on haptic gloves can also contribute to hand tracking instability, and achieving continuous sensing functionality remains a challenge (Munisami et al. 2023). Human factors, including age, sex, arm dominance, and location, can also influence tactile perception outcomes (Abdenaceur et al. 2018). The higher discrepancies observed for sand sponge grades 60 and 80, which had more significant roughness, also indicate the constraints of the data recording equipment.

- Hardware Constraints: The vibration motors and sensors used were low-cost, which limited their precision, especially for higher voltages.

- Sample Size: Testing was conducted with a small sample of twenty participants, which may not represent the broader population.

- Focus on Roughness: The study did not explore other tactile properties, such as elasticity, temperature, or force, which may impact the realism of haptic feedback.

This research demonstrates the potential of low-cost, vibration-based haptic technology to significantly enhance VR immersion by replicating tactile sensations. By addressing current limitations such as lack of technology and sole focus on roughness, and building off these findings, future developments in haptic systems can pave the way for more immersive, accessible, lightweight, and versatile VR experiences, bridging the gap between the virtual and physical worlds.

Future Plans

To enhance haptic gloves, machine learning models, notably Random Forest, could be useful for correlating surface roughness with materials to generate precise vibrations, outperforming traditional methods (Kathrin et al. 2022). Integrating multimodal sensing like pressure and temperature improves object recognition accuracy (Ye et al. 2023), while accurate virtual collision detection is fundamental for coherent feedback (Masimo 2002). Future development aims for full motion and force replication for rich multisensory experiences, extending vibrotactile motors to more body parts as a cost-effective solution, and using ML to link vibrations with grip types (Claudio & Domenico 2024). Significant challenges include slower tactile reaction times in VR compared to visual feedback, requiring faster actuators and data transmission, alongside hardware limitations. Optimization techniques like neural network pruning are essential for deploying complex ML models on resource-constrained IoT edge devices (Sibi et al. 2023). Moreover, effective haptic design must account for human tactile perception, which is influenced by age, sex, nerve, and body location, generally declining with age and varying in sensitivity across the body (Emily et al. 2025) . Despite efforts for low-cost devices, recognition accuracy and response delays remain limitations (Seungchae et al. 2023).

Conclusion

This study successfully developed a cost-effective haptic glove capable of simulating surface roughness in virtual reality (VR) environments using vibration feedback. The glove achieved a 93.2% accuracy rate in distinguishing textures with voltage differences greater than 0.29 V. Supporting the feasibility of simplistic and cost-effective designs, research also highlights vibrotactile stimulation as a common, low-cost feedback method using off-the-shelf components, which can be reconfigured for various body locations like the upper arm, shoulder, or lower back, showing discrimination accuracies up to 90% for single vibrations and 66% for two simultaneous vibrations. Participants in the initial study ranked roughness ratios accurately at lower voltage levels, but discrepancies arose at higher voltages, likely due to motor limitations and inherent bias, issues further complicated by the observation that optimal feedback locations vary and common armband designs may not always be effective. Reaction times in VR were approximately 364 ms slower than normal reaction times, highlighting the need for system optimizations and more appropriate components, addressing existing challenges with bulky, wired, and poorly adaptable haptic systems. The findings demonstrate the feasibility of more simplistic designs for replicating roughness, which, alongside contributions to theoretical understanding by correlating roughness with vibration intensity, are particularly useful for accessible haptic devices in training, rehabilitation, and entertainment

(Yanisa et al. 2024). While the primary objective of creating a simplistic, vibration-based haptic glove to replicate surface roughness was met and volunteers successfully distinguished textures with significant differences, the discrepancies at certain voltages and slow reaction times highlight limitations that must be addressed, necessitating further comparative studies on feedback strategies and stimulation sites.

References

Abdouni, A., Moreau, G., Vargiolu, R., & Zahouani, H. (2018). Static and active tactile perception and touch anisotropy: aging and gender effect. *Scientific Reports*, *8*(1), 14240. https://doi.org/10.1038/s41598-018-32724-4

Adilzhan, A., Matteo R., & Zhanat K. (2022). Haptic Devices: Wearability-Based Taxonomy and Literature Review. *IEEE Access*, *10*, 91923–91947. https://doi.org/10.1109/access.2022.3202986

Angkanapiwat, Y., Slepyan, A., Greene, R. J., & Thakor, N. (2024). SensoPatch: A Reconfigurable Haptic Feedback with High-Density Tactile Sensing Glove. *ArXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2409.19155

Aug. A., Slepyan, A., Levenshus, E., & Thakor, N. (2022). Haptic Touch: A retrofittable tactile sensing glove and haptic feedback armband for scalable and robust sensory feedback, *2022 9th IEEE RAS/EMBS International Conference for Biomedical Robotics and Biomechatronics (BioRob)*, Seoul, Korea, Republic of, 2022, pp. 01–06, doi: 10.1109/BioRob52689.2022.9925475.

