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Los Angeles

Human-in-the-loop Teleoperation
for Tactile-driven Physical Interactions
in Unstructured Environments

A dissertation submitted in partial satisfaction
of the requirements for the degree
Doctor of Philosophy in Mechanical Engineering

by

Lionel Yulan Zhang

2023

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ABSTRACT OF THE DISSERTATION

Human-in-the-loop Teleoperation for Tactile-driven Physical Interactions in Unstructured Environments

by

Lionel Yulan Zhang

Doctor of Philosophy in Mechanical Engineering

University of California, Los Angeles, 2023

Professor Veronica Santos, Chair

The unpredictability of unstructured environments poses a significant challenge to fully autonomous systems. A human in the loop can provide high-level decisions that leverage experience, context, and human creativity. Allowing humans to operate remotely through teleoperation improves flexibility and safety in hazardous conditions. Our work addresses human-in-the-loop teleoperation applications in assistive robotics and hazardous environments with granular materials. We demonstrate the critical role that haptic feedback plays in enabling humans and robots to operate in unstructured environments effectively.

In study #1, we developed a tactile-based proximity sensing framework for estimating the distance to buried objects in granular materials by exploiting granular media jamming. As a sensorized robot finger displaces granular material towards a buried object, jamming granular particles leads to increased fingertip contact forces. A tactile sensor effectively acts

as a proximity sensor when moved through granular materials. Using our framework, the distance to a buried object can be estimated using solely haptic feedback.

In study #2, we developed a structured approach for estimating the orientation and diameter of cables buried in sand using a deformable, vision-based tactile sensor. Our orientation estimation method identifies the contact region of the cable by employing a proximity function that takes extracted image features as input. Our approach is compared with existing image feature extraction methods, including PCA and maximally stable extremal regions. Our framework demonstrates the effectiveness of tactile sensing when an object is partially or fully occluded in granular materials.

In study #3, we designed a telepresence system with real-time auditory, visual, and haptic feedback. The system comprises a modified Stretch mobile manipulator with additional controllable degrees of freedom in the wrist and fingers. The operator interface consists of a virtual reality headset and a haptic glove. The operator controls the remote robot using intuitive controls based on motion tracking. To convey tactile information, the operator receives electrical impulses to stimulate the afferent sensory nerves of each finger driven by tactile feedback from the robot hand.

In summary, we developed tactile-based systems and approaches to enhance human-in-the-loop teleoperation for applications in unstructured environments, such as in the home and in granular materials.

The dissertation of Lionel Yulan Zhang is approved.

Dustin J. Tyler

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University of California, Los Angeles

2023

To my beloved family . . .

My wife, Annie, whose unwavering love and encouragement

have guided me throughout my academic journey;

My parents, Bonnie and Barry, who taught me

the importance of hard work and perseverance;

My sister, Shannon, whose continuous support

has been a constant source of motivation.

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CHAPTER 1

Introduction

1.1 Motivation

Fully autonomous systems face considerable challenges when deployed in unstructured environments since they are often tested in controlled, structured settings. To overcome this challenge, involving humans in the decision-making process enables shared autonomy human-robot systems that can leverage human experience, situational awareness, and creativity. Teleoperation, which enables humans to operate remotely, adds flexibility and safety in hazardous conditions. Our research focuses on the application of human-in-the-loop teleoperation in assistive robotics and hazardous environments with granular materials. We demonstrate that haptic feedback is critical in facilitating effective operation for both humans and robots in unstructured environments.

1.1.1 Robotic Applications in Granular Material Environments

The risk of hazardous operations in granular material environments such as search and rescue, archaeology, and demining could be greatly reduced through the use of teleoperated robots. In this way, the human operator would be able to work from a safe location. For hazardous environments involving granular materials, tactile sensing can be invaluable, since the objects of interest that are not visible may still be haptically salient. Humans can quickly

identify and locate objects buried within granular materials such as sand, grain, and soil using tactile feedback rather than visual feedback. However, it remains a challenge to apply similar skills to robots. One of the primary challenges of working within granular materials is being able to distinguish between the object of interest and the surrounding granular material in the tactile data. The granular particles such as sand and gravel cause unwanted noise in the tactile data. Therefore, it is necessary to develop algorithms that can enable the robot to efficiently, haptically explore the search region. Chapters [2](#) and [3](#) present new tactile-driven capabilities for robots working in granular material environments.

1.1.2 Medical Applications for Telepresence Systems

Assistive robotics for persons with disabilities help provide them with functional independence while reducing the burden of caregivers. Robotic systems are often capable of assisting individuals with daily activities such as retrieving objects and self-feeding. While autonomous robotic systems excel at repetitive tasks in controlled environments, a human operator in the loop is often necessary for tasks in unstructured environments and for providing social interaction and emotional connection. The sense of touch is especially important for the robot operator to effectively assist the individual with physical needs. Real-time haptic feedback is also crucial for preserving the human-to-human connection regardless of distance, in addition to real-time visual, auditory, and physical interactions. Chapter [4](#) addresses the design of a teleoperated service-type social robot.

1.2 Contributions

The work in this dissertation investigates tactile-based approaches for improving human-in-the-loop teleoperation in unstructured environments. For robots in granular material environments, the sense of touch is invaluable when raking through granular materials since vision-based methods can only provide information about the surface. We successfully leverage tactile data to perceive objects and cables buried in granular materials. For a teleoperation system, the addition of haptic feedback with intuitive controls improves task performance while increasing the sense of immersion of the human operator. Haptic feedback and cues can also provide the operator with information about the robot’s intended action in a shared autonomy configuration.

Chapter 2 presents a framework for the tactile-based proximity sensing of objects buried in granular materials by leveraging granular media jamming. As a tool pushes granular material toward a buried obstacle, the granular particles become compacted and jam together. This leads to a greater force exerted on the tool. By using theoretical models of soil failure, the distance to the object can be estimated based on when this increase in force occurs. In this way, the tactile sensor effectively functions as a proximity sensor when used in granular materials. By employing our approach, we can estimate the distance to an object buried within the material by relying exclusively on the sense of touch.

Chapter 3 presents a systematic framework for the tactile perception of cables buried in sand using a deformable, vision-based tactile sensor. Our framework first estimates the region on the heightmap collected by the tactile sensor that most likely corresponds to a cable. The contact region of the cable is found using a proposed proximity function. The results are compared with existing methods of image feature extraction methods, such as PCA and

maximally stable extremal regions (MSER), for orientation estimation. The diameter of the cable is then estimated using: (i) a method that directly measures curvature from the heightmap and (ii) a method that minimizes the variance of distances between the center of a cylindrical cable and the points on the heightmap. Our framework demonstrates the efficacy of the sense of touch for sensing cables partially or fully buried in granular materials.

Chapter 4 describes the system architecture and interface for a teleoperation system that provides real-time visual, auditory, and haptic feedback to the human operator. The robotic system consists of a modified Stretch mobile manipulator with additional degrees of freedom in the wrist and fingers. The operator system consists of a VR headset and an electric-stimulation-based haptic glove. The operator controls the remote robot using intuitive controls based on motion tracking. Tactile data from the robot hand is felt by the operator through electrical stimulations. In this way, the individual receiving assistance can be provided real-time visual, auditory, and physical interactions regardless of distance. This system could be used by family, friends, and caregivers to remotely assist and interact with individuals with disabilities.

Chapter 5 summarizes the dissertation and presents opportunities for future work to build on the research in this dissertation.

CHAPTER 2

A Framework for Tactile-based Proximity Sensing of Buried Objects via Granular Media Jamming

2.1 Abstract

There are many hazardous tasks that involve granular materials, such as demining and search and rescue. In these examples, tactile sensing can be invaluable, since the objects of interest are often not visible but may still be haptically salient. As a tool, such as a robot finger, approaches a buried object, the displaced granular material ahead of the tool's path forms a wedge-shaped failure zone in the direction of movement. As the granular material in the failure zone makes contact with a buried object, the granular particles begin to compact, leading to granular media jamming. This causes an increase in contact force felt on the robot finger without the finger making direct contact with the buried object. The point at which this force transition occurs can be estimated using theoretical models of soil failure during soil-tool interactions. In this work, we present a tactile-based proximity sensing framework that leverages empirical models of granular material failure zones to haptically determine the distance from a sensorized robot fingertip to an object buried in granular material. We investigated the effects of the frictional properties of granular materials on proximity sensing accuracy by studying glass beads, poppy seeds, and playground sand. For fingertip

depths of 3 cm and 4 cm, and for object depths ranging from 0.5 cm - 3.5 cm, we estimated the distance from a sensorized robot finger to a buried object during haptic exploration in granular materials. The mean absolute errors in estimated distance were 0.7 cm, 0.6 cm, and 1.0 cm for glass beads, poppy seeds, and playground sand, respectively.

2.2 Introduction

For certain robot tasks, vision-based approaches are ineffective and the sense of touch becomes invaluable for situational awareness. Although vision-based methods are ideal for planning manipulation, such approaches fail when the target object is visually occluded. This work is largely motivated by applications in which robots are used for the haptic search of buried objects that may be delicate and/or dangerous, such as demining. The challenges of locating, excavating, and extracting a buried object are compounded by the complex dynamics and behaviors of granular materials. Operators of remote robots must often rely on computer vision with a limited field of view from the robot’s on-board cameras. The teleoperator’s task of locating buried objects would be aided by robots that could semi-autonomously map out a search area within granular materials. In this work, we present a novel framework for perceiving the proximity of an artificial fingertip to a buried object that relies upon the sense of touch and granular media jamming. We refer to this capability as *tactile-based proximity sensing*.

The objective of this work is to characterize granular media jamming effects for a sensorized robot fingertip. The long-term goal is to exploit the empirical models developed here in order to haptically locate objects buried in granular materials. Our work leverages the literature on soil failure and provides new insights into the behavior of granular materials

that can be applied to robotic applications. Our novel contributions are:

- The development of a novel, model-based framework for using a tactile sensor as a proximity sensor when employed in granular materials.
- The advancement of tactile-based proximity sensing in granular materials by characterizing and leveraging the effects of granular media jamming.
- The analysis of our tactile-based proximity sensing framework in a real-world setting using different granular materials: playground sand, glass beads, and poppy seeds.

2.3 Related Works

2.3.1 Granular Material-Tool Interaction: Plate Drag

For decades, researchers have investigated the interactions between dry granular materials and rigid plates, specifically in the context of soil-tool interactions. Both simulated and physical experiments have been conducted in this area [55, 103, 35]. As a plate moves across the surface of granular materials, granular particles ahead of the plate form a wedge-shaped volume, which is also referred to as a “failure zone” [32]. As the plate continues to advance, the particles in the failure zone move forward in the direction of plate movement and upward toward the surface of the granular material. The particles outside of this wedge-shaped volume remain mostly stationary.

Swick and Perumpral developed a 3D analytical model for the failure zone of granular material in front of a plate [103]. The model consists of a central wedge whose width matches that of the plate. When viewed from the top, both sides of the central wedge are bordered by crescent-shaped regions. The failure zone is assumed to be symmetrical in relation to the

axis along which the plate moves. A “shear band” separates the flowing and stable regions. The shear band originates from the bottom edge of the plate and extends upwards towards the free surface of the granular material. As the plate advances, both the angle of the shear band and the drag force on the plate increase after the shear band fully develops. When the drag force becomes large enough to disturb the more stable surrounding particles, a new shear band emerges that again grows as the plate advances. The cycle of shear band nucleation is repeated as the plate moves across and through the granular material [55].

Currently, there are few studies that investigate the use of a sensorized hand/gripper in granular materials [45, 95, 46]. Schenck et al. developed predictive models for enabling a robotic control policy to manipulate granular material into a desired shape. Jia and Santos used multimodal data from a sensorized fingertip in a neural network to haptically distinguish contact with a buried object from contact with the surrounding granular materials. Jia et al. designed a continuous occupancy map algorithm for locating an object buried in granular materials. The mapping algorithm uses a sensor model based on conservative estimates of the soil-tool interaction without considering granular media jamming. Our tactile-based proximity sensing framework could be combined with the sensor model in [46] to improve the accuracy of the occupancy maps.

In contrast, there are numerous studies on the interaction between soil and tillage implements [76], [104, 15, 6]. However, the studies on soil tillage generally measure tool forces with a load cell mounted above the free surface of the granular material. In our prior work [45] and in this work, we collect data on granular material-tool interactions from within the granular material via sensorized fingertips. This work advances our prior work [45, 46] by incorporating an analytical model for the failure surface of granular materials in order to enhance the accuracy of tactile-based proximity sensing, and by characterizing granular

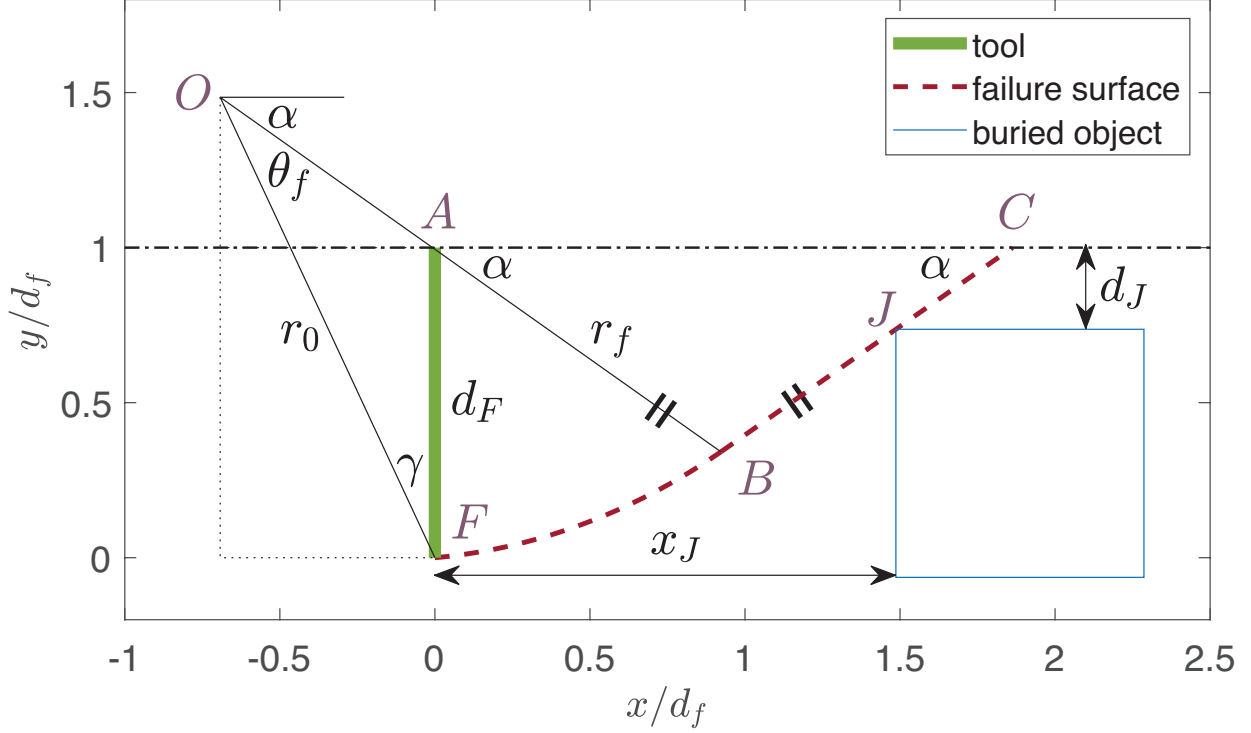


Figure 2.1: Schematic of the composite log-spiral failure surface based on the work by [Soltanbeigi et al.](#), consisting of a logarithmic curve FB and linear section BC. Point J denotes the top-left corner of a buried object. As a robotic finger at depth d_F rakes towards an object buried at depth d_J , the failure surface FC will make contact with the buried object at a distance x_J .

media jamming with a real robot for multiple materials.

2.3.2 Granular Material Failure Surface

As a tool is raked through granular material, displaced particles form a “failure surface” with the surrounding undisturbed media [32]. Both the digging force and failure surface shape are dependent on granular material properties such as internal friction angle [72],

surface roughness [5], and particle size [66], as well as tool depth [4]. Intuitively, the internal friction angle is a measure of shear strength due to the interlocking of the granular particles. The Coulomb theory [18] and Rankine theory [91] are classical approaches that are widely used as fundamental models for estimating the passive pressure of soil backfill on retaining walls. Both of these approaches assume a planar failure surface based on the limit equilibrium approach. In the Rankine approach, the interface friction angle δ between the wall and soil is assumed to be negligible and the failure surface is inclined at an angle $\alpha = 45^\circ - \varphi/2$, where φ is the internal friction angle of the granular material. However, the wall is unlikely to be smooth in a real-world scenario, which causes the Rankine approach to underestimate the passive earth pressure [107]. In the Coulomb approach, the failure surface is assumed to be at an angle θ to the horizontal such that the passive pressure acting on the retaining wall is minimized. Although the Coulomb approach takes into account the wall-soil friction angle, it tends to overestimate the passive earth pressure for larger wall-soil friction angle values.

Terzaghi found that the failure surface should be curved if the wall friction angle is non-negligible [107]. He proposed the log-spiral method, which has been widely used in various limit equilibrium methods for describing a composite failure surface [99, 61]. The composite failure surface consists of a logarithmic curve starting at the base of the wall, which is tangent to a linear portion that continues to the soil surface.

Few studies have employed the original log-spiral method [107] for determining the failure surface due to challenges with implementation. The challenge is primarily due to the lack of a closed-form solution and the consideration of numerous factors that may be difficult to measure such as soil weight, soil cohesion, and additional loading from material piled on the surface. Liu et al. proposed a modified log-spiral method that is solved using optimization

techniques and root-finding algorithms [61]. However, the complexity of the modified log-spiral method still makes it difficult to obtain the geometric properties of the logarithmic spiral. In 2020, Soltanbeigi et al. presented a simplified log-spiral model that is solely a function of soil friction angle φ . In their work, the failure surfaces of two different sands at varying relative densities were studied using particle image velocimetry. Their results pointed to a linear relationship between the sand’s angle of internal friction and a parameter of the logarithmic spiral. Due to its computational simplicity, we use the Soltanbeigi et al. model in this work, shown in Figure 2.1.

2.3.3 Interparticle Interactions in Granular Materials

As granular particles experience compression, *granular media jamming* may occur [28]. This phenomenon is due to the particles forming “force chains” along the direction of compression [12]. A force chain consists of the set of particles in direct contact with one another that form a chain under compression and along which a force can be transmitted. The contact network has been observed to be composed of a strong branch-like network and a weak network that behaves like an interstitial fluid [88]. In this jammed state, the material behaves like a solid and the strong network of force chains can support a shear stress indefinitely [28]. The strength of these force chains depends on granular material properties such as internal friction, packing fraction, and surface roughness [76, 5, 66].

2.4 Modeling Framework

2.4.1 Modeling the Granular Material Failure Surface

In this work, a sensorized robot finger will be used as the tool to be raked through different granular materials. As the finger moves through the granular materials, a failure surface will form ahead of the finger. When the granular material failure surface encounters a buried object, we expect that force chains will form due to granular media jamming, which can be sensed by the robot finger from within the granular material. We surmise that the granular material failure surface model is crucial to accurately estimating the proximity, or distance, of the fingertip to the buried object.

