Hand Grip Pressure Visualization for Task Assistance

Aman Sariya* Andrew Huard† Ishan Jain‡ Arthur Caetano§ Tobias Höllerer ¶ Misha Sra ‖

Department of Computer Science, University of California, Santa Barbara, USA

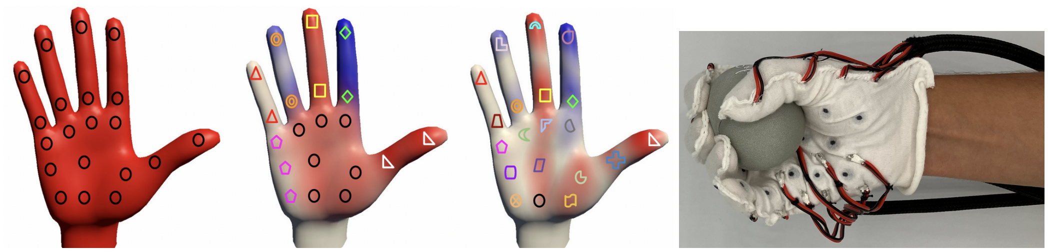

Figure 1: Data from the pressure glove with 20 sensors is visualized in three Levels of Detail (LoD) to the study participants. The LoD ranges from low (left) to medium (middle) and high (right) with sensor groups shown in the same color and shape for each LoD. On the far right is the user wearing the pressure-sensing glove with a thumb-abducted, power grip with pad opposition.

Abstract

Tacit knowledge of hand grip force and pressure is essential for effective tool use and object manipulation. However, this information is challenging to communicate in virtual training scenarios. To address this, we introduce realtime hand grip pressure visualization that provides users with feedback on when to tighten or loosen their grip and which specific parts of the hand require adjustment. By offering task-specific visual pressure cues, users can learn and fine-tune their grasp for specific objects and tasks. Our pilot study tested three different visualization levels of detail and results indicate the medium level to outperform the low and high levels of detail.

Index Terms: hand grip, pressure, visual feedback, mixed reality

1 Introduction

Tacit knowledge, an implicit understanding from experience, is crucial in professional and practical skills that involve applying force, balance, pressure, or spatial awareness, and poses challenges in virtual training. In this work, we present a pressure visualization technique for mixed reality (AR) skill acquisition using a custom-designed glove. This glove provides real-time visual feedback on grip pressure, helping users adjust their grasp. Unlike haptic feedback which simulates tactile sensations of touch or force when interacting with virtual objects, our method visually guides users on the required force to grasp a physical object, making tacit pressure knowledge more accessible. This approach is beneficial in fields like physical therapy, medical procedures, manufacturing, sports, music, handicrafts, art, and culinary arts. Our visualization uses varying Levels of Detail (LoD) to assess how effectively users achieve an ideal pressure, offering insights into the relationship between visual feedback complexity, understandability and corresponding grasp modification.

*e-mail: amansariya@ucsb.edu
†e-mail: huard@ucsb.edu
‡e-mail:ed.ishanjain@ucsb.edu
§e-mail:caetano@ucsb.edu
¶e-mail:holl@ucsb.edu
‖e-mail:sra@ucsb.edu

2 System Design

The system consists of four components: (1) a custom glove with 20 Force Sensitive Resistors (FSRs) for pressure sensing, (2) an Arduino Uno R3 to aggregate and streams pressure data to computer running a Node.js server, (3) Photon Realtime to stream data from the server to a Unity application deployed on a Meta Quest 3.

Glove The glove has 20 FSRs with sensor locations determined based on an empirical assessment of tactile sensitivity while grasping various objects and are distributed between the finger joint locations, fingertips, and the palm (Figure 1).

We use Feix et al's. [3] definition of grasp, "A grasp is every static hand posture with which an object can be held securely with one hand, irrespective of the hand orientation."

Server The Node.js server establishes a serial connection with the Arduino via the `serialport` library and listens for incoming data from the pressure sensors in the glove. The data transmission includes sensor readings and a checksum for data integrity verification. To enable real-time communication and synchronization of sensor data with the Unity application, we use the Photon Realtime service as direct communication from an Arduino to the Meta Quest over USB is not allowed.

Unity Application The Unity 2022.3.0 application manipulates the texture of a 3D hand model based on pressure data. It receives data streamed from the server, normalizes it and updates it as the current pressure value for that particular sensor in a ScriptableObject. We then flood-fill the hand model to update the visualization. Depending on the LoD we are dealing with, we perform a logical grouping of the sensor values.

2.1 Levels of Detail (LoD)

Figure 1 shows the different LoDs and the logical of the pressure sensors in each. Red indicates that the user is not applying enough pressure and needs to increase it while blue indicates too much pressure. We calculate the error by subtracting the ideal pressure from the user pressure. If the error is positive, it indicates that the user needs to apply more pressure, and the absolute value (that lies between 0 and 1) is used to determine the color from a gradient between white to red. Similarly, if the error is negative, it indicates that the user needs to apply less force, and the absolute value (that lies between 0 and 1) is used to determine the color from a gradient between white to blue. This error is calculated every frame and the colors are updated every 0.5 seconds

In the high level of detail, each sensor directly maps to a region on the hand, and the error is the absolute difference between the ideal and user-applied pressures for that sensor. In the medium level of detail, sensors are grouped, and the error for each cluster is the maximum error among the sensors in that group. In the low level of detail, all sensors are grouped into a single cluster, and the error is the maximum error among all sensors, with colors updated every 0.5 seconds to indicate if more or less pressure is needed.