Bergamasco, M. (2002). Haptic interfaces: the study of force and tactile feedback systems. *IEEE*, 15–20. https://doi.org/10.1109/roman.1995.531929

Dewapura, P. W., & Harsha, M. (2025). AI-driven Haptic Cues for Haptic Object Reproduction. *IEEE Access*, *13*(65737), 1–1. https://doi.org/10.1109/access.2025.3555929

Faisal, M., Zhu, H., Fedwa Laamarti, & Abdulmotaleb El Saddik. (2024). A Haptic Glove for Immersive VR Texture and Dynamic Event Simulation. *IEEE*, 1–2. https://doi.org/10.1109/icir64558.2024.10976841

Kim, S., Ko, J., Shin, C., Lim, R., & Doug Young Suh. (2023). Haptic Glove with Haptic Feedback for Elastic Objects at a Low Cost. *Journal of Appropriate Technology*, *9*(3), 102–118. https://doi.org/10.37675/jat.2023.00437

Konkol, K., Geiger, A., & Ginzler, T. (2022). Machine Learning improves use of Haptic Glove for engineers in Virtual Reality. *AHFE International*. https://doi.org/10.54941/ahfe100979

Kosinski, R. (2013). *A Literature Review on Reaction Time*. Clemson University. http://www.cognaction.org/cogs105/readings/clemson.rt.pdf

Minopoulos, G. M., Memos, V. A., Stergiou, K. D., Stergiou, C. L., & Psannis, K. E. (2023). A Medical Image Visualization Technique Assisted with AI-Based Haptic Feedback for Robotic Surgery and Healthcare. *Applied Sciences*, *13*(6), 3592. https://doi.org/10.3390/app13063592

Nazih, M., Majid, R., Pedram, F., & Javad, D. (2024). A Brief Review on Recent Advances in Haptic Technology for Human-Computer Interaction: Force, Tactile, and Surface Haptic Feedback. *IEEE*, *2*, 34–39. https://doi.org/10.1109/icict62343.2024.00012

Pacchierotti, C., & Prattichizzo, D. (2024). Cutaneous/Tactile Haptic Feedback in Robotic Teleoperation: Motivation, Survey, and Perspectives. *IEEE Transactions on Robotics*, *40*, 978–998. https://doi.org/10.1109/tro.2023.3344027

Qiu, Y., Wang, Z., Zhu, P., Su, B., Wei, C., Tian, Y., Zhang, Z., Chai, H., Liu, A., Liang, L., & Wu, H. (2023). A multisensory-feedback tactile glove with dense coverage of sensing arrays for object recognition. *Chemical Engineering Journal*, *455*, 140890. https://doi.org/10.1016/j.cej.2022.140890

Shanmugam, M., Kanagaraj Venusamy, Subin, S., S Srivatsan, & Naresh Kumar O. (2023). A Comprehensive Review of Haptic Gloves: Advances, Challenges, and Future Directions. *IEEE*. https://doi.org/10.1109/icears56392.2023.10085607

Chakkaravarthy, S., John, M., Cruz, V., Kumar, R., Anitha, S., & Karthikeyan, S. (2023). MetaHap: A Low Cost Haptic Glove for Metaverse. *IFIP Advances in Information and Communication Technology*, *683*, 362–372. https://doi.org/10.1007/978-3-031-45878-1_25

Tirrell, E. M., Nahid Kalantaryardebily, Feldbush, A. C., Sydnor, L., Grubb, C., Parcetich, K., & Netta Gurari. (2025). Considerations for tactile perceptual assessments: impact of arm dominance, nerve, location, and sex in young and older adults. *Experimental Brain Research*, *243*(4). https://doi.org/10.1007/s00221-025-07044-5

Trinitatova, D., & Tsetserukou, D. (2023). Study of the Effectiveness of a Wearable Haptic Interface With Cutaneous and Vibrotactile Feedback for VR-Based Teleoperation. *IEEE Transactions on Haptics*, *16*(4), 463–469. https://doi.org/10.1109/toh.2023.3265713

Zhu, J., Song, A., Shang, K., & Wei, Z. (2024). *A wearable smart glove for tactile interaction*. *29*, 160–164. https://doi.org/10.1145/3674746.3674771