We adopted the simplified model proposed by [Soltanbeigi et al.](#) in 2020 that defines the logarithmic spiral as a function of the soil friction angle [102]. It is important to note that the [Soltanbeigi et al.](#) model is limited to vertical retaining systems that translate horizontally. In our study, we make the simplifying approximation that the sensorized robot finger can be modeled as a rigid plane that is oriented vertically and perpendicular to the free surface of the granular material.

Consider the representation of the [Soltanbeigi et al.](#) model in Figure 2.1. The figure shows a plate represented by $\overline{AF}$ at depth d_F being raked from left to right towards an object buried at depth d_J . The displaced granular material forms a failure surface FC comprised of a logarithmic spiral portion FB and a linear portion $\overline{BC}$. Point O denotes the center of the logarithmic spiral with distances r_0 and r_f to points F and B , respectively. As the plate approaches the buried object, the failure surface will make contact with the buried object at point J at a distance x_J ahead of the plate, initiating the onset of granular media jamming.

The results of [Soltanbeigi et al.](#) indicated a linear relationship between γ (the angle $\angle OFA$ as shown in Figure 2.1) and φ (the angle of internal friction that is unique to the granular material), as given in Eq. 2.1.

$$\gamma = \varphi + 5^\circ \quad (2.1)$$

Using the method proposed by [Soltanbeigi et al.](#) the entire failure surface can be modeled for a given internal friction angle φ , which can be measured using a triaxial shear test. The following equations detail how points along the failure surface can be calculated.

In order to determine points along the log-spiral portion of the failure surface, it is necessary to find the initial radius r_0 given the geometry in Figure 2.1. Given the failure surface inclination angle α and tool depth d_F , r_0 can be calculated using Eq. 2.2 and 2.3.

$$\theta_f = 90^\circ - \gamma - \alpha \quad (2.2)$$

$$r_0 = d_F \tan(\gamma) \left(\frac{\sin(\alpha)}{\sin(\theta_f)} + \frac{1}{\sin(\gamma)} \right) \quad (2.3)$$

Given an origin $(0,0)$ at the tip of the tool (plate) at point F , the points (x_i, y_i) along the log-spiral portion of the failure surface can then be calculated using Eq. 2.4, 2.5, and 2.6, where $\theta_i \in [0, \theta_f]$. Each gradual increase in θ_i results in a new r_i , until $\theta_i = \theta_f$ and r_i is equal to r_f .

$$r_i = r_0 e^{\theta_i \tan \varphi} \quad (2.4)$$

$$x_i = r_i \sin(\gamma + \theta_i) - r_0 \sin(\gamma) \quad (2.5)$$

$$y_i = -r_i \cos(\gamma + \theta_i) + r_0 \cos(\gamma) \quad (2.6)$$

After calculating the coordinates of point B at (x_B, y_B) , it is straightforward to plot the remaining linear portion at an incline of $\alpha = 45^\circ - (\varphi/2)$ relative to the horizontal, free surface of the granular material.

2.4.2 Modeling the Proximity of a Robot Finger Relative to a Buried Object

As the robot finger is raked through granular materials, the displaced wedge of granular material will be bounded by the failure surface described in Section 2.4.1. We expect the sensorized robot finger to measure an increase in contact force on the fingertip as the failure surface makes increasing contact with a buried object.

Using a model of the geometry of the failure surface (Figure 2.1), the distance between the robot finger and the buried object can be calculated when a threshold on fingertip contact force has been met.

Consider an object that has been buried at a depth d_J , and a point J that constitutes the first intersection between the buried object and the failure surface. If point J lies along the linear portion of the failure surface ($d_J \leq \overline{AB} \sin \alpha$), the distance x_J is straightforward to calculate based on the geometry of the failure surface. The distance $\overline{AB}$ is the leg length of the isosceles triangle ABC (Eq. 2.7). If instead, point J lies along the log-spiral portion of the failure surface, θ_J can first be solved through Equations 2.4 and 2.6 with root-finding algorithms using the bisection method. Then, x_J can be calculated with Eq. 2.5.

Thus, we define the distance to the buried object x_J using:

$$\overline{AB} = r_f - \frac{d_F \sin \gamma}{\sin \theta_f} \quad (2.7)$$

$$x_J = \begin{cases} 2\overline{AB} \cos \alpha - d_J \cot \alpha & \text{if } d_J \leq \overline{AB} \sin \alpha \\ \text{Solve for } \theta_J, \text{ then use Eq. 2.5} & \text{otherwise} \end{cases} \quad (2.8)$$

2.4.3 Detecting the Onset of Granular Media Jamming

As the robot finger is raked through granular material, the contact force on the fingertip will be relatively constant with small fluctuations due to the stick-slip nature of granular materials [3]. In preliminary studies, we observed that the contact force increases exponentially as the robot fingertip approaches a buried object. Thus, we define the “onset of granular media jamming” as the timepoint at which the time series of the average contact force transitions from a linear phase to an exponential phase.

Consider a time series $\{F_i\}_{i=1}^N$ of contact force measurements from a sensorized robot fingertip for $i = 1 \dots N$ timesteps. We calculate a centered moving average $\{s_i\}_{i=1}^N$ using Eq. 2.9, where the window size n is adjusted according to Eq. 2.10 for data points near the start and end of the time series.

$$s_i = \frac{1}{n} \sum_{i-(n-1)/2}^{i+(n-1)/2} F_i \quad (2.9)$$

$$n = \begin{cases} i - 1 & \text{if } i \leq (n - 1)/2 \\ N - i & \text{if } i > N - (n - 1)/2 \\ n & \text{otherwise} \end{cases} \quad (2.10)$$

The onset of granular media jamming is defined at time j when the average contact force transitions from a linear phase to an exponential phase. This transition is identified by applying two criteria to the time derivative of average contact force $\dot{s}$. First, $\dot{s}$ must exceed the value of the running average $\dot{s}_{avg}$ prior to the onset of granular media jamming; $\dot{s}_{avg}$ is assumed to be relatively constant during the linear phase of s . Simultaneously, time j must mark the instant at which all subsequent $\dot{s}_i$ values exceed the value of $\dot{s}_j$ for the remainder of the time series $i \in (j, N]$ (Figure 2.2).

$$j = \underset{j \in [1, N]}{\operatorname{argmin}} (\dot{s}_j > \dot{s}_{avg} \text{ and } \dot{s}_j < \dot{s}_i) \forall i \in (j, N] \quad (2.11)$$

2.5 Experimental Methods

We deployed the modeling framework described in Section 3.4.1 with a real robot in a custom testbed filled with granular material (Figure 2.3). The testbed was 65 cm long by 40 cm wide and the bed of granular material was 12 cm deep. A 7-DOF robot arm (Whole Arm Manipulator (WAM), Barrett Technology, Newton, MA) was used to rake a sensorized robot finger through the granular material. The custom end effector consisted of a 3D-printed fixture for a finger having two different sensors. A 6-DOF force/torque transducer (Nano25, ATI Industrial Automation, Inc., Apex, NC) sampled data at 100 Hz from the proximal base of the finger, above the free surface of the granular material.

The fingertip was comprised of a multimodal, deformable tactile sensor (BioTac, SynTouch, Inc., Montrose, CA) capable of sensing fingerpad deformation, vibration, and temperature [119]. In this study, we sampled the BioTac’s 19 electrodes at 100 Hz in order to measure fingerpad deformation. We sampled the embedded hydrophone at 100 Hz as a mea-

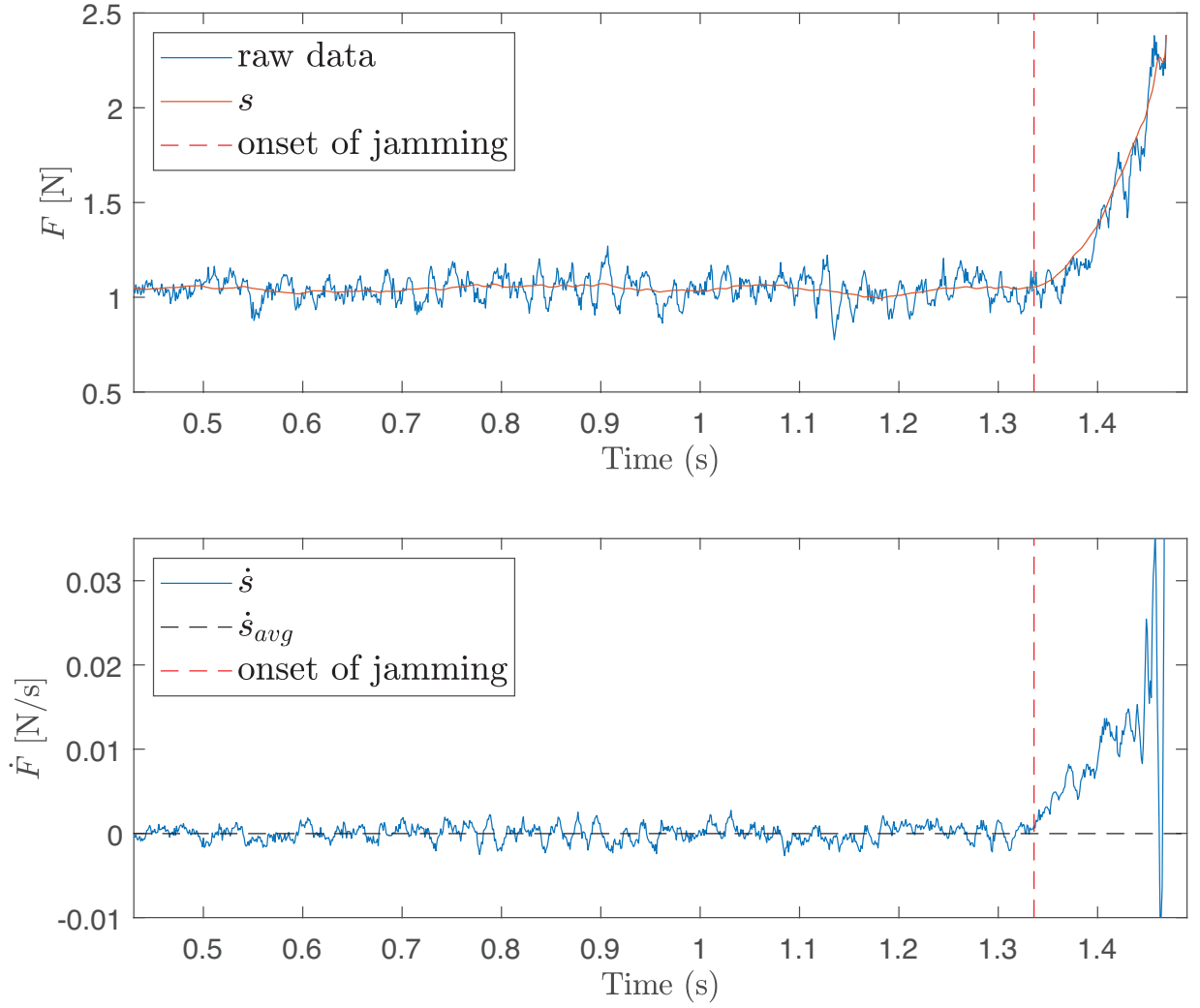


Figure 2.2: Top: First, the raw data were smoothed using a centered moving average to obtain s . Bottom: Next, the derivative of s was computed to obtain $\dot{s}$, and a running average was used to obtain $\dot{s}_{avg}$ prior to granular media jamming. The onset of jamming at time j was defined as the first timestep at which $\dot{s}_j > \dot{s}_{avg}$ and $\dot{s}_j < \dot{s}_i$ for all i from $(j + 1)$ and onwards.

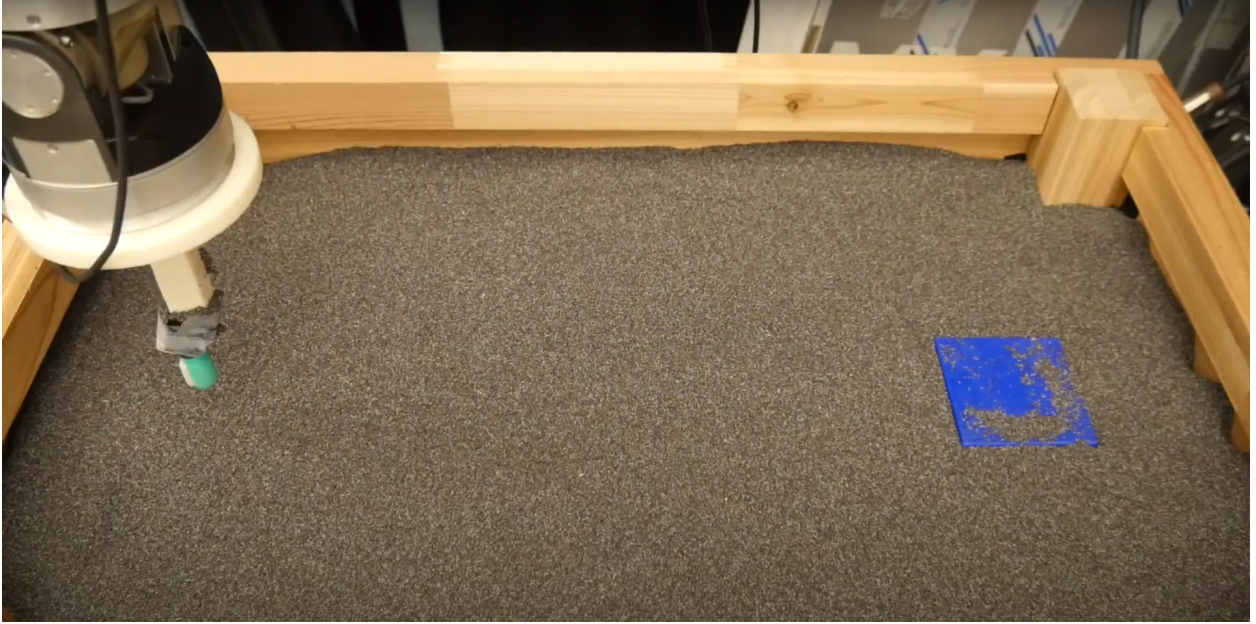


Figure 2.3: Experimental setup: Once submerged, a single sensorized robot finger is raked in a straight line across a bed of granular material (poppy seeds shown) from left to right. The buried object (blue cube) is exposed for clarity here, but is completely covered by granular material during experimental trials.

sure of overall fluid pressure within the deformable fingerpad. A simple neural network was trained on the electrode array data in order to estimate the magnitude of the contact force at the fingertip. The electrode data were normalized and shuffled before being trained on a neural network consisting of a single hidden layer with 800 nodes using the *tanh* activation function. Regularization and early stopping were used to prevent overfitting.

A rigid cube having sides of 7.6 cm in length was used as the buried object for all trials. The cube was fixed in place within the bed of granular material using a 3D-printed fixture mounted behind the cube (Figure 2.4).

As shown in Table 2.1, we investigated the effects of five independent experimental vari-

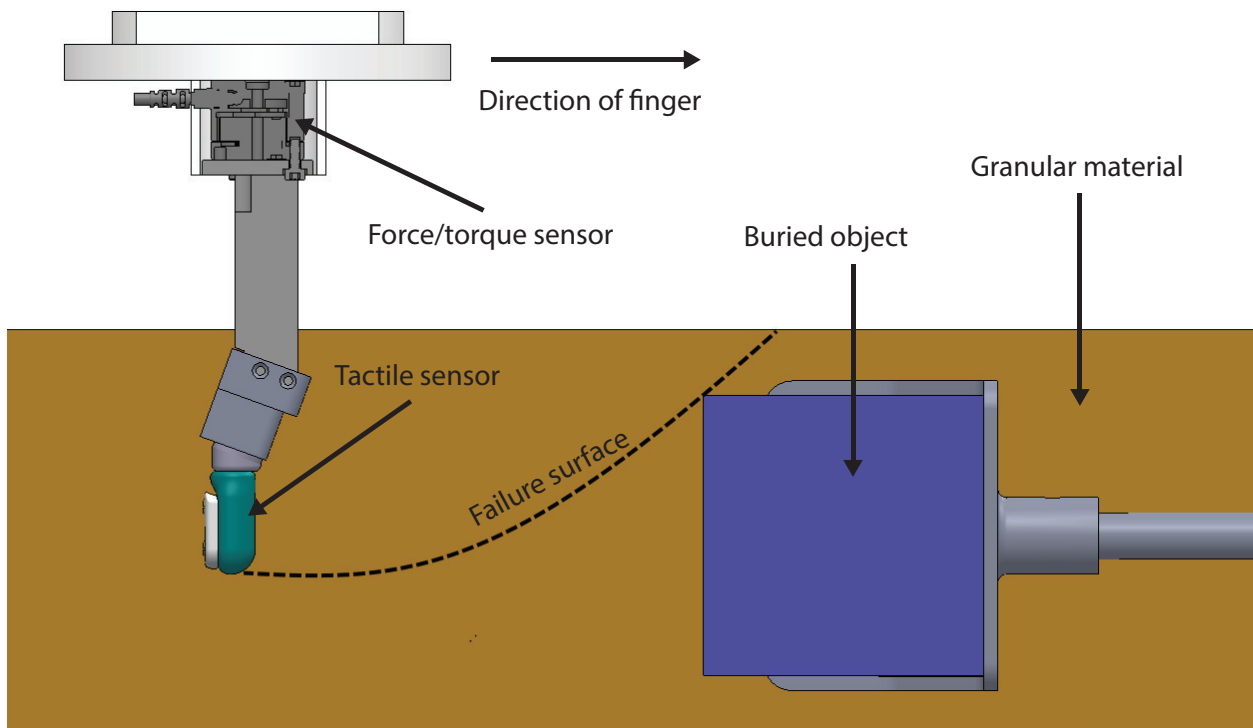


Figure 2.4: Cross-sectional schematic of the experimental setup: As the robot finger is raked through the granular material from left to right, the failure surface moves ahead of the finger until it contacts the buried object. The custom end effector enables measurement of force/torque at the proximal base of the finger and multimodal data from within the granular material via a BioTac sensor fingertip.

ables on the physical interactions between the robot finger, granular material, and buried object. To observe the effects of varying granular material properties, we studied glass beads, poppy seeds, and playground sand. The glass beads (A-Series Technical Quality Glass Spheres P-0337, Potters Industries) had diameters ranging from 0.6 - 0.8 mm. The poppy seeds (Regal Spice) were relatively spherical with estimated diameters ranging from 1 - 2 mm. The playground sand particles (Premium Play Sand, Quikrete), if crudely represented as spheres, had estimated diameters ranging from 0.1 - 2 mm.

Fingertip depth was either 3 cm or 4 cm. Fingertip depths greater than 4 cm were not considered in order to minimize damage to the submerged tactile sensor. For the fingertip depth of 3 cm, the object was buried at depths ranging from 0.5 cm to 2.5 cm in increments of 0.5 cm. For the fingertip depth of 4 cm, the object was buried at depths ranging from 0.5 cm to 3.5 cm in increments of 0.75 cm.

We tested our tactile-based proximity sensing framework using contact forces estimated with the BioTac fingertip from within the granular material, as well as benchmark force/torque data measured outside of the granular material, as is commonly done in the literature [46]. In a post hoc analysis, we evaluated two models for the failure surface: the simplified logarithmic spiral model developed by [Soltanbeigi et al.](#) and a benchmark model based on classical Rankine theory [91]. Five trials were conducted for each combination of fingertip depth (2 levels), obstacle depth (levels varied according to fingertip depth), and granular material (3 levels) resulting in a total of 150 trials. Trials were conducted in blocks according to granular material type.

For each granular material type, the granular material was poured into an empty testbed and leveled by hand. The depth of the buried object was checked using a ruler. The trajectory of the 7-DOF robot arm was calculated for each fingertip depth and tested using

Table 2.1: Experimental Variables and Levels

Independent Variable	Levels
Granular material	Glass beads, Poppy seeds, Playground sand
Fingertip depth	3 cm, 4 cm
Object depth	0.5 cm - 3.5 cm, depending on fingertip depth
Sensor location	Fingertip force within the granular material, Torque at the base of the finger outside the granular material
Failure surface model	Logarithmic spiral based on internal friction angle [102], Classical Rankine theory [91]

MoveIt! [17], an open-source motion planner, prior to deployment on the real robot. The motion consisted of driving the robot fingertip into the granular material at a slight angle until the specified fingertip depth was achieved and the fingertip was 40 cm away from the buried object. The fingertip was then raked through the granular material, horizontally and in a straight line towards the buried object at a speed of 2 cm/s.

To minimize potential damage to the sensorized fingertip, each trial was aborted if the estimated force from the BioTac sensor exceeded a threshold of 9 N. After each trial, the finger was lifted out of the testbed and the granular material in the entire testbed was thoroughly loosened manually with an upward lifting motion. This was done to prevent residual compaction from affecting subsequent trials and to reset the packing fraction of the granular material [84]. The surface of the granular material was then leveled by hand such that the object was buried to the specified depth for the next trial.

2.6 Results and Discussion

Our goal is to develop a framework for tactile-based proximity sensing in granular material types. In Section 2.6.1, we examine the effects of different granular materials. In Section 2.6.2, we compare the log-spiral model of the failure surface [102] against the classical Rankine model [91]. In Section 2.6.3, we investigate the effects of fingertip depth. In Section 2.6.4, we compare the differences between using torque data collected at the base of the finger outside of the granular material versus force data estimated from within the granular material using a sensorized robot fingertip.

2.6.1 Effect of Granular Material Type

We collected data using glass beads, poppy seeds, and playground sand to observe the effects of frictional properties on tactile-based proximity sensing. Figure 2.5 shows the points at which the onset of jamming was detected in the torque data collected at the base of the finger, from outside the granular material. The method for calculating the onset of jamming is described in Section 2.4.3. If the log-spiral failure surface was a perfect model for determining when the failure wedge first contacts the buried object, the plotted onset of jamming points would lie on the failure surface curve. Points to the left of their respective failure surface curve indicate that the estimated distance to the object using the log-spiral failure surface model was greater than the actual distance to the buried object. Points to the right of their respective failure surface curve indicate that the estimated distance to the object was less than the actual remaining distance to the buried object.

The angle of internal friction φ was measured for each material using a triaxial shear test [41] at a confining pressure of 5 kPa. The angle of internal friction was 22°, 30°, and

Table 2.2: Absolute Estimation Error Mean $\pm$ Standard Deviation using the Log-spiral and Rankine Failure Surface Models

Log-spiral	Glass beads	Poppy seeds	Playground sand
Fingertip force	0.8 ± 0.5 cm	1.0 ± 0.4 cm	1.2 ± 1.3 cm
Finger torque	0.7 ± 0.4 cm	0.6 ± 0.3 cm	1.0 ± 1.1 cm
Rankine	Glass beads	Poppy seeds	Playground sand
Fingertip force	1.7 ± 0.8 cm	1.2 ± 1.0 cm	1.9 ± 1.7 cm
Finger torque	1.2 ± 0.7 cm	1.2 ± 0.6 cm	2.2 ± 1.4 cm

38° for the glass beads, poppy seeds, and playground sand, respectively. The larger the angle of internal friction, the shallower the slope of the theoretical log-spiral failure surface curves (Figure 2.5). The distances to the buried object at the onset of jamming followed a similar trend; the perceived exponential increase in contact force (or torque) on the finger occurred closest to the buried object for glass beads, and furthest from the buried object for playground sand. These results suggest that the angle of internal friction of the granular material plays a significant role in determining the granular material failure surface, which is, in turn, crucial for the accuracy of our tactile-based proximity sensing framework.

2.6.2 Comparison of Soil Failure Models

We compared the accuracy of the log-spiral failure surface model ([102]) with the classical Rankine model [91] for estimating the distance of the robot fingertip to a buried object. Figure 2.6 shows the points at which the onset of jamming was detected using torque data collected at the base of the finger outside of the granular material and using contact force

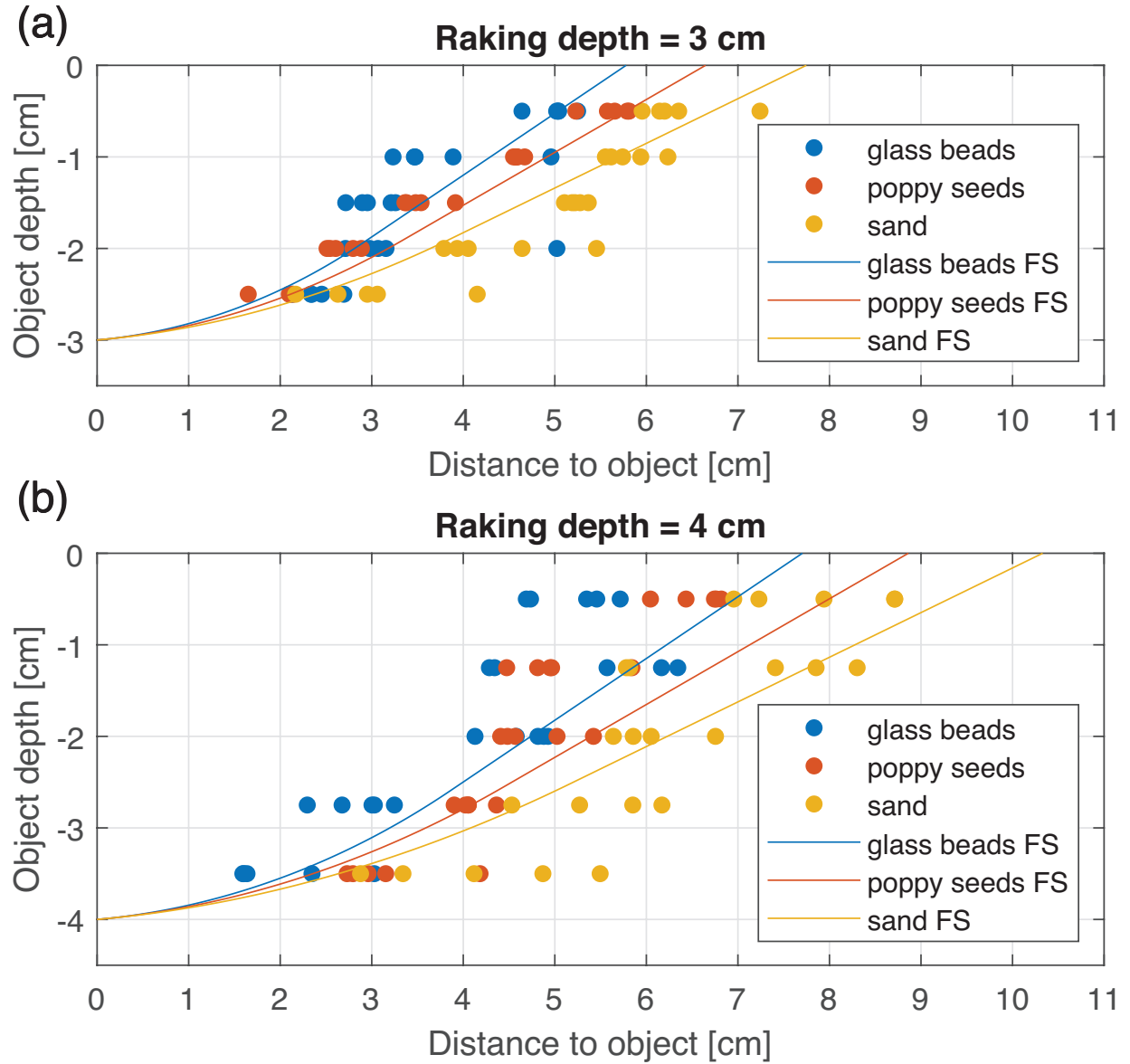


Figure 2.5: The distance to the buried object at the onset of jamming is shown for all three granular material types, for various object depths, and for fingertip depths of (a) 3 cm and (b) 4 cm. The onset of jamming was determined per Section 2.4.3 using torque data collected at the base of the finger outside of the granular material. The theoretical log-spiral failure surface (FS) curves [102] are shown for each granular media type.

on the fingertip (estimated from the BioTac electrode impedance data) within the granular material. Regardless of the source of the sensor data, the perceived onset of jamming followed the log-spiral failure surface curve more closely than that based on the classical Rankine model.

Table 2.2 shows the absolute estimation error mean and standard deviation for both the log-spiral and Rankine models of the failure surface. Two-sample t-tests for each granular material showed that the accuracy of detecting the onset of jamming was statistically significantly better when using the log-spiral model for the failure surface as compared to using the Rankine model. The two-sample t-tests tested a null hypothesis that estimation errors from using the log-spiral and Rankine models came from normal distributions having equal means and variances. The alternative hypothesis was that the mean of estimation errors using the log-spiral model was less than that using the Rankine model. The estimation errors for each material were verified for normality using the Kolmogorov-Smirnoff test. For all three granular material types, the null hypothesis was rejected for an $\alpha = 0.05$.

2.6.3 Effect of Fingertip Depth

We collected data at fingertip depths of 3 cm and 4 cm to examine the effects on the accuracy of tactile-based proximity sensing. Figure 2.7 shows the estimation errors for distance to the buried object using the torque data collected at the base of the finger outside of the granular material. Figure 2.8 shows the estimation errors for distance to the buried object using the fingertip force based on the BioTac electrode impedance data from within the granular material. A positive estimation error indicates that the actual distance to the buried object was greater than the estimated distance, whereas a negative estimation error indicates that the actual distance was less than the estimated distance.

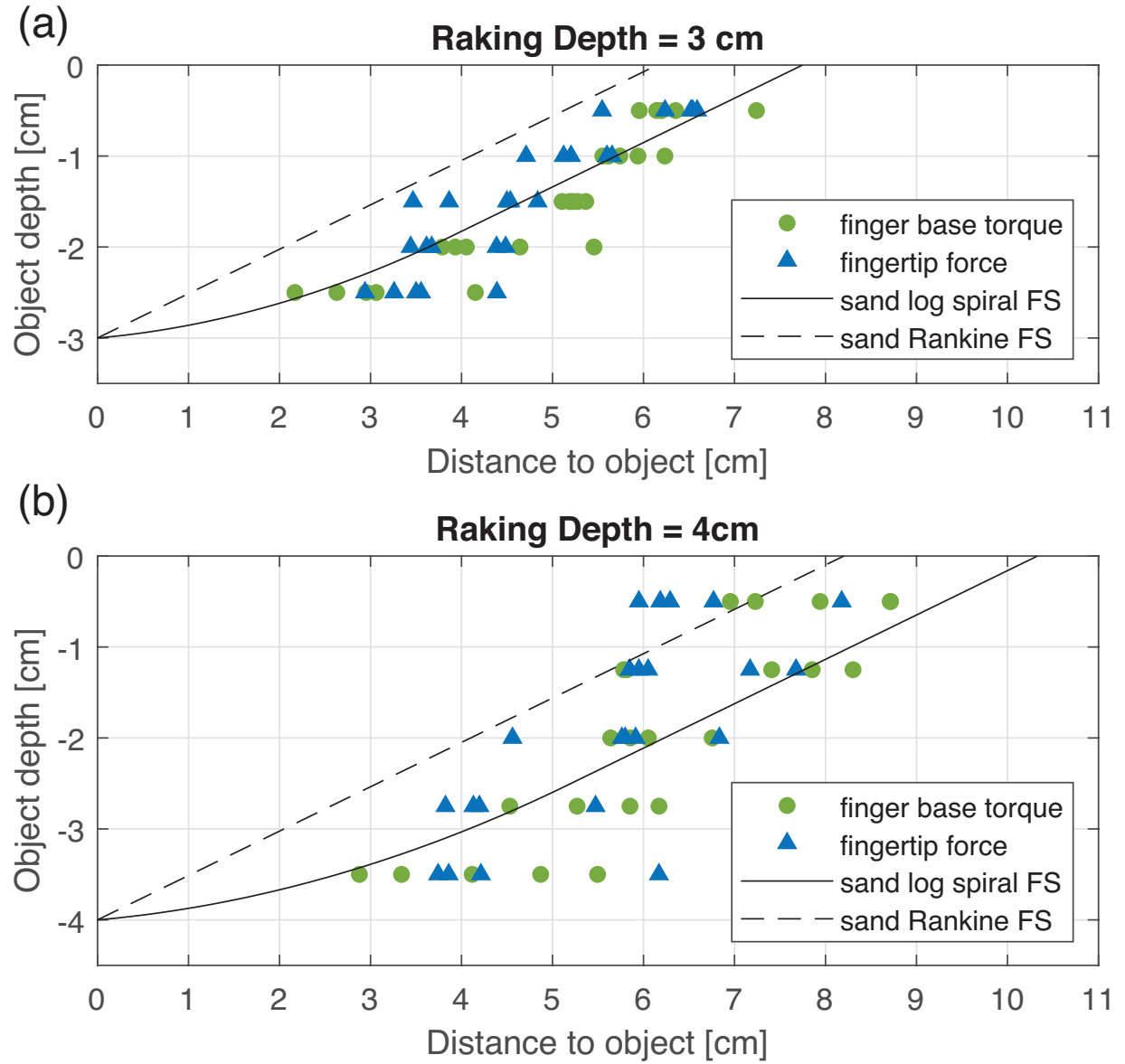


Figure 2.6: The distance to the buried object at the onset of jamming is shown for playground sand, for both sensor sources (finger torque, fingertip force), for various object depths, and for fingertip depths of (a) 3 cm and (b) 4 cm. The onset of jamming was determined per Section 2.4.3. The experimental data followed the theoretical log-spiral failure surface (FS) curve more closely than the Rankine failure surface curve.

For both fingertip depths of 3 cm and 4 cm, the actual distance tended to be less than the estimated distance at shallower object depths. In contrast, the actual distance tended to be greater than the estimated distance at deeper object depths. This suggests that the true failure surface has a steeper slope (larger α in Figure 2.1) than the estimated failure surface for each material. A steeper slope corresponds to a smaller angle of internal friction φ , which can be explained by the shallow fingertip depth for which these experiments were conducted. The estimated failure surfaces were based on the angle of internal friction from triaxial stress tests conducted at a confining pressure of 5 kPa, which corresponds roughly to a depth of 10 - 20 cm [19].

The estimation errors for a fingertip depth of 4 cm have a larger variance compared to those for a fingertip depth of 3 cm. This may be due to an increase in stick-slip fluctuations at greater fingertip depths when the finger is moved through granular material [3]. While the log-spiral failure surface model appears promising, the model may need to be modified for shallower fingertip depths to account for a smaller angle of internal friction.

2.6.4 Effect of Sensor Data Source: Finger Torque vs. Fingertip Force

We collected torque data at the base of the finger outside the granular material as well as fingerpad deformation data (mapped to fingertip force) within the granular material. Figure 2.9 shows representative time series data for finger torque and fingertip force.

Table 2.2 summarizes the absolute estimation error results using both sources of sensor data. At first glance, the finger torque data appear to yield more accurate estimates than the fingertip force data, as suggested by the smaller absolute error mean values for finger torque. However, two-sample t-tests conducted for each granular material type suggested that estimation accuracy is not statistically significantly different for finger torque versus

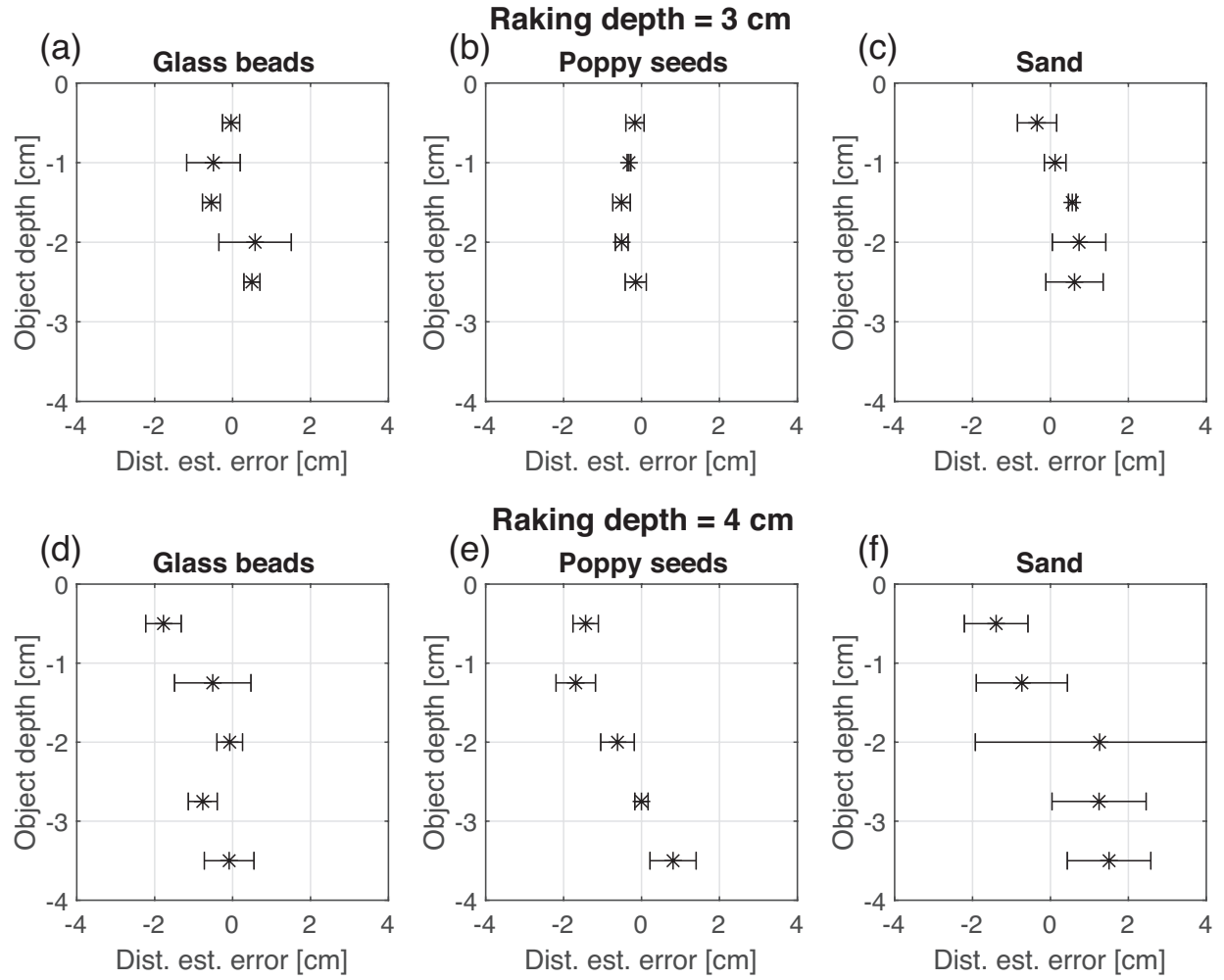


Figure 2.7: The estimation error for distance to the buried object are shown for all three granular material types, when using the torque data collected at the base of the finger outside of the granular material, for various object depths, and for fingertip depths of (a)-(c) 3 cm and (d)-(f) 4 cm. The mean errors (asterisks) and standard deviation (whiskers) are shown.

fingertip force. The two-sample t-tests tested a null hypothesis that estimation errors from finger torque and fingertip force came from normal distributions having equal means and variances. The alternative hypothesis was that the mean of estimation errors when using finger torque data was less than that when using fingertip force data. The estimation errors

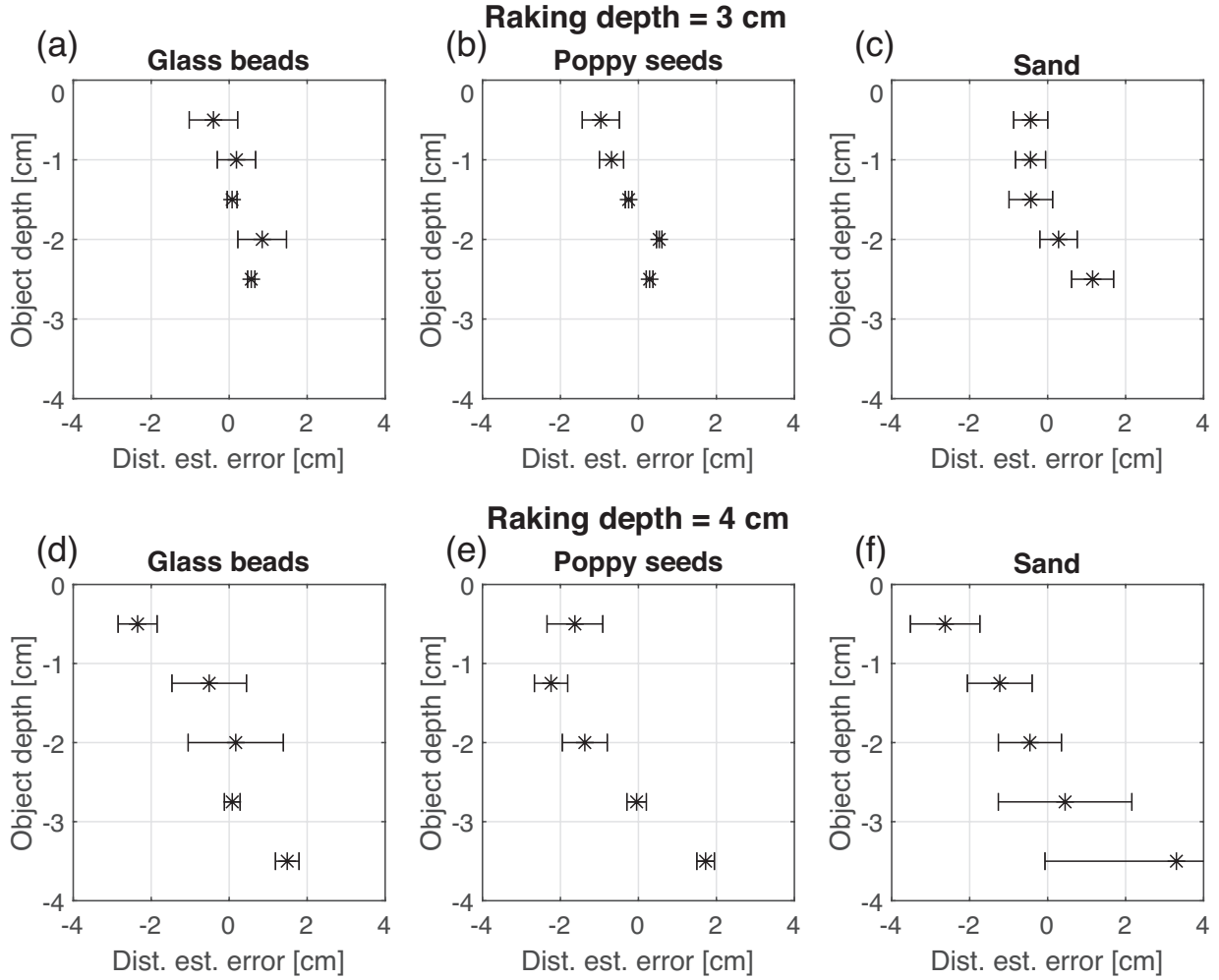


Figure 2.8: The estimation error for distance to the buried object are shown for all three granular material types, when using the fingertip force data collected within the granular material, for various object depths, and for fingertip depths of (a)-(c) 3 cm and (d)-(f) 4 cm. The mean errors (asterisks) and standard deviation (whiskers) are shown.

were verified for normality using the Kolmogorov-Smirnoff test. For glass beads, poppy seeds, and playground sand, we failed to reject the null hypothesis with p-values of 0.95, 0.45, and 0.12, respectively ($\alpha = 0.05$). These results suggest that either finger torque data or fingertip force data can be successfully used to detect the onset of jamming, and,

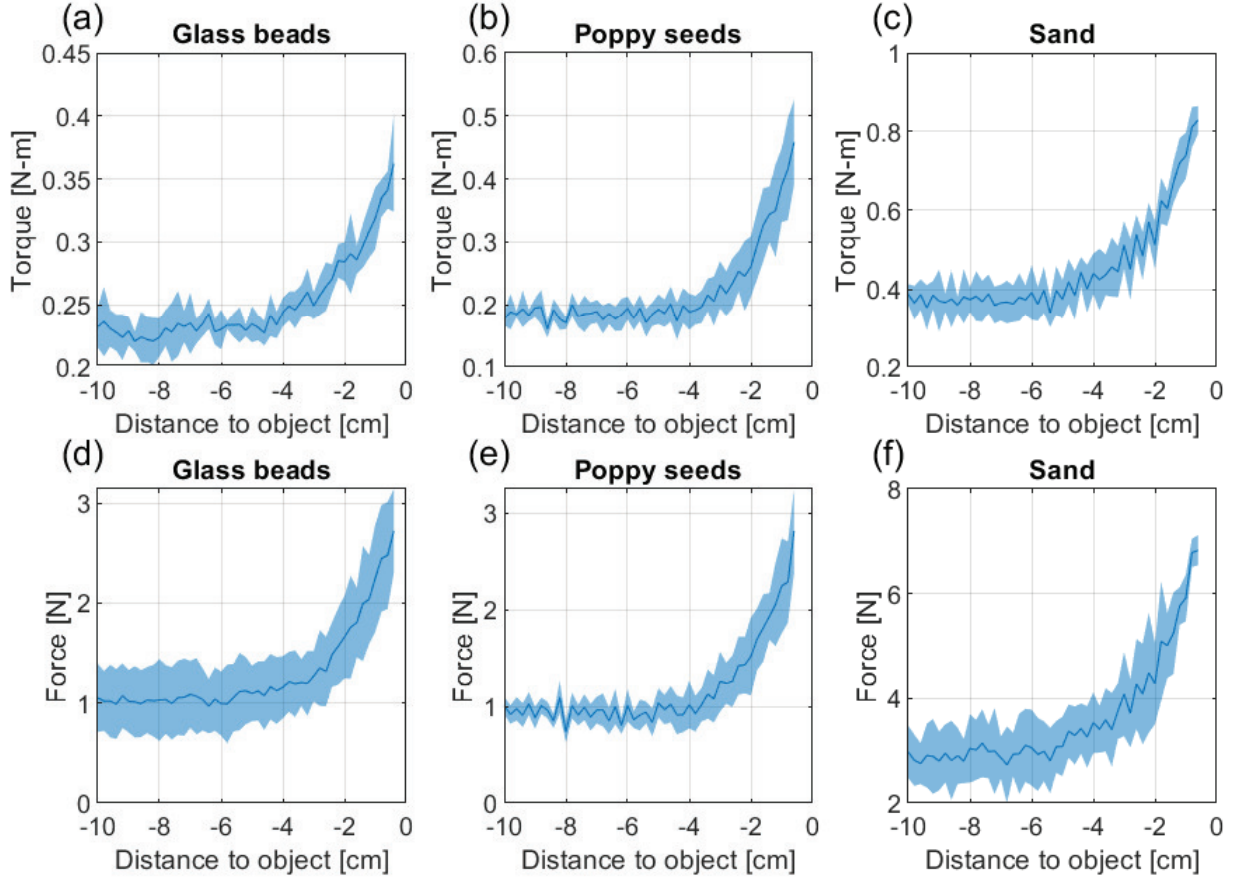


Figure 2.9: Representative time series data are shown for (a)-(c) torque data collected at the base of the finger outside of the granular material and (d)-(f) fingertip force estimated from fingerpad deformation within the granular material. The mean (solid line) and standard deviation (shaded region) are shown for all trials, with a fingertip depth of 4 cm and object depth of 2 cm. Data are shown for all three granular material types.

thus, for estimating the distance of a robot finger to an object buried in granular material.

2.7 Conclusion

In this work, we developed and demonstrated a novel framework for tactile-based proximity sensing in granular material. We estimated the distance of a sensorized robot fingertip to an object buried in granular material using an established failure surface model and the sense of touch. By leveraging granular media jamming, a tactile sensor can be used as a proximity sensor within in granular materials. We conducted experiments on real robots using three different granular material types (glass beads, poppy seeds, and playground sand), and our results suggest that the simplified log-spiral method by [Soltanbeigi et al.](#) can be successfully used to detect the onset of granular media jamming and to estimate the distance of a sensorized robot fingertip to a buried object.

One limitation of the log-spiral method by [Soltanbeigi et al.](#) is that their experiments were conducted using only two different types of sand. It has not been verified whether or not their simplified model holds true for other granular material types. While our results show that using the same log-spiral model for glass beads and poppy seeds was adequate, further experiments are necessary for determining whether or not the model accurately describes the behavior of other granular materials. Another limitation, as described in Section 2.6.3, is that the simplified log-spiral model relies critically on the internal friction angle of the granular material. An internal friction angle that is measured using a triaxial shear test, which simulates a specific tool depth, may not apply for real world applications conducted at shallower tool depths.

In the work of [Jia et al.](#), the robot explores a non-homogeneous sand mixture using a sensor model to carefully delineate a buried object. The accuracy of the sensor model relies on a conservative estimate of the distance to a buried object based on the rupture distance

of the granular material failure surface. The sensor model used by [Jia et al.](#), which relies on rupture distance, could be improved by the failure surface modeling efforts proposed in this work in order to obtain more accurate estimates of distance between the robot fingertip and a buried object.

For field applications involving an unidentified granular material and no access to a triaxial shear testing setup, the angle of internal friction of the granular material could be estimated by measuring the angle of repose. This can be done by slowly pouring the material into a cone shape and measuring the base angle of the resulting cone, as an estimate of the angle of repose. In this way, our proposed tactile-based proximity sensing framework could be deployed in the field even if the properties of the granular material environment are initially known.

CHAPTER 3

Tactile Perception of Cables Buried in Granular Materials

This study was conducted in collaboration with Eunsuk Chong, Kevin Hsu, Bowen Wang, and Veronica J. Santos.

3.1 Abstract

We present a systematic framework for the tactile perception of cables buried in granular materials using a deformable, vision-based tactile sensor that outputs heightmap of the deformed contact surface. First, we estimate cable orientation using a proposed proximity function for elliptical contact region of the cable which takes extracted image features as input. We compare several image feature extraction methods including existing methods: PCA and maximally stable extremal regions (MSER). We propose a new method, heightmap thresholding with automatic scaling (HTAS), which uses feature extraction layers based on the heightmap image Hessian and entropy. Second, we estimate cable diameter using a scaled version of the elliptical contact region. The most accurate estimates were achieved by averaging the results from two methods: (i) directly measuring curvature from heightmap, (ii) minimizing the variance of distances between the center line of a cylindrical cable and points on heightmap. In our experiments, we test our proposed framework to estimate the orientation and diameter of buried cables ranging in diameter from 1.6 mm to 8.3 mm,

reporting mean errors of 4.0° and 1.8 mm, respectively.

3.2 Introduction

The robotic grasp and manipulation of deformable linear objects (DLOs) remain challenging for a number of tasks, such as knot tying [16, 38, 111], wire insertion [22], and cable following [100]. For each of these tasks, robot planning and control require knowledge of DLO characteristics and pose. When gravitational effects are considered for DLO modeling, the mass, length, and stiffness of the DLO are also considered [97, 128]. The diameter or cross-sectional area of the DLO can be used to estimate mass and/or stiffness, properties which have been used for modeling and manipulation planning [70].

Most state-of-the-art motion planners for DLOs rely on knowledge of DLO configuration that is treated as a global measure of system state [133, 105]. DLO configuration has been important for applications such as product assembly [81] and rope manipulation [69]. However, one can also consider a local measure of DLO configuration, such as the orientation of a DLO (string, wire, electrical cable, etc.) with respect to robot fingertips. Knowledge of DLO orientation with respect to a gripper has been used for cable following [100] and locating the endpoint of a cable for insertion in manufacturing tasks [22].

Cable configuration information is most commonly acquired using cameras [70, 112, 1], which require direct line of sight to the cable. Clutter can often be tolerated, such as with a bundled mass of cables, but line of sight is required [98]. In many field robotics applications, however, direct line of sight is not achievable. For example, in visually occluded environments, such as within granular materials, the estimation of cable configuration is nontrivial (e.g., cable system construction, maintenance, or demining tasks [30]). Visual

occlusion drastically limits the usefulness of vision-based sensors and the effectiveness of existing vision-based cable characterization methods developed with line of sight assumed. For cable manipulation in visually occluded scenarios, tactile sensing can be used to complement vision-based sensing.

Granular materials poses problems for both vision-based and tactile sensing methods. If a cable is lightly covered by granular materials, it may be possible to visually identify the contours of the cable with appropriate camera perspective and lighting conditions using traditional thresholding and segmentation methods. However, the visual saliency of the cable will depend upon the depth of cable burial as well as the homogeneity of the granular material that dominates the image.

The premise for the use of tactile sensing in granular materials is that objects of interest that may not be visually salient may be haptically salient. That is, the sense of touch may enable effective segmentation of a cable from the background noise posed by the granular material itself if contact with the cable and granular material can be encoded distinctly in tactile sensor data. Using touch to locate objects within granular materials is a nontrivial problem [106] that increases in difficulty as the nonhomogeneity of the granular material increases. For instance, small rocks become an additional source of noise on top of that posed by sand when haptically searching for a buried cable. Furthermore, the "field of view" of a tactile sensor is limited to its sensorized contact area. Only a small portion of a cable may be observed by the tactile sensor at any given time. In practice, one must also consider the potential for damage to the sensor surface due to puncture or wear by the granular material. Protective measures such as the application of protective films can also degrade sensing range and resolution.

In this work, we present a framework for the tactile perception of cables for field robotics

applications. Specifically, we focus on the tactile perception of the orientation and diameter of cables buried in granular material using a deformable, vision-based tactile sensor. We compare several image processing methods for estimating cable orientation given the heightmap obtained from the tactile sensor. We introduce a custom proximity function for detecting the elliptical contact region of cables as heightmap that is further processed to estimate cable diameter from local geometry.

We show that cable orientation and diameter can be effectively estimated even when the cable is fully buried in granular material and is not visible. To the best of our knowledge, our work is the first study among existing literature on tactile perception of deformable linear objects in granular material with experimental results.

The remainder of the paper is organized as follows. In Section 3.3, we review prior works related to vision-based tactile sensors and the estimation of cable orientation and diameter. We detail our experimental framework in Section 3.4. Our experimental results are reported and discussed in Section 3.5, followed by concluding remarks in Section 3.6.

3.3 Related Work

The cable orientation and diameter that we seek to estimate in this work are directly related to local geometry of the cable shape. Vision-based tactile sensors, in particular, can be used to reconstruct local geometry the of cable shape with high spatial resolution. In the following sections, we describe the various types of vision-based tactile sensors as well as their pros and cons. We also provide a brief review of existing studies on the tactile perception of cable orientation and diameter.

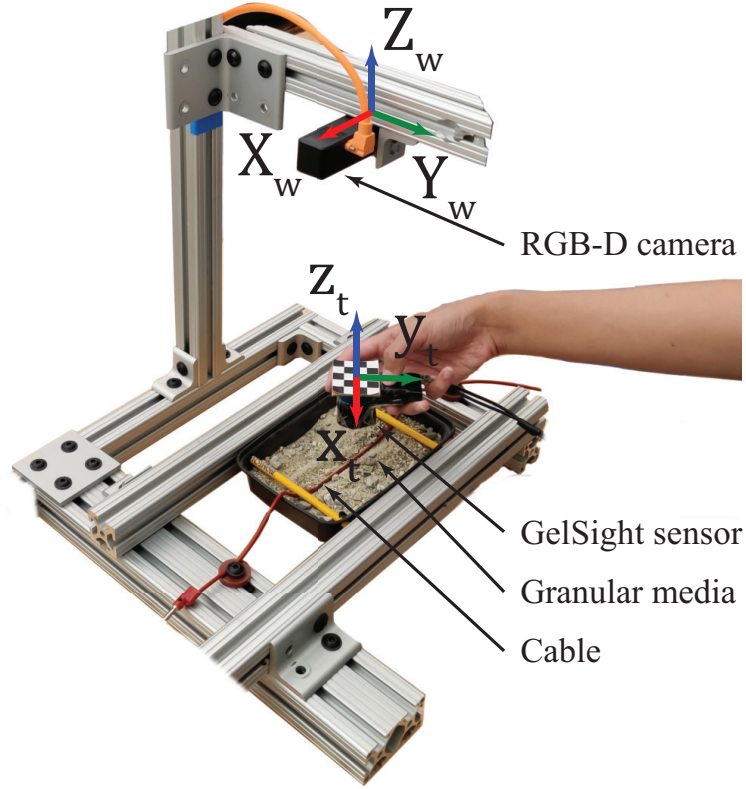


Figure 3.1: Experimental setup used for data collection. A GelSight sensor was manually pressed against a cable within a granular material testbed. The cable was fixed horizontally and aligned with the world (w) x -axis X_w of an RGB-D camera that recorded the position and orientation of a local tactile sensor (t) reference frame attached to the GelSight sensor.

3.3.1 Vision-based Tactile Sensors

Tactile sensors employ a variety of transduction techniques, including capacitive, piezoresistive, piezoelectric, inductive, and vision-based approaches [109]. Vision-based tactile sensors have become a popular choice with the advancements of computer vision techniques. In this subsection, we review vision-based tactile sensors and their sensing capabilities. Most vision-based tactile sensors utilize a deformable fingerpad to transduce mechanical stimuli into changes in light-based signals. Such sensors have increased in popularity thanks to

the availability of low-cost cameras and raw image outputs that can be processed using well-established computer vision techniques. Vision-based tactile sensors are divided into three categories based on transduction mechanisms [101]: *light conductive plates, marker displacement, and reflective membranes*.

Sensors that use light conductive plates typically consist of an elastic membrane attached to one side of an internally lit conductive plate [65, 40, 7]. When the sensing surface is not in contact with any object, a baseline level of LED light is internally reflected within the light conductive plate. Upon contact with an object, the elastic membrane deforms and LED light is scattered at the contact areas due to changes in the total internal reflection conditions [40]. The main disadvantage of light conductive plates is that, with current plate-based form factors, only two-dimensional object profiles can be measured.

An optics-based tactile sensor was developed that measures the amount of light traveled through an elastomer [85]. The sensor is capable of performing touch localization and force detection. Instead of detecting scattered light as used in the light conductive plate method, the sensor directly measures the change in light traveled from light emitters to receivers embedded in the elastomer. Although the sensor provides a rich amount of data from its numerous LED/diode pairs, ground truth data is required for each tactile characteristic predictor (e.g. location, force). Whether the sensor is capable of detecting shear forces is not stated in the study.

Marker displacement is commonly used for tactile sensing for its ease of use and wide range of measurable quantities [94, 20, 51]. Typically, an array of dot-shaped markers is printed on an elastomeric sensing pad. By monitoring the optical flow induced by the marker position changes, tactile information such as force [51, 94], shear [20], slip [43] and torque [123] can be measured. The primary disadvantage of marker-based methods is that

spatial measurement resolution is determined by the spacing of the discrete elements being tracked. Spatial resolution can often be limited due to volumetric constraints on the sensor itself. There are also sensors that similarly track the deformation of an array on the sensor surface, but without markers. For instance, a suite of sensors called TacTip [116] relies on the displacement of physical pins attached to the sensing surface.

Reflective membranes enable the acquisition of tactile data with high spatial resolution [78, 27, 50, 58]. A reflective coating is applied to the inner surface of a deformable fingerpad that reflects light from several internal light sources. An internal camera captures varying brightness levels on the coating that occurs when the sensing pad is deformed. Using photometric stereo [48], the deformation of the sensing pad is estimated from measurements of the internally reflected light. An image created by the reflected light is then transformed into a heightmap, where each height value corresponds to the local 3D deformation of the fingerpad. Although measurements are subject to the discrete nature of digital camera images, the fine pixel resolution provided by low-cost cameras can provide relatively high spatial resolution. An open source-based sensor, DIGIT (Meta Platforms, Inc.), is one of the most recent examples of a reflective membrane sensor [58]. DIGIT is designed to be a low-cost, compact, and high-resolution alternative to existing tactile sensors. Remaining challenges for reflective membrane-based tactile sensing include low sampling (frame) rates and volumetric requirements for the cameras.

Some vision-based tactile sensor designs have combined marker displacement with reflective membranes [78, 27]. The GelSight sensor [48] employs a deformable elastomeric fingerpad whose internal surface is illuminated by three LEDs of different colors. Using photometric stereo techniques, the tactile images can be mapped to a heightmap that reflects microscale geometric features of the deformed fingerpad. Dot-shaped markers are distributed

either evenly [23] or arbitrarily [124] between the elastomer base and reflective membrane. The GelSight has also been designed with a more compact form factor called GelSlim [24].

The GelSight sensor has been used for estimating normal force [125], shear force and slip [124], and object hardness [126]. It has also been used for performing cable following and insertion tasks [100], [59] and for detecting lumps for biomedical palpation applications [122]. More specialized applications of the GelSight include evaluating grasp quality [10], fusing tactile data with point cloud information from an RGB-D camera for object tracking [42], and mapping of tactile data to the motion of a robot end-effector for surface tracking [64].

In our study, we use the GelSight sensor to estimate the orientation and diameter of cables buried in granular material. We leverage the heightmap produced by the GelSight sensor to distinguish between cables and granular material, and to characterize features that are directly related to local geometry of the fingerpad.

3.3.2 Tactile Characterization of Cables

Vision-based tactile sensors have been used to identify rigid objects buried in granular material [82]. However, based on our literature review, we have been unable to find other evidence of tactile sensors being used to characterize DLOs, such as cables, in granular material. In this subsection, we review the tactile perception of cable orientation and diameter in open-air environments. We also state potential issues when directly applying existing approaches to scenarios involving granular materials in order to motivate our methods described in Section 3.4.

3.3.2.1 Cable Orientation

When using vision-based tactile sensors, the main challenge for estimating cable orientation in granular materials is distinguishing cable-related features from the surrounding material. In [100], cable orientation was estimated based on the heightmap obtained from a gripper-mounted GelSight sensor for a robotic cable manipulation task. In the study, one end of the cable was held in the air by an unsensorized gripper while the other end of the cable was tracked by a gripper outfitted with a GelSight sensor. The heightmap was filtered to isolate pixels whose deformation values exceeded a threshold. Principal component analysis (PCA) was then applied to these pixels and the direction of the first principal component was assumed to align with the orientation of the cable. In granular material environments, however, the heightmap is effectively polluted by noise resulting from contact with the granular particles surrounding the cable [46]. The application of a single height threshold and PCA may no longer produce accurate estimates of cable orientation.

An end-to-end data-driven image processing technique could be used to estimate cable orientation since a heightmap can be directly treated as a monochrome image. For instance, convolutional neural networks (CNNs) have been applied to tactile image classification tasks [127, 31]. However, CNN models require large amounts of training data. In [126], a CNN model using GelSight sensor data used 7000 video clips, which was equivalent to approximately 140,000 to 210,000 heightmaps based on the reported sampling rate.

If the number of heightmaps is relatively small as in this work, methods that more heavily rely on prior domain knowledge are preferred. One such approach is the use of traditional blob detection methods capable of detecting regions in an image that differ from surrounding regions [56, 131]. Blob detectors are a class of modules that are designed to

detect regions in the image that are either brighter or darker than the surrounding area [21]. [56] proposed a generalized Laplacian of Gaussian filter to detect elliptical blob structure in images. [131] further developed a computationally efficient blob detector, termed the Hessian-based Difference of Gaussians, which is an efficient unsupervised technique for blobs segmentation that is robust to changes in perspective, scaling, and illumination.

Affine invariant detection could also be used to detect regions of an image that are invariant with respect to image transformation [68, 49, 74]. Among affine invariant detection schemes, a representative method is the maximally stable extremal region detector (MSER) [68], which is known for its robustness to image transformations such as changes in viewpoint, illumination, and scaling. MSER considers numerous thresholdings of an image based on pixel intensity. The method outputs maximally stable regions which remain largely unchanged across a range of thresholds [68]. In this work, we use MSER as a representative benchmark for affine invariant detection methods.

3.3.2.2 Cable Diameter

Estimating the diameter of a cable from a tactile sensor is typically achieved by extracting curvature information made from local contacts. In [29], cable diameter is estimated using a cylindrical tactile sensor covered with an array of capacitors. However, due to low resolution of the 4x4 array of strain measurements, diameter estimates required matching the tactile data to an assumed contact model. A gradient search was used to identify the parameters of the convex second-order shape that best fit the data according to a Hertz contact model.

In [14], two complementary methods are proposed for estimation of curvature by fingertip tactile sensors: one by rolling a finger to estimate curvature, and another by sliding multiple fingers along a surface. This approach requires a temporal series of tactile data. In this work,

while GelSight marker positions can be analyzed using optical flow techniques, we seek to estimate cable diameter from a 3D heightmap generated by a single static contact with the GelSight sensor pad.

In [118], the radius of curvature is estimated by applying machine learning techniques to data collected with a deformable, multimodal tactile sensor fingertip called BioTac. Although the BioTac captures changes in impedance from numerous electrodes on the finger core, it is difficult to determine fingerpad deformation directly from this data. Since the GelSight is capable of directly measuring local geometry, we elect to implement methods based on physical interpretations rather than machine learning mappings in our study.

3.4 Tactile Perception of Cable Orientation and Diameter in Granular Materials

In this section, we describe our methodology for detecting and characterizing cables using a vision-based tactile sensor. Cable characterization is conducted in two stages: (i) estimation of cable orientation, and (ii) estimation of cable diameter.

3.4.1 Overall Framework

In order to assess our methodology, we conducted experiments in several different granular material environments with systematic variation of tactile/visual occlusion. We suggest and compare several image processing methods for the cable orientation estimate $\hat{\theta}$ given the heightmap obtained from a GelSight sensor (Sections 3.4.2.1 and 3.4.2.2). The methods are combined with a custom function for scoring the output region determined by each method (Section 3.4.2.3). By leveraging the orientation estimate, we define a region of interest

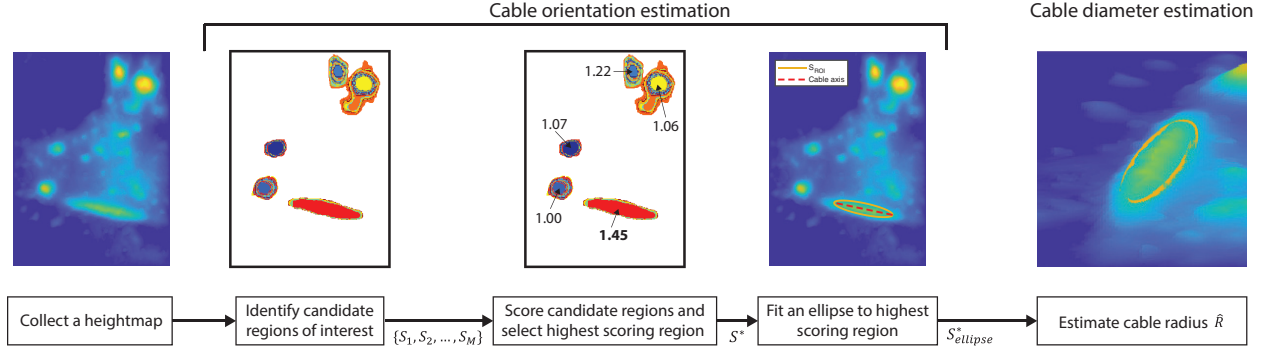


Figure 3.2: The workflow for the tactile perception of a cable partially buried in a non-homogeneous sand mixture. A representative example is shown for a 1.6 mm diameter cable.

(Section 3.4.3.1), and interpret the geometrical shape of the heightmap within the region in order to estimate cable diameter $\hat{\delta}$. We combine information of local curvature and entire shape from the heightmap within the region of interest (Sections 3.4.3.2—3.4.3.4). The workflow for our tactile perception framework is illustrated in Figure 3.2.

3.4.2 Estimation of Cable Orientation

Given a heightmap Z , our approach for estimating cable orientation was divided into two steps: i) identifying candidate regions $\{S_1, S_2, \dots, S_M\}$ of the heightmap that may include a cable and ii) scoring the candidate regions based on how likely they were generated by a cable. The highest scoring region S^* , a contiguous group of pixels in the heightmap, was then used to estimate the orientation of the cable with respect to the tactile sensor.

To determine candidate regions of the heightmap that may indicate contact with cables, we compared five different approaches: principal component analysis (PCA), the maximally stable extremal region detector (MSER) from [68], a novel method proposed in our work that

we refer to as heightmap thresholding with automatic scaling (HTAS), and two variations on HTAS. The two variations are the result of two different geometric features used for masking: concavity derived from the Hessian matrix and ridges detected using entropy.

3.4.2.1 Heightmap Thresholding with Automatic Scaling (HTAS)

Applying PCA to the heightmap as a benchmark method, we observed that the use of a single universal threshold for deformation, as in She et al. [100], does not work well for granular material environments due to noise from the surrounding granular particles. Instead, we observed that there is often an ideal deformation threshold for each heightmap, which depends upon what is in contact with the sensor pad as well as the contact force. As such, we developed a method for automatically scaling the deformation threshold. We tested multiple thresholds within a certain range and identified the best-performing threshold value for each heightmap.

Consider a heightmap Z for which the height (or sensor pad deformation) at pixel coordinates (x, y) is denoted as $Z(x, y)$. Given a constant height threshold η , we define a region segmentation function ϕ that takes a thresholded heightmap Z_η as input and outputs a set of region segments, as follows:

$$\begin{aligned} \phi(Z_\eta) &= \{S_1, S_2, \dots, S_M\}, \\ Z_\eta(x, y) &= \begin{cases} 1 & \text{if } Z(x, y) > \eta \\ 0 & \text{otherwise} \end{cases}, \end{aligned} \tag{3.1}$$

where S_m denotes the m -th region segment consisting of a fully connected region with values of 1 in Z_η .

Over a range of height threshold η values, we perform the region segmentation according

to Equation (3.1). Specifically, we constrain the search domain to be $\eta \in \{z_{10\%}, z_{20\%}, \dots, z_{70\%}\}$ where $z_{p\%}$ denotes the p percentile height of the given heightmap. We then select the best performing threshold η^* which results in the highest score according to the custom function:

$$\eta^* = \operatorname{argmax}_{\eta} \left\{ \max_{S_m \in \phi(Z_\eta)} V(S_m) \right\}, \quad (3.2)$$

where $V(\cdot)$ is a custom scoring function defined in Section 3.4.2.3. The corresponding region S^* is then obtained:

$$S^* = \operatorname{argmax}_{S_m \in \phi(Z_{\eta^*})} \{V(S_m)\} \quad (3.3)$$

In Section 3.4.2.3, we define a scoring function $V(\cdot)$ that is designed to benefit elliptical regions that are indicative of contact with cables having a circular cross-section. Thus, the region S^* is the most likely region to be in contact with a cable. The use of a range of height threshold values provides a degree of assurance that S^* has not been narrowly identified by a single height threshold that may not be tuned for the environment in which the cable lies.

3.4.2.2 Feature-based Masking

In order to further utilize heightmap information, we introduce two masks based on local geometric features that are directly related to cable characteristics: concavity and ridges. We define a masking function $C(x, y)$, which we combine with the heightmap thresholding process described in Section 3.4.2.1. When we combine the feature-based masks, we replace Z_η in Equation (3.1) by $\tilde{Z}_\eta$ where:

$$\tilde{Z}_\eta(x, y) = Z_\eta(x, y) C(x, y). \quad (3.4)$$

Feature #1: Concavity of the Heightmap When the elastomeric GelSight sensor pad is pressed against a convex object such as a cable, the pad will not wrap entirely around the

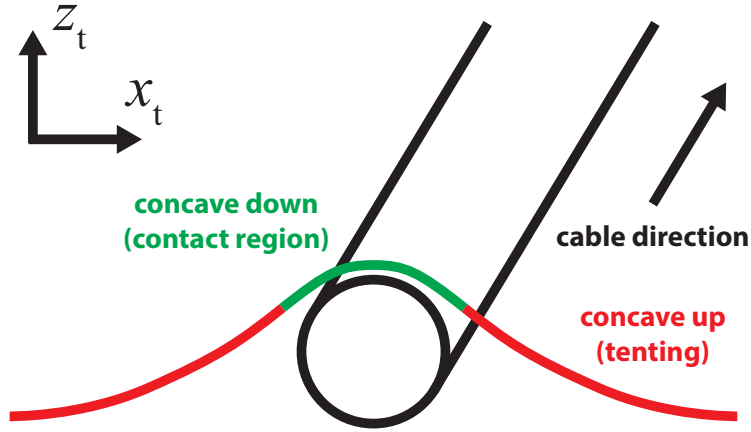


Figure 3.3: When the GelSight sensor pad is pressed against a cable, there will be a non-contact area on the pad immediately surrounding the contact area. In order to isolate the heightmap data that correspond to contacts with a cable, we mask out these "tenting" areas by masking out concave-up regions.

object's surface. There will be a non-contact area on the pad immediately surrounding the contact area. We will refer to this occurrence as "tenting" (Figure 3.3). In order to exclude the heightmap pixels in the tented area, we defined a Hessian-based criterion. The criterion masks out the region where the local 3D shape of the heightmap at point (x, y) is concave-up with respect to the heightmap coordinate system (the z_t axis of the local tactile sensor reference frame points into the sensor pad as shown in Figure 3.1). That is, we seek heightmap regions in which points belong to surfaces that are concave down with respect to both $\hat{x}$ and $\hat{y}$ directions unless those points are saddle points.

Given a heightmap Z , the Hessian matrix is determined by

$$\text{Hess} = \begin{bmatrix} D_{\hat{x}\hat{x}} & D_{\hat{x}\hat{y}} \\ D_{\hat{y}\hat{x}} & D_{\hat{y}\hat{y}} \end{bmatrix}, \quad (3.5)$$

where $\hat{x}$ and $\hat{y}$ denote the x -axis and the y -axis unit vectors, respectively, and D_{uv} denotes

the second partial derivative of the heightmap with respect to unit vectors u and v in the xy -plane. For a direction u , a heightmap point belongs to a surface that is concave-up if $\det(\text{Hess}) > 0$ and $D_{uu} > 0$ or to a surface that is concave-down if $\det(\text{Hess}) > 0$ and $D_{uu} < 0$. It is a saddle point if $\det(\text{Hess}) < 0$. We define the Hessian-based masking criterion C_{Hess} as:

$$C_{\text{Hess}}(x, y) = \begin{cases} 1 & \text{if } D_{\hat{x}\hat{x}} < \epsilon \text{ and } D_{\hat{y}\hat{y}} < \epsilon \\ 0 & \text{otherwise} \end{cases}. \quad (3.6)$$

We set a small nonzero value of 0.01 for ϵ (determined based on our pilot experiments) in order to allow for minor deviations of cables with respect to either the $\hat{x}$ or $\hat{y}$ direction. Note that if the ground truth direction of a cable is known for u , one can ideally expect $D_{uu} = 0$ to be locally true along the length of the cable and $D_{vv} < 0$, where $u \perp v$. Equation (3.6) is applied to the heightmap in order to detect concave-down regions.

Feature #2: Ridges in the Heightmap When a cable is in contact with the sensor pad, the corresponding contact region of the heightmap forms a 3D ridge shape. In order to search for ridges in the heightmap, we defined an entropy-based criterion to identify the region containing a ridge.

In the field of information theory, entropy is used to quantify the amount of information in a random variable that is drawn from a distribution [108]. In general, we can calculate the entropy of a histogram $\mathcal{X}$ using a binary logarithm so that the entropy is quantified in units of bits.

$$\text{entropy}(\mathcal{X}) = - \sum_{x \in \text{bins of } \mathcal{X}} p(x) \log_2 p(x). \quad (3.7)$$

Given a full heightmap Z , the local entropy can be calculated for a smaller square subregion (window) of Z . The local entropy can be obtained using a histogram of height for each

window centered at (x, y) . By moving the window over rows and columns of the heightmap with a step size of 1 pixel (for border regions of the input data, we assume symmetric values with respect to each border), we obtain a local entropy filter [33] applied to the full heightmap. We denote the filtered heightmap as $H(Z)$, of which each (x, y) component is the local entropy calculated at the point (x, y) .

We applied the local entropy filter to the original heightmap as well as to the *differential heightmap*. Given a heightmap Z , the differential heightmap with respect to a small displacement $\tilde{u}$ can be numerically computed as:

$$\Delta_{\tilde{u}}Z(x, y) = Z(x + \tilde{u}_x, y + \tilde{u}_y) - Z(x, y). \quad (3.8)$$

In an ideal case, the histogram of $\Delta_{\tilde{u}}Z$ at a local region where $\tilde{u}$ is normal to the ridge direction, would have a greater frequency at the center of a semi-cylindrical ridge region as compared to that for original histogram Z since $\Delta_{\tilde{u}}Z$ is monotonously decreasing while Z is symmetric along the $\tilde{u}$ direction. This results in the output of the local entropy filter applied to $\Delta_{\tilde{u}}Z$ at the region $H(\Delta_{\tilde{u}}Z)$ being greater than the filter output $H(Z)$ at the same region. In practice, we observed that the cross-sections of ridge shapes generated by cables were relatively triangular, rather than completely semi-circular, round at the ridge region and flat at the surrounding region. We believe this phenomenon is due to tenting around the contact region.

From the above observations, we expect the value of $H(\Delta_{\tilde{u}}Z) - H(Z)$ to exceed a threshold for the ridge region. Since we have no prior information about ridge direction, we instead use a lower bound of $\Delta_{\tilde{u}}Z(x, y)$ which can be determined as

$$H_{\text{LB}}(Z) = \max(H(\Delta_{\hat{x}}Z), H(\Delta_{\hat{y}}Z)), \quad (3.9)$$

where we considered a 1 pixel displacement for each of the $\hat{x}$ and $\hat{y}$ directions. The

entropy-based masking function criterion C_{ent} is defined as:

$$C_{\text{ent}}(x, y) = \begin{cases} 1 & \text{if } H_{\text{LB}}(Z) - H(Z) > j \text{ and } H(Z) > k, \\ 0 & \text{otherwise} \end{cases}, \quad (3.10)$$

where j and k are threshold criteria for the entropy of the differential heightmap and that of the original heightmap, respectively. We set $j = 0.6$ and $k = 1.5$ based on experience with our heightmap data.

3.4.2.3 Scoring the Candidate Regions of the Heightmap

Once a set of candidate regions $\{S_1, S_2, \dots, S_M\}$ of the heightmap was identified, each region was scored. We observed that the GelSight heightmap typically featured elliptical shapes when pressed against cylindrical cables (Figure 3.4). This was due to the combination of the convex shape of the undeformed GelSight sensing pad and the convex shape of the cable. Accordingly, we designed a scoring function such that candidate regions that most resembled ellipses would score the highest. We could then estimate the orientation of the cable using the major axis of the best-fit ellipse. For each candidate region, we defined the best-fit ellipse as an ellipse with the same second moment of area (area moment of inertia) as the candidate region.

The scoring function consisted of weighted terms related to three features of the candidate regions: eccentricity, solidity, and area. The eccentricity of the best-fit ellipse of a region is the ratio of the distance between the ellipse's two foci and the length of the major axis. This measure ranges from 0 for a circle to 1 for a line segment.

The solidity of each candidate region of the heightmap was defined as the total area of the region divided by the area of the smallest convex hull that circumscribed the region.

This measure ranges from 0 to 1, and has a maximum value of 1 for the ideal case when the region entirely comprises the smallest convex hull.

The area of each candidate region was measured as the total number of pixels in the region.

Given the m -th candidate region S_m , we defined the scoring function $V(S_m)$ as follows:

$$V(S_m) = \text{eccentricity} + \alpha \cdot \text{solidity} + \beta \cdot \text{area}, \quad (3.11)$$

where α and β were user-defined coefficients. We set $\alpha = 0.5$ and $\beta = 10^{-5}$, which we observed to be effective from pilot studies. If all scores calculated according to Equation (3.11) were below a user-defined threshold, it was assumed that the tactile sensor was not contacting a cable. The candidate region that scored the highest, S^* , was considered as the most likely region that is in contact with a cable.

We assumed that the longitudinal axis of the cable aligned with the major axis of the ellipse that fit S^* the best. The major axis orientation of the ellipse was output as the estimated orientation of the cable $\hat{\theta}$.

3.4.3 Estimation of Cable Diameter

In this subsection, we introduce three methods to estimate cable diameter $\hat{\delta}$ from the Gel-Sight heightmap: (i) using the average curvature of the heightmap, (ii) minimizing the variance of the distance between the central axis of the cable and the surface of the heightmap, and (iii) a combination of the prior two methods.

3.4.3.1 Region of Interest for Diameter Estimation

After estimating cable orientation, as detailed in Section 3.4.2, we obtained the region S^* and a corresponding best-fit ellipse. In an open air scenario, one can estimate cable diameter using the local curvature information encoded in the heightmap. When a cable is surrounded by granular material, however, the local curvature of the heightmap does not necessarily correspond to the curvature of the cable.

The region S^* may contain areas that are not directly related to cable curvature, especially at the periphery of S^* due to tenting or incomplete cable-sensor contact. Thus, we next determine the region of interest S_{ROI} , from which we extract curvature information. We define S_{ROI} as an ellipse by scaling the major and minor axes of the best-fit ellipse of S^* to 80% (a scaling factor determined based on our pilot experiments).

3.4.3.2 Method #1: Average Curvature (AC)

Consider a unit vector u normal to the cable direction in the xy -plane. Local curvature of the heightmap Z at (x, y) can be directly computed as follows:

$$\kappa_u(x, y) = \frac{|D_{uu}Z(x, y)|}{(1 + D_uZ(x, y))^{\frac{3}{2}}}, \quad (3.12)$$

where D_uZ and $D_{uu}Z$ are the directional derivative and the second directional derivative of Z , respectively, with respect to u . The average curvature $\bar{\kappa}_u$ can be evaluated by averaging Equation (3.12) over S_{ROI} . Assuming the cable shape is cylindrical, we discard local curvature values at (x, y) locations where $D_{uu}Z \geq 0$ (recall that this corresponds to concave-up regions to be masked out, as stated in Section 3.4.2.2). The estimated cable diameter based on the average curvature is then:

$$\hat{\delta}_{\text{AC}} = 2/\bar{\kappa}_u. \quad (3.13)$$

3.4.3.3 Method #2: Minimizing Variance of Cable Center-to-Heightmap Distance (Min-Var)

For an ideal cylindrical cable, the minimum distance between the central axis of the cable and any point on the outer surface of the cable must be constant. We treat the major axis of S_{ROI} as a segment of the cable's central axis projected onto the xy -plane. From the (x, y) positions of the central axis, we estimate the depth z_{cable} of the cable's central axis, which is used to estimate cable diameter. Let $\text{dist}(Z(x, y), z_{\text{cable}})$ be the squared Euclidean distance between the heightmap value $Z(x, y)$ and the central axis of the cable located at z_{cable} , given the (x, y) position of the central axis with respect to the local tactile sensor frame. The z_{cable} that minimizes the variance of the distances between the heightmap and the central axis of the cable can be found using optimization via:

$$\min_{z_{\text{cable}}} \{\text{var}_{S_{\text{ROI}}}(\text{dist}(Z(x, y), z_{\text{cable}}))\}, \quad (3.14)$$

where var denotes variance calculated over S_{ROI} . An analytical solution of Equation (3.14) can be obtained directly using the following first-order necessary condition:

$$z_{\text{cable}}^* = \frac{\overline{a_{xy}^T a_{xy} Z} - \overline{a_{xy}^T a_{xy}} \overline{Z} + \overline{Z^3} - \overline{Z^2} \overline{Z}}{2(\overline{Z^2} - \overline{Z}^2)}, \quad (3.15)$$

where

$$a_{xy} = (vv^T - I) \left(c - \begin{bmatrix} x \\ y \end{bmatrix} \right), \quad (3.16)$$

v is a unit vector in the direction of the central axis, c is the (x, y) center position of S_{ROI} , an overline indicates a mean operation, and $\overline{Z}$ denotes the mean of $Z(x, y)$ over S_{ROI} .

From the resultant z_{cable}^* , the cable diameter can be estimated as:

$$\hat{\delta}_{\text{MinVar}} = \frac{2}{N} \sum_{(x, y) \in S_{\text{ROI}}} \text{dist}(Z(x, y), z_{\text{cable}}^*), \quad (3.17)$$

where N is number of data points in S_{ROI} .

3.4.3.4 Method #3: Combination of Average Curvature and Variance Minimization with Smoothing

In order to reduce noise and smooth the heightmap surface, we preprocess the heightmap by applying a moving average filter. The performance of each Method #1 (AC) or #2 (MinVar) varies according to the filter size. We found that the diameter estimate could be improved by simply combining Methods #1 and #2. That is, we evaluate $\hat{\delta}_{\text{AC}}$ and $\hat{\delta}_{\text{MinVar}}$ over a set of filter sizes in an online manner; we used $\{1, 2, \dots, 8\}$ pixels. We then choose the common filter size that produces the most similar $\hat{\delta}_{\text{AC}}$ and $\hat{\delta}_{\text{MinVar}}$ values for each estimate of cable diameter. A further discussion with experimental results is provided in Section 3.5.3. Finally, we use mean of the two values as the combined estimate of cable diameter:

$$\hat{\delta}_{\text{AC+MinVar}} = \frac{\hat{\delta}_{\text{AC}} + \hat{\delta}_{\text{MinVar}}}{2}. \quad (3.18)$$

In theory, the heightmap from the GelSight sensor should match the physical height profile of the deformed contact surface. In practice, however, there was a discrepancy between (AC+MinVar) estimates and ground truth values for cable diameter, even for the simplest experimental condition (cable on a flat table). To solve this problem, we linearly fit the cable diameter estimates to the ground truth values and apply the linear fit to all estimation methods regardless of experimental condition.

3.5 Experimental Procedure and Evaluation

3.5.1 Experimental Setup

A 200 mm x 130 mm x 50 mm testbed was filled with granular material (Figure 3.1). A force/torque sensor (Nano-25, ATI Industrial Automation) was mounted beneath the testbed in order to measure contact forces applied by a handheld vision-based tactile sensor (GelSight [23]). An RGB-D camera (MYNT EYE D-50) mounted 300 mm above the granular material surface was used to establish a world reference frame and a ground truth for the relative position and orientation between the tactile sensor and each cable.

The GelSight sensor had a $18.4 \text{ mm} \times 13.5 \text{ mm}$ sensing area [23]. The sensor was lightly wrapped in a single layer of transparent film dressing (Tegaderm, 3M) in order to protect the sensor from intrusion by granular material and to minimize wear of the elastomeric fingerpad. With our data collection set-up, the heightmap sampling rate was 10 Hz. Each heightmap constituted a tactile image in which pixel intensity corresponded to the amount of sensor pad indentation [48].

For this work, we considered only cables with circular cross-sections. Six different cable diameters were used in the experiment (Table 3.1), with only a single cable in the granular material testbed at any one time. We chose common types of electrical cables whose diameter ranged from 1.6 mm for a single-stranded wire to 8.3 mm for a power cable. Each cable was fixed at 0° with respect to the world x -axis (X_w in Figure 3.1). A nominal tension was applied to keep each cable taut throughout the experiment.

For each cable diameter, two experimental factors were varied: environment and extent of burial. The three different environments were a flat table, homogeneous sand (HS) comprised of playground sand, or a non-homogeneous sand mixture (NHS) consisting of playground

Table 3.1: Cables used for data collection

Cable number	Diameter (mm)	Cable description
1	1.6	Single stranded wire
2	2.0	Single stranded wire
3	3.6	Banana cable
4	5.1	Cable housing
5	6.4	Power supply cable
6	8.3	Power supply cable

sand and gravel. We also tested three different extents of burial: the cable was placed on top of the surface, partially buried, or fully buried. To partially bury a cable, the cable was first buried entirely, and then the surface of the granular material was scraped with a flat tool until the cable was visually exposed. To fully bury a cable, thin layers of granular material were added on top of the cable until it was no longer visible. In total, seven different experimental conditions were tested (Table 3.2).

Representative GelSight heightmaps are shown in Figure 3.4 for three cable cases and two granular material types (homogeneous sand, non-homogeneous sand mixture). The first two columns (i, ii) show homogeneous sand cases (A.i: cable 4; B.i: cable 3; C.i: cable 5). The last two columns (iii, iv) show non-homogeneous sand mixture cases (A.iii: cable 5; B.iii: cable 5; C.iii: cable 4). From top to bottom, Figure 3.4 shows cases where the cable is laying on top (A), partially buried (B), and fully buried (C). The amount of GelSight sensor pad deformation is shown with a colored heightmap that is normalized for minimum (blue) and maximum (yellow) deformation.

Thirty trials were conducted for each combination of cable diameter and experimental

Table 3.2: Experimental conditions

Abbr.	Condition of cable
Table	lying on top of the table
HS-top	lying on top of homogeneous sand
HS-part	partially buried in homogeneous sand
HS-full	fully buried in homogeneous sand
NHS-top	lying on top of a non-homogeneous sand mixture
NHS-part	partially buried in a non-homogeneous sand mixture
NHS-full	fully buried in a non-homogeneous sand mixture

conditions, resulting in a total of 1,260 heightmap samples. At the beginning of each trial, the testbed was reset by randomly mixing the granular material. The GelSight sensor was pressed against the cable by hand using contact forces ranging from approximately 3-18 N, as determined from the force/torque sensor data upon completion of the experiments. For each set of 30 trials, the orientation of the GelSight sensor was varied randomly from -90° to 90° about the world z -axis (Z_w in Figure 3.1), with 0° representing the configuration in which the local tactile sensor reference frame was aligned with the world reference frame. Following a calibration procedure, the orientation of the GelSight sensor was estimated using a checkerboard pattern attached to the back of the sensor.

3.5.2 Estimation of Cable Orientation

We compared five methods for estimating cable orientation as described in Section 3.4.2: benchmark methods (i) the PCA-based method used for a GelSight-based cable manipulation task in She et al. [100], and (ii) MSER [68], as well as variations on our proposed methods (iii)

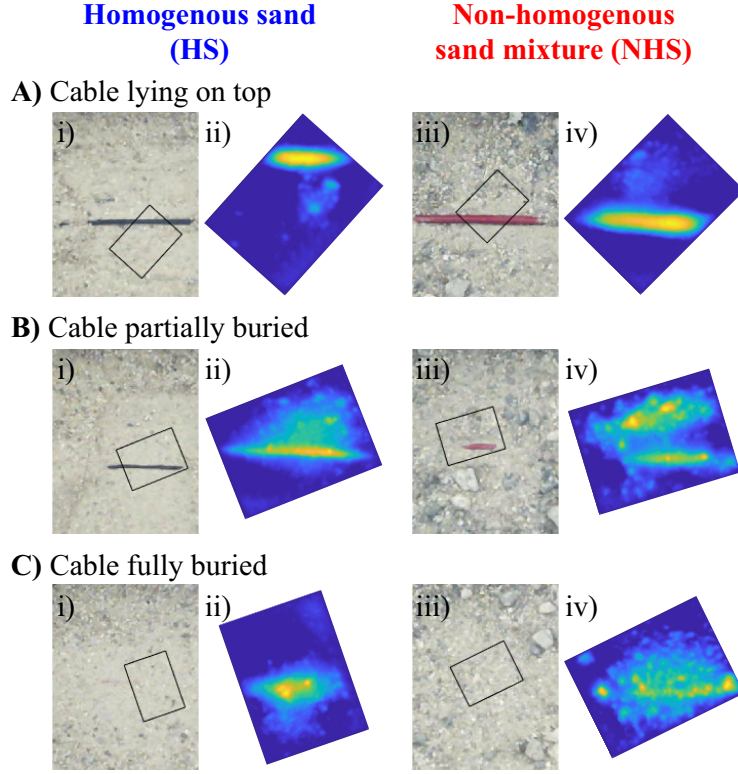


Figure 3.4: Examples of cables and granular material cases used in our study. First two columns (i, ii) show homogeneous sand cases (A.i: Cable 4; B.i: Cable 3; C.i: Cable 5). Last two columns (iii, iv) show non-homogeneous sand mixture cases (A.iii: Cable 5; B.iii: Cable 5; C.iii: Cable 4). From top to bottom, figures show cases where the cable is laying on top (A), partially buried (B), and fully buried (C). In each heightmap, the color represents the normalized deformation ranging from minimum (blue) to maximum (yellow). The black rectangle shows the approximate area of the GelSight sensing surface during data collection.

heightmap thresholding with automatic scaling (HTAS), (iv) HTAS combined with Hessian-based filtering for concavity, and (v) HTAS combined with entropy-based filtering for ridges.

We ran Matlab R2020a on a PC with an Intel Core i5-9600K CPU at 3.70 GHz. In this computational environment, the HTAS method took 41.3 ms per heightmap. An additional

Table 3.3: Errors in estimates of cable orientation are reported as mean (standard deviation) in degrees for cables that were successfully detected. The success rates for cable detection are reported as percentages. The best results are highlighted in bold for each experimental condition.

	PCA	MSER	HTAS	HTAS+Hessian	HTAS+Entropy
Table	1.32 (1.33)	1.23 (1.36)	1.26 (1.37)	1.16 (1.24)	1.32 (1.29)
	100.0%	100.0%	100.0%	100.0%	100.0%
HS-top	2.49 (6.32)	1.67 (1.50)	1.71 (1.42)	1.72 (1.46)	1.87 (1.52)
	97.8%	100.0%	100.0%	100.0%	100.0%
HS-part	4.68 (10.4)	2.07 (1.53)	2.40 (1.80)	2.16 (1.67)	2.27 (1.74)
	63.3%	93.9%	92.8%	96.1%	92.8%
HS-full	11.5 (17.9)	2.79 (2.86)	3.26 (3.55)	3.18 (3.65)	3.33 (3.51)
	33.3%	62.8%	71.1%	71.1%	71.1%
NHS-top	3.72 (11.8)	1.25 (0.96)	1.64 (4.09)	1.53 (4.20)	1.29 (1.24)
	86.1%	99.4%	98.9%	98.9%	98.9%
NHS-part	30.9 (29.1)	5.55 (11.1)	5.99 (11.9)	3.92 (8.59)	5.32 (9.93)
	11.7%	87.2%	87.2%	90.6%	87.8%
NHS-full	15.8 (20.9)	6.22 (9.99)	6.19 (10.2)	7.74 (14.2)	6.25 (10.1)
	2.8%	58.3%	63.3%	63.9%	63.9%

22.4 ms and 82.7 ms were needed for the Hessian-based and entropy-based filters, respectively.

3.5.2.1 Results

The five orientation estimation methods were applied to each of the seven experimental conditions (Table 3.2). The overall results, averaged across the six cable types, are reported in Table 3.3. Errors in cable orientation estimates are reported as mean (standard deviation) for cables that were successfully detected for each experimental condition. The success rate for cable detection is reported as a percentage out of $n = 180$ trials (30 trials per each of 6 cables from Table 3.1). A cable was considered to be successfully detected if the score of the highest scoring region ($V(S^*)$, per Equation (3.11)) exceeded a threshold of 1.4, defined according to pilot studies.

The PCA method in She et al. [100] was used as a baseline approach because it was previously used in open air conditions. PCA resulted in reasonably accurate estimates of cable orientation for the Table, HS-top, and NHS-top cases, averaging an orientation estimation error of 2.51° . The performance for these cases is comparable to the orientation estimation achieved by other studies where the tactile sensor makes direct contact with the cable. For example, in De Gregorio et al. [22], their orientation estimation error was under 5° for a 2 mm and 3.5 mm diameter wire, and in Li et al. [59] their average orientation estimation error for a USB connector was 1.15° . As expected, the estimates were most accurate for the Table condition in which the sensor pad contacted the cable only and granular material were not present (Table 3.3). Errors in cable orientation estimates increased when granular materials were introduced, but were the smallest when the cable was lying on top of the granular material. PCA performed the worst (mean error of 30.9°) when the cable was partially buried in the non-homogeneous sand mixture.

For most conditions (4 out of 7), MSER performed the best at estimating cable orientation

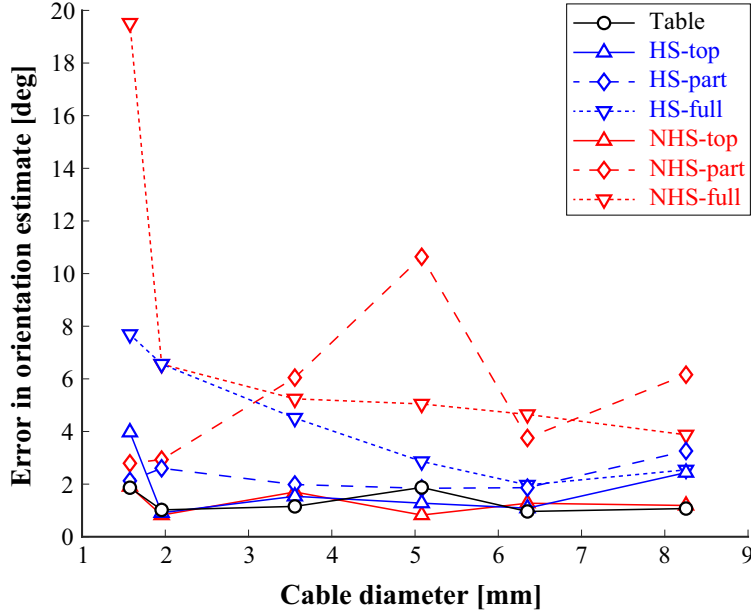


Figure 3.5: Mean error for cable orientation estimates using the MSER method as a function of cable diameter and experimental condition.

in terms of mean error. Averaging across all granular material conditions (HS-part, HS-full, NHS-part, and NHS-full), MSER resulted in an average cable orientation error of 4.1° .

HTAS-based methods performed similarly or slightly worse as compared to MSER with regards to error. However, HTAS-based methods outperformed MSER in terms of success rate, particularly for the partially and fully buried cases (i.e. HS-part, NHS-part, HS-full, NHS-full). The HTAS-Hessian method performed the best in terms of success rate. As will be discussed in Section 3.5.3, HTAS+Entropy emerged as the preferred cable orientation method once the subsequent estimation of cable diameter was considered.

Average orientation estimation error using MSER for each experimental condition and cable are shown in Figure 3.5. Based on our results, the difficulty of the cases could be ranked in order of increasing difficulty as $\text{Table} \approx \text{HS-top} \approx \text{NHS-top} \prec \text{HS-part} \prec \text{HS-full} \prec \text{NHS-part} \prec \text{NHS-full}$. As shown in Figure 3.5, when the cable was fully buried, the error increased

as the cable diameter decreased. Especially for Cable 1 (1.57 mm) and Cable 2 (1.96 mm), the errors in orientation estimates for the fully buried cases (HS-full, NHS-full) were larger than those for the partially buried condition in the non-homogeneous sand mixture. Similar trends in orientation estimation error were also observed using the HTAS-based methods.

3.5.3 Estimation of Cable Diameter

Each of the five orientation estimation methods produces a different region S^* that directly affects the diameter estimation result. In a pilot study, we compared the diameter estimation results using the region S^* that resulted from each of the five orientation estimation methods. We found that the region S^* produced by the HTAS+Entropy method resulted in the smallest mean and standard deviation of error in the estimates of cable diameter. Thus, the HTAS+Entropy method was used as a precursor to the estimation of cable diameter in order to obtain S^* throughout this work.

Table 3.4: Errors in estimates of cable diameter are reported as mean (standard deviation) in mm across all six cables. The best results are highlighted in bold for each orientation estimation method.

	All cases	*-part and *-full cases
PCA	2.05 (2.21)	2.67 (2.61)
MSER	1.77 (1.76)	2.50 (2.10)
HTAS	2.19 (2.83)	2.94 (3.09)
HTAS+Hessian	1.60 (1.92)	2.09 (2.20)
HTAS+Entropy	1.78 (2.71)	2.45 (3.22)

*-part = partially buried; *-full = fully buried

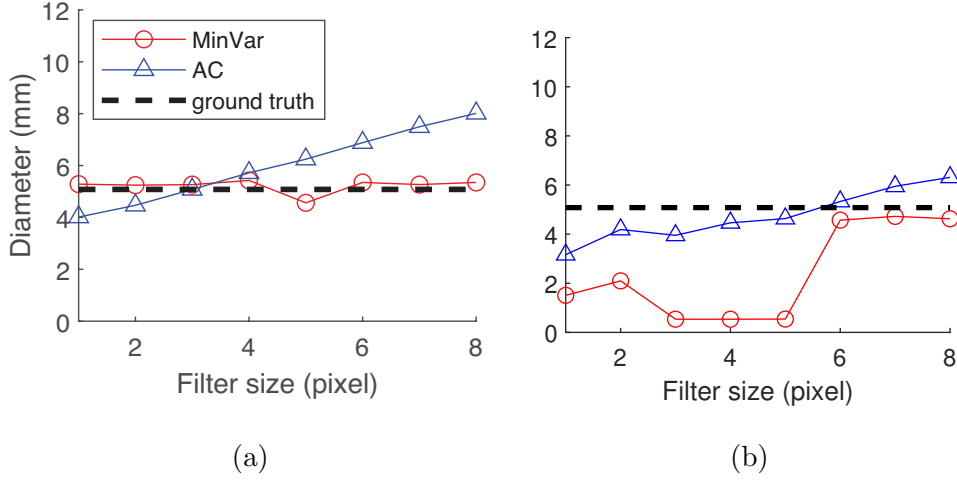


Figure 3.6: Two representative cable diameter estimates resulting from different filter window sizes using: average curvature (AC) and variance minimization (MinVar) methods. (a): Cable 5 (6.35 mm), HS-full. (b): Cable 4 (5.08 mm), NHS-full. We chose the filter size for each estimate where estimated diameter from the two approaches were the closest. The complete diameter estimation performance for all the cases are reported in Table 3.5.

3.5.3.1 Results

We compared three methods for cable diameter estimation, Section 3.4.2: (i) average curvature (AC), (ii) minimizing variance of cable center-to-heightmap distances (MinVar), and (iii) a combination of average curvature and variance minimization with smoothing (AC+MinVar). In our computational environment, each diameter estimate was calculated within 10.1 ms, 8.9 ms, and 104.2 ms on average for the AC, MinVar, and AC+MinVar methods, respectively.

Although local curvature at each point of the heightmap can be directly determined using the AC method, we found that accuracy of the cable diameter estimate was improved when additional heightmap information from the surrounding region was incorporated. In

Table 3.5: Errors in estimates of cable diameter are reported as mean (standard deviation) in mm across all six cables. The best results are highlighted in bold for each experimental condition.

	AC	MinVar	AC+MinVar
Table	2.96 (1.28)	1.77 (1.37)	0.83 (0.79)
HS-top	3.18 (1.32)	1.79 (1.50)	0.89 (0.85)
HS-part	3.21 (1.57)	1.83 (2.14)	1.43 (1.27)
HS-full	5.44 (3.31)	2.55 (1.90)	2.42 (2.03)
NHS-top	2.88 (1.45)	1.90 (1.77)	1.10 (1.71)
NHS-part	3.63 (2.90)	2.12 (2.26)	1.42 (1.23)
NHS-full	3.71 (3.14)	3.46 (2.42)	2.39 (1.95)

AC = average curvature; MinVar = optimizing variance of cable center-to-heightmap distances

particular, the AC method was sensitive to sand particles due to the large curvature of the particles relative to that of the cable. In order to reduce the sensitivity of the estimates of cable diameter to sand particles, we tested various sizes of filters with both the AC and MinVar methods (Figure 3.6). Filters of size $w \times w$ were tested, ranging from $w = 1$ -8 pixels ($w = 1$ corresponds to a no-filter baseline). For the AC and MinVar methods, a constant filter size of 5 was used for all experimental conditions and cables.

With the AC method, as the filter size increased, estimates of cable diameter also increased (Figure 3.6). This artificial increase in estimated cable diameter was likely due to the overall shape of the heightmap becoming flattened when averaging over a larger area of the heightmap. The ideal filter size would smooth out the effects of sand particles within

the heightmap, but it is not desirable for the averaging filter to excessively flatten the local heightmap shape. With the MinVar method, estimates of cable diameter were relatively consistent regardless of the filter size. The MinVar method was less sensitive to local, particle-induced peaks on the heightmap since its estimates of cable diameter were based on the position of a collection of points comprising a surface.

By combining the AC and MinVar methods, which incorporate different spatial scales of heightmap information, we achieved the smallest variance in estimates of cable diameter. Table 3.5 shows the results for all three cable diameter estimation methods (AC, MinVar, AC+MinVar) for $n = 180$ trials. The best-performing filter size (5x5) for smoothing the heightmap was used for both the AC and MinVar methods. For all experimental conditions, the AC+MinVar method outperformed the MinVar method alone, which, in turn, outperformed the AC method alone. Averaged across all experimental conditions, mean errors in estimates of cable diameter were 3.57 mm, 2.20 mm, and 1.50 mm for the AC, MinVar, and AC+MinVar methods, respectively. For the flat table condition, the mean errors in estimates of cable diameter were 2.96 mm, 1.77 mm, and 0.83 mm for the AC, MinVar, and AC+MinVar methods, respectively. Although there haven't been many studies on surface curvature estimation from a single touch, these results are comparable to other studies where the tactile sensor makes direct contact with the object. In Fearing and Binford [29], for cylinder diameters less than 10 mm, their estimation diameter errors were 1.6 mm, 0.0 mm, 1.5 mm and 0.8 mm for 10 mm, 7 mm, 3 mm, and 0.3 mm diameter cylinders, respectively. In Liu et al. [62], they proposed an object curvature estimation method based on an artificial neural network algorithm through a sparse tactile sensor array. Using the ANN algorithm, the average diameter estimation error was 5.5 mm for cylinders ranging from 2 mm to 20 mm diameter.

The AC+MinVar method likely outperformed the AC and MinVar methods separately because the filter size is chosen dynamically instead of being fixed. The filter size has a significant impact on diameter estimate, and the optimal size will vary depending on the what is captured by the sensor. AC and MinVar both use a constant filter size, while AC+MinVar attempts to find the best filter size based on the different information each method provides (local vs overall shape).

As expected, for each method and granular material type, errors in estimates of cable diameter increased as the degree of cable burial increased. An exception to this is the HS-full performance of the AC method being worse than the NHS-full performance. A possible explanation could be that the HS-full heightmap data is nearly "flat" after smoothing since the cable is fully buried in the granular material. The NHS-full data is also mostly "flat", but due to the presence of small rocks in the mixture, the GelSight may be capturing information on these other objects in the environment which have a curvature that is closer to the actual cable diameter than the HS-full estimate. The AC+MinVar method was fairly robust to the granular material type (homogeneous sand vs. non-homogeneous sand mixture). A comparison of cable diameter estimates across all three methods are shown for a representative experimental condition (NHS-part) as a function of cable diameter in Figure 3.7.

3.5.4 Demonstration

As reported in Section 3.5.3, the best pipeline for estimating cable diameter is the pairing of HTAS+Entropy for cable orientation followed by AC+MinVar for cable diameter. To demonstrate this pipeline, we created a test scenario using six types of cables (Table 3.1) to form four capital letters, "UCLA" (Figure 3.8a).

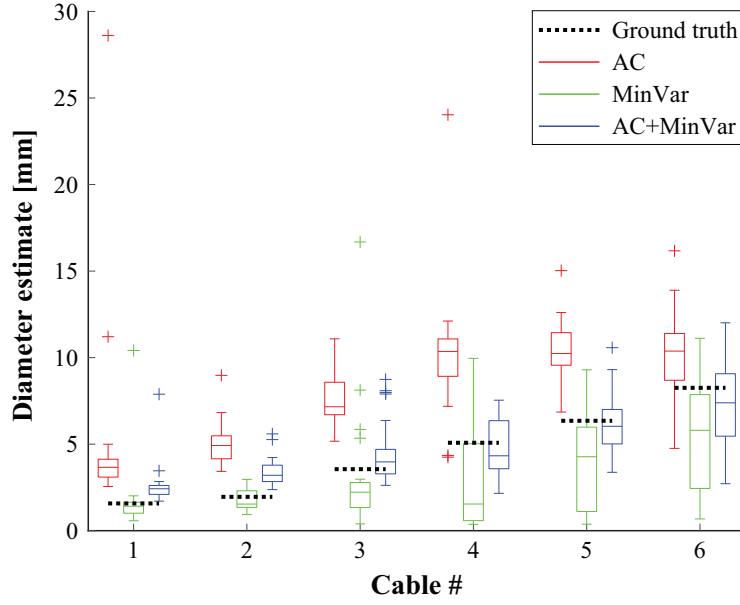
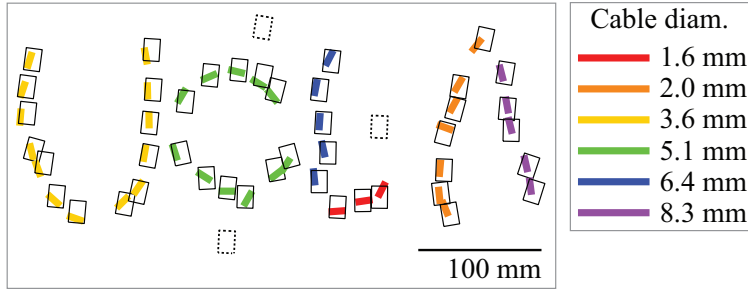


Figure 3.7: Diameter estimates for NHS-part cases using AC (left, red), MinVar (middle, green), and AC+MinVar (right, blue) methods. The ground truth cable diameter is shown via dotted lines. Each boxplot indicates the 25th, 50th, and 75th percentiles. The whiskers extend to the most extreme data points that are not considered outliers (“+”) having values of more than 1.5 times the interquartile range from the bottom or top of the box.

The experimental setup was similar to that described in Section 3.5.1, but the granular material testbed was larger (380 mm by 500 mm) and filled only with the non-homogeneous sand mixture. Cable segments were partially or fully buried. The GelSight sensor was manually pressed against different portions of the letters, approximately evenly spaced along the cables. Of the 47 total contacts, three contacts purposely did not involve contact with a buried cable. Each contact between the GelSight sensor and the testbed lasted approximately 2 sec, resulting in approximately 20 frames of GelSight heightmap data per contact (effective sampling rate of 10.4 Hz). The position and orientation of the GelSight for were calculated as before, using the calibrated checkerboard pattern attached to the back of the sensor.



(a) Physical set-up



(b) Tactile sensor-based reconstruction

Figure 3.8: a) Cable configuration for a demonstration using all types of cables listed in Table 3.1. Segments of each cable were partially or fully buried in a non-homogeneous sand mixture. b) Cable orientation estimates for all exploratory movements using the HTAS+Entropy method. Black rectangles represent the GelSight sensing area. Dotted black rectangles represent trials purposely taken where there were no cables.

To demonstrate the performance of the HTAS+Entropy and AC+MinVar methods for estimating cable orientation and diameter, we haptically reconstructed the "UCLA" cable configuration (Figure 3.8b). It should be noted that the crossbar of the letter "A" was inadvertently skipped during data collection.

Using the custom scoring function $V(\cdot)$ defined in Equation (3.11), we compared the scores for contacts with the non-homogeneous sand mixture only ($n = 218$ total contacts across the rectangles with dotted outlines in Figure 3.8b) to the scores for contacts with a

cable partially buried in the non-homogeneous sand mixture ($n = 900$ total contacts across the rectangles with solid outlines). The cable detection success rate was 95.1%. The estimates for cable orientation using the HTAS+Entropy method were sufficiently accurate to make the letters "UCLA" legible when the tactile sensor location and estimated cable orientation data were combined. The diameter estimation was calculated using the combination of average curvature and variance minimization with smoothing (AC+MinVar) described in Section 3.4.3.4. The overall average error in estimates of cable diameter was 1.35 mm with a standard deviation of 1.16 mm. The average error in estimates of each cable diameter ranged from 0.57 mm for the 5.1 mm cable to 2.00 mm for the 1.6 mm cable.

3.6 Conclusion and Future Work

In this work, we present a practical framework for the tactile perception of cables buried in granular material. We developed and evaluated methods for estimating cable orientation and diameter under challenging experimental conditions in which cables were buried in granular material to various extents.

We successfully demonstrated the best performing methods (MSER for cable orientation, AC+MinVar for cable diameter) under the challenging condition of cables partially or fully buried in a non-homogeneous sand mixture.

For estimating cable orientation, we compared the performance of PCA, MSER, and variations on an automatic thresholding strategy (HTAS, HTAS+Hessian, HTAS+Entropy). MSER yielded the lowest estimation error with a mean (standard deviation) of 4.0° (7.7°) for cables fully buried in homogeneous sand or a non-homogeneous sand mixture. However, HTAS and its variants outperformed PCA and MSER with regards to the rate of successful

cable detection.

For estimating cable diameter, we compared the performance of an average curvature method (AC), a method that uses optimization to estimate cable depth (MinVar), and their combination (AC+MinVar). The AC+MinVar method yielded the lower estimation error with a mean (standard deviation) of 1.8 mm (1.7 mm) for cables fully buried in homogeneous sand or a non-homogeneous sand mixture.

Our proposed tactile perception methods could be used to advance robotic capabilities for cable detection, identification, grasp, and manipulation in natural, field environments involving granular materials. Future work includes incorporating the estimated cable pose into robotic exploration strategies for object search in granular materials. Following cables lying on and within the seabed pose yet another common challenge [80]: tactile perception in granular materials while underwater. Future work is necessary to investigate whether the perception methods developed for land-based experimental conditions, as in this work, can be directly applied to underwater scenarios.

CHAPTER 4

Design of a Teleoperated Service-type Social Robot

This study was conducted in collaboration with Luis Mesias (co-first author), Xufei Wang, Kenneth Loparo, Nicholas Zingale, Dustin Tyler, Emily L. Graczyk, Veronica J. Santos, and Michael J. Fu.

4.1 Abstract

Assistive robots for persons with disabilities help provide individuals with functional independence while reducing the burden on caregivers. These systems are often capable of assisting individuals with daily activities such as retrieving objects and feeding. While autonomous robotic systems excel at repetitive tasks in controlled environments, a human operator in the loop is often necessary for tasks in unstructured environments. In this paper, we outline the design process of an immersive, multimodal, and intuitive teleoperated robotic system. The robotic system consisted of a Stretch RE1 mobile manipulator with a TASKA prosthetic hand outfitted with tactile sensors. The operator was presented with a low latency, binocular video stream displayed through a virtual reality (VR) headset, bidirectional audio capabilities, an electrical stimulation-based haptic feedback glove, and intuitive controls based on motion tracking of the operator's hand and body. The system architecture of this novel telerobotic system was designed to enhance the operator's intuitive

and immersive experience.

4.2 Introduction

Modern robots have moved out of structured manufacturing environments and into dynamic, unstructured environments, such as the home. Assistive robots have the promise of enabling functional independence and improving the quality of life for older adults and individuals with disabilities, while also reducing caregiver burden. Our long-term objective is to advance assistive human-robot systems for activities of daily living (ADLs), such as retrieving objects and keeping one’s living area clean.

In the United States, there are an estimated 296,000 people with spinal cord injury (SCI), with 17,900 new cases every year. Within this population, more than 50% have complete tetraplegia (paralysis of all four limbs) or incomplete tetraplegia (weakness in all four limbs) [13]. Due to their limited mobility, this population depends on nurses or caregivers to perform daily activities or to operate their assistive technologies. Aside from home care, people with SCI also live in long-term care and assisted living facilities, which isolates them from family members [63].

One approach to the development of assistive robots for people with disabilities is to create fully autonomous systems [120]. However, the unpredictability of home environments poses a significant challenge to fully autonomous algorithms that were designed for structured conditions. Furthermore, an autonomous robot cannot provide the social connection and interactions that a caregiver does, which might be especially important for patients in long-term care facilities.

To overcome these challenges, a teleoperation framework for assistive robots in the home

enables a human operator to pilot the robot in real-time, and therefore to address unpredictable conditions while providing social interaction and emotional connection. However, unlike live-in caregivers, who provide assistance up to 24 hours a day based on the patient’s needs [92], a remote robot operator would not need to be physically present and could become available at a moment’s notice to help when needed or called. This could potentially reduce the burden on health aides and caregivers and simultaneously allow individuals with disabilities to have more privacy. To this end, we have developed a teleoperated human-robot system that has the potential to enable a friend, family member, or caregiver to provide remote support to a person with disabilities (Figure 4.1). Our novel contributions are:

1. Developing an immersive and multimodal teleoperated *service-type social robot* [9] using intuitive controls based on motion tracking.
2. Integrating electrical stimulation-based haptic feedback into the interfaces of the remote *operator* (the individual controlling the robot).
3. Preserving human-to-human connection between the *recipient* (the individual receiving assistance from the robot) and the operator through real-time visual, auditory, haptic, and physical interactions regardless of distance.

4.3 Background

4.3.1 Assistive Technology Recipient Needs

To better understand the impact of a teleoperated human-robot system, we interviewed various assistive technology recipients and their caregivers. All interviewees provided written informed consent to participate in these interviews, which were approved by the Metro Health

System Institutional Review Board. One of the interviewees had a spinal cord injury that left him paralyzed from the shoulders down. In the interview, he described how he uses a myriad of assistive technologies such as lifts, voice recognition software, and remote controllers to perform his everyday tasks. However, caregiver assistance is essential to use most of these devices.

In another study, an interviewee with spinal cord injury resulting in complete paralysis of all four limbs described the burden of his daily care on his family, especially while experiencing staffing shortages during the COVID-19 pandemic: “I have nurses and aides that come to help...But like with anything else during this COVID time, we lost a lot of that help and aides just because agencies lost people... it’s unfortunate, and it’s put more on my mom to help out... She’s pretty much with me 24/7.” The interviewee also described his feelings of social isolation that resulted from his injury: “Unfortunately, after this injury, it’s maybe brought you away from some people in a sense. I don’t always have my phone with me, or I don’t have the luxury of having my independence to just drive somewhere on my own” [39].

4.3.2 Assistive Social Robotics

[Broekens et al.](#) presents social robots as another type of assistive robot [9]. [Vandemeulebroucke et al.](#) classify social robots as either companion-type or service-type robots [110]. Companion-type robots focus mainly on capabilities related to social interactions. This category is mainly comprised of autonomous robots that talk or interact with the recipient to provide companionship. *Service-type social robots* combine social interaction with assistive functions [9]. In this paper, we will mainly focus on service-type social robots.

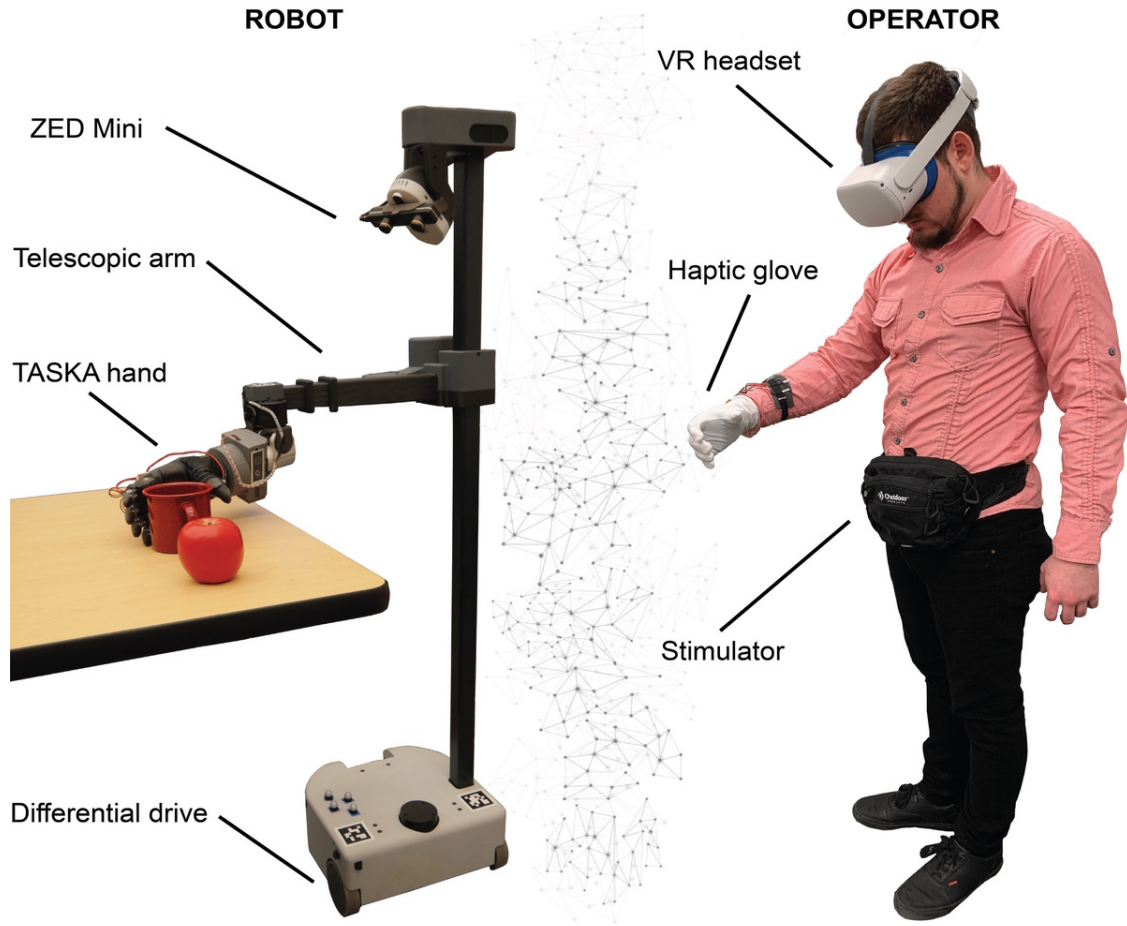


Figure 4.1: The Sensa robot consisted of a Stretch RE1 modified with a sensorized TASKA prosthetic hand and a ZED Mini binocular camera. The operator equipment consisted of a virtual reality headset, a custom skin-surface electrical stimulator, and a custom haptic glove with embedded stimulation electrodes.

4.3.2.1 Addressing Physical Interaction Needs

Performing unscripted tasks in unstructured environments is still a challenge for automation. Most research on autonomous assistive robots focus on a subset of common tasks, for example, retrieving/delivering objects [87] and cleaning [26]. These systems are typically designed for a single assistive function. However, the elderly and people with disabilities

need assistance with a variety of daily care needs including preparing food, eating, dispensing and taking medicine, and cleaning [36]. Therefore, a teleoperated robot approach might improve versatility and enable the robot to accomplish many care tasks even in unpredictable environments.

For providing general everyday assistance, assistive robots often allow the recipient or a remote operator to manually control the robot in order to perform tasks [37]. However, the manual control interfaces can sometimes be unintuitive, frustrating to use, and require a long time to complete tasks [37]. In addition, when it comes to controlling assistive technologies, the requirements vary greatly depending on the recipient population and their needs. Older adults prefer an easy-to-understand user interface (UI), while assistive technology recipients with limited movement capabilities, such as individuals with paralysis resulting from SCI, prefer voice control [63]. On the other hand, scripted voice commands can be difficult for senior citizens because specific voice commands can be difficult to remember [9]. Therefore, neither of these control technologies can serve the entire assistive technology recipient base.

Teleoperated robot systems remove the burden of unintuitive control interfaces on the recipient by allowing a remote operator to control the robot. To support recipients with a variety of interaction capabilities, a desirable feature for a teleoperation system is the ability to communicate via natural, unscripted visual and auditory cues. For example, Wu et al. stated that their participants wanted the robots to be able to understand gestures, so the robots could have some degree of independence and function according to context [121].

4.3.2.2 Addressing Social Needs

People interacting with robots also mentioned they valued social skills, social interaction, and human-like communication. On the other hand, older adults had conflicted opinions

about robot autonomy, and preferred robots with autonomous capabilities but under constant human supervision [110]. These preferences align more closely with a human nurse rather than a robot. To fulfill this role, the robot would have to not only have multiple degrees of freedom (DOFs), but also the perception and intellect of a human. This describes a teleoperated robot with visual, auditory, and gesturing capabilities.

Another aspect of interactivity is the aesthetics of the assistive robot. Recipient preferences can be divided into three groups. The first group preferred human-like appearances because they were perceived as being more relatable. The second group preferred machine-like robots due to the uncanny nature of human-like robots. The last group preferred a combination of the two previous robots because they mixed the best of both appearances. This third group preferred a robot with hands or an anthropomorphic robot [110]. These differing aesthetic preferences, highlight that socially assistive teleoperation robots should use an aesthetic that does not negatively affect the interaction between the operator and the recipient.

Many existing assistive technologies consist of small robot with scripted speech, but without any assistive capabilities. For example, Paro is a robot imitating a baby seal that interacts with the recipient through its senses [93]. Outside this common model, Louie et al. used video conference technology to bring together the recipient with relatives over long distances [63]. The participants of this study enjoyed the video conference feature because it allowed them to interact with their families more often. The video conference application and the robotic interface were two separate applications in this study housed on the same robot, which means the family member could not make use of the robotic interface to interact with the assistive technology recipient or its environment.

4.3.3 A Teleoperated Social Robot

A teleoperated robotic interface helps reduce the physical burden on the recipient and caregiver. However, social interaction is also important for recipients. To address both physical and social needs, we embarked on creating a teleoperated robotic interface that could be easily controlled by a family member (operator) to help and interact with the assistive technology recipient. The daily tasks that the assistive robot must perform are unique to every assistive technology recipient and need to be performed in various unstructured environments. While an autonomous assistive system could not be trained on all possible tasks, a family member could remotely connect to the robot and help the assistive technology recipient with all tasks.

A multi-university collaboration consisting of Case Western Reserve University (CWRU), University of California Los Angeles (UCLA), Cleveland State University (CSU), University of Colorado Boulder (CUB), and University of Wyoming (UW) formed to develop an immersive, directly teleoperated robotic avatar system, which preserves the human-to-human connection between the assistive technology recipient and the caregiver (operator). In addition, our approach was designed to optimize the immersiveness of the teleoperation experience for the robot operator.

4.3.4 Immersive Teleoperation

It is desirable for the robot operator to be able to seamlessly integrate with the telerobotic interface in order to perform dexterous tasks successfully. Immersive teleoperation has been found to improve task efficiency and situational awareness over conventional methods (e.g. computer monitor) [67]. Immersion can be improved by the intuitiveness of the robotic

controls and the usefulness of the sensory feedback.

4.3.4.1 Intuitive Controls

A typical teleoperation system consists of a joystick as a remote control device [44]. However, the use of joysticks is usually limited to low degree-of-freedom robotic systems. Hand tracking methods have been adopted to allow the operator to control the robot by performing natural motions with their own hands [25]. This mode of control provides the operator freedom of movement and enables them to perform actions intuitively. Although existing studies have had mixed conclusions regarding the benefits of hand tracking versus handheld controllers for simple tasks [53], hand/finger tracking is useful for controlling high degree-of-freedom, multi-digit robot grippers [75]. Furthermore, motion tracking interfaces may reduce the cognitive burden of robot use, since other, more complex interfaces for high degree-of-freedom robots might require the operator to focus predominantly on the controls themselves rather than the goals of the task, interactions with the recipient, and social connection with the recipient.

4.3.4.2 Visuotactile Feedback

Vision and touch are two key feedback modalities that are important for the operator to understand the robot's immediate environment and to effectively interact with it. Typically, the robot is equipped with cameras and the video is streamed to the operator's computer monitor. This setup has the advantage of displaying multiple perspectives to the operator in order to reduce the effect of occlusion by the robot or other objects in the environment. However, modern virtual reality headsets with head tracking capabilities can enable the operator to view the robot's surroundings from a first-person perspective by streaming binocular

video into the headset. Binocular video allows the operator to have stereo-vision of the environment, which decreases depth-related errors in hand-eye coordination tasks [2].

Haptic feedback is essential for the operator to understand the interactions between the robot and the environment, typically through tactile sensing capabilities on the robot end effector. In teleoperation tasks, the most commonly used haptic feedback is vibrational feedback. [Nakanishi et al.](#) used a teleoperation control unit that uses virtual reality (VR) and vibrational feedback to control Toyota’s Human Control Robot and perform daily activities such as opening drawers, storing groceries, and interacting with humans in home environments [77]. The team used the vibrational feedback provided by the Oculus Rift controllers to provide haptic feedback. However, the team reported that the lack of force feedback caused the operators to apply more force than needed on daily tasks.

4.4 Methods

4.4.1 The Sensa System

The Sensa is a novel, proof-of-concept system with a human-in-the-loop neurally connected to the system via force-scaled tactile feedback, audiovisual feedback, and intuitive controls. The goal of the system is to provide a means for family members or caregivers to provide assistance to people with disabilities or the elderly, and in so doing connect people both physically and emotionally. Sensa (Figure 4.1) consisted of a Stretch RE1 robot (Hello Robot, Inc., Martinez, CA), which has a mobile base, a head with tilt/pan camera movements, and a three-degree of freedom gantry-based arm. The standard 1-DOF gripper was upgraded to a sensorized multi-DOF prosthetic hand (TASKATM Prosthetics, Christchurch, New Zealand). The Stretch RE1’s standard depth camera was replaced with a ZED Mini

binocular camera (Stereolabs, Inc., San Francisco, CA) to provide a first-person perspective to the operator. In addition to the existing horizontal LIDAR sensor, a custom vertical LIDAR sensor was added to detect the underside of tables in order to avoid collision with the edge of a table. The operator interface (Figure 4.1) consisted of a Meta Quest 2 virtual reality headset (Meta Platforms, Inc., Menlo Park, CA) for audiovisual communications with the operator and a custom haptic glove that provided touch information to the operator via surface electrical stimulation of each individual finger and the palm.

During development, the robot was located at a laboratory at UCLA but was controlled by human operators at CWRU. Due to travel restrictions related to the COVID-19 pandemic, the entire development process occurred remotely between these two sites, such that the robot and human operator were never in the same city. Sensa was used to demonstrate several mock scenarios where the use of an avatar could be advantageous. Some of the scenarios tested were shaking hands with the recipient in another location, manipulating and handing over objects, performing a celebratory toast, and cleaning a wound. These scenarios were tested with over a dozen naive operators in order to gain user experience feedback.

The subsequent sections describe the design choices made to satisfy the physical and social needs of an assistive technology recipient. Future improvements that would further enable this proof-of-concept system to lead to better physical and social connections between operator and recipient are also discussed.

4.4.2 Sensa Manipulation Capabilities

In order to effectively assist individuals with disabilities in activities of daily living around the home, Sensa was designed to satisfy requirements of both dexterity and mobility.

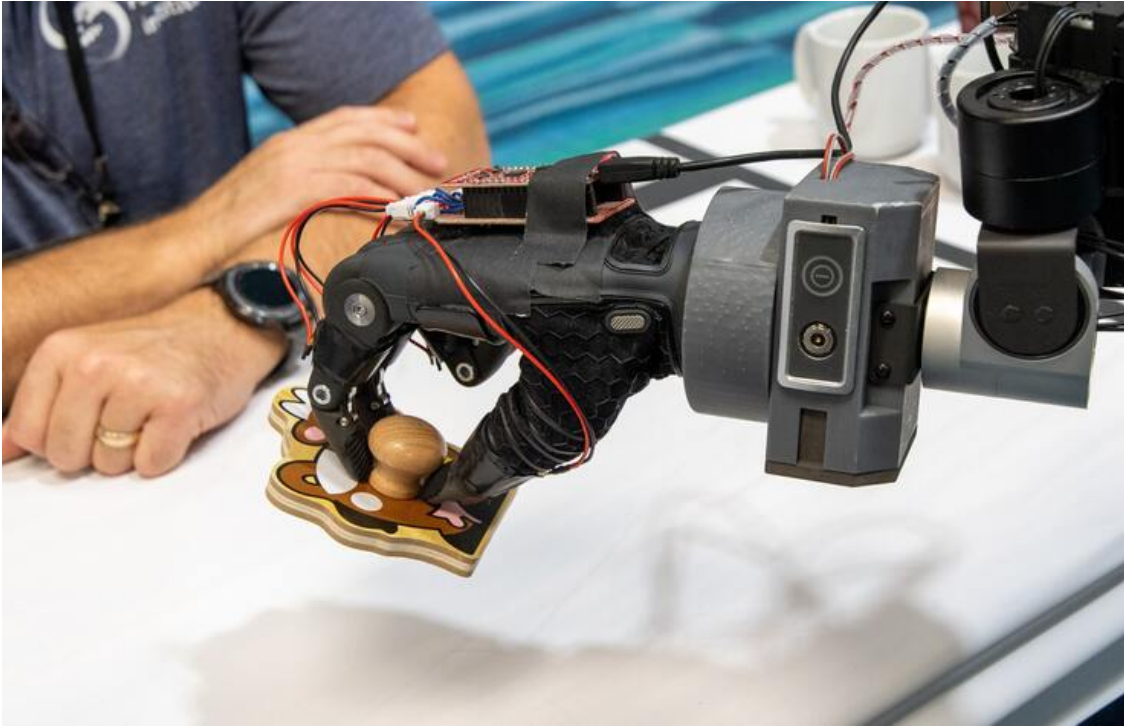


Figure 4.2: Close-up of the five-digit prosthetic hand (TASKATM Prosthetics) picking up a child’s puzzle piece using a pinch grasp.

4.4.2.1 Implementation

Sensa consisted of the 6-DOF Stretch RE1 mobile manipulator robot, which was designed for use in the home for people with disabilities. The Stretch RE1 is a human-safe, compact, lightweight, and relatively low-cost mobile manipulator that is capable of performing a large range of tasks semi-autonomously or teleoperated through a website interface. Tasks that the Stretch RE1 can perform include wiping a countertop, opening a door, and moving laundry from the dryer to a basket [52].

The standard end-effector of the Stretch robot is an unsensorized, compliant, 1-DOF grabbing tool with rubber fingertips. In order to increase the dexterity and grip strength of the end-effector, the default end-effector was upgraded to the TASKA prosthetic hand,

which has a 12.5 N grip force (Figure 4.2). The thumb has 2 DOFs (flexion/extension and adduction/abduction), while the other four fingers each have one DOF (flexion/extension). The standard grasp was a power grasp, in which all five fingers curled with the thumb opposing the other four fingers. For fine manipulation tasks, the operator could curl in their ring and pinky fingers to enter a pinch grasp mode (Figure 4.2). The Stretch RE1 robot was also upgraded to include a 2-DOF wrist (Stretch Dex Wrist, Hello Robot, Inc., Martinez, CA), whose motors have a 10 N-m stall torque.

We designed two modes of control for teleoperating Sensa: manipulation and drive. The manipulation mode is the default mode for interacting with the environment and performing tasks. In manipulation mode, Sensa has 13 DOF (pan and tilt head movements, 3D hand location, 3D wrist rotation, and flexion/extension for each of the five fingers). The drive mode is useful for moving to a different room or approaching a table. In drive mode, Sensa has 4 DOF (pan and tilt head movements, forward/reverse translation and clockwise/counterclockwise rotation of the wheeled base).

4.4.3 Operator Interface

In order to improve task performance, the operator control and sensing capabilities were augmented via electrical stimulation-based haptic feedback, high-resolution low latency stereoscopic video, and one-to-one control of the robot using natural hand and head gestures.

4.4.3.1 Implementation

Sensa’s streamlined operator interface consisted of a Quest 2, a custom skin-surface electrical stimulation pulse generator, and a haptic glove that delivered haptic electrical