3 Preliminary User Study

The primary goal of the study is to study the impact of the granularity of information on user accuracy for pressure guidance in mixed reality. The task selected that the user has to perform is to simply grab a soft physiotherapy ball and manipulate the applied pressure to match the ideal pressure based on the visualization they are seeing. The grasp chosen is a thumb-abducted, power grip with pad opposition (Figure 1).

3.1 Selecting Ideal Pressure

A precondition for our visualization is the existence of an ideal pressure for the user to reproduce, which can be defined by pressure distribution over the hand, grasp type, object properties, and individual motor abilities [3, 5, 1]. Creating an example ground truth allowed us to evaluate the effectiveness of different levels of detail (LoDs) in guiding users to adjust their grasp. We introduced a 20-dimensional Grasp Pressure Vector (GPV) to represent hand sensor pressure values. Pressure readings from a participant performing ten grasp-and-release cycles on a physiotherapy ball were recorded, and peak values were averaged to form the GPV, representing the natural pressure application. These were scaled by random values between 0.25 and 0.75 to create varying intensities, in order to prevent users from memorizing and consequently ignoring the guidance.

3.2 Methodology

Our preliminary study consisted of 6 participants (3 female, 3 male, with an age range of 22-35). Each participant put on the glove and was given a medium stiffness therapy ball[1] to grasp. They were then shown a 3D model of a hand where red and blue colors represented different aspects of their grip pressure in realtime. The participants were instructed to adjust their grip to minimize either the red or blue color intensity on the model. The task had a time limit of 2 minutes. Participants performed the task 3 times and filled out questionnaires after each task. Each task consisted of a different LoD. This was balanced on a Latin Square across all participants. Along with this, every task across all subjects had a different ideal pressure value derived from the GPV that they had to match to minimize any learning effects. After each task, participants filled the System Usability Scale (SUS) [2] and NASA Task Load Index (NASA-TLX) [4] questionnaires to gauge visualization usability and workload respectively. After the last task, they filled out an open-ended questionnaire.

4 Preliminary Results

For each participant, the norm of error for each LoD was calculated for the 120 seconds given for each task (Sec 2.1). Figure 2 shows a graph with average error norm for all participants over time. The lower the value, the closer all the participants were on an average to their respective ideal values. After aggregating the SUS assessments across all participants per LoD, we got the following scores: 1) Low LoD: 70, 2) Medium LoD: 72.50, 3) High LoD: 78.33. The average SUS score across all LoDs was 73.61. The score indicates that visual feedback as a whole had a usability that is considered above average. However, the High LoD was considered the most

[1] https://shorturl.at/MTGkD

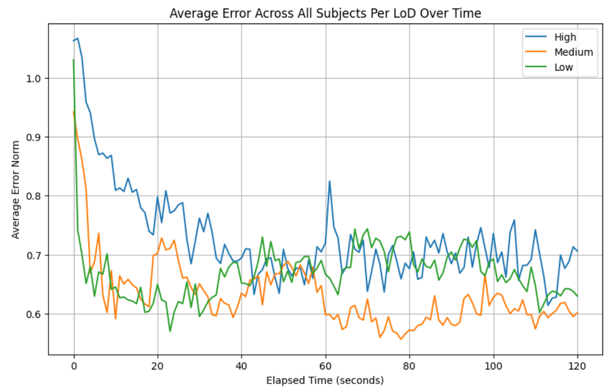

Figure 2: Average error norm across all subject for each LoD over the time given for each task (120 seconds)

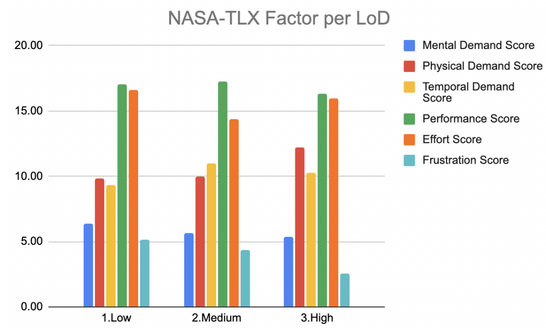

Figure 3: Workload factor contributions by LoD

usable. We calculated a breakdown of the contribution of all 6 workload factors towards overall workload for each LoD, and the values indicate that performance and effort are the largest contributors (Figure 3).

The last questionnaire consisted of subjective statements on a Likert Scale. Scores were higher than 4 out of 5 on: “The visual feedback was useful”, “visual feedback helped in performing the task”, “visual feedback directly impacted my performance”, “the color coding of the 3D pressure-guiding hand was easy to understand”. Scores were lower than 4 on: “I felt like the system understood the pressure I was applying to the object well enough”, “the mapping of my actual hand to the 3D hand was accurate.”

5 Discussion

Figure 2 indicates that convergence and learning is improved using a medium LoD. Additionally, for each LoD, we calculated 3 ratios. These include the ratio of average accuracy and usability, average accuracy and performance workload score, and average accuracy and effort workload score. All of these ratios had the highest value for the medium LoD, indicating that in our preliminary study, the medium LoD provides enough gain in accuracy to potentially offset the disadvantages of slightly lower usability and slightly higher workload scores as compared to the other LoDs.

This preliminary data makes a promising case for the medium LoD with improvement over all the measured factors: accuracy, usability, and reduced workload. We believe this may be because the number of variables that users need to consider is lower than in the high LoD scenario while providing more information than the low LoD case. Additional research is needed to dive deeper into the level of granularity and how it affects human understanding of a pressure-based physical task.

Acknowledgments

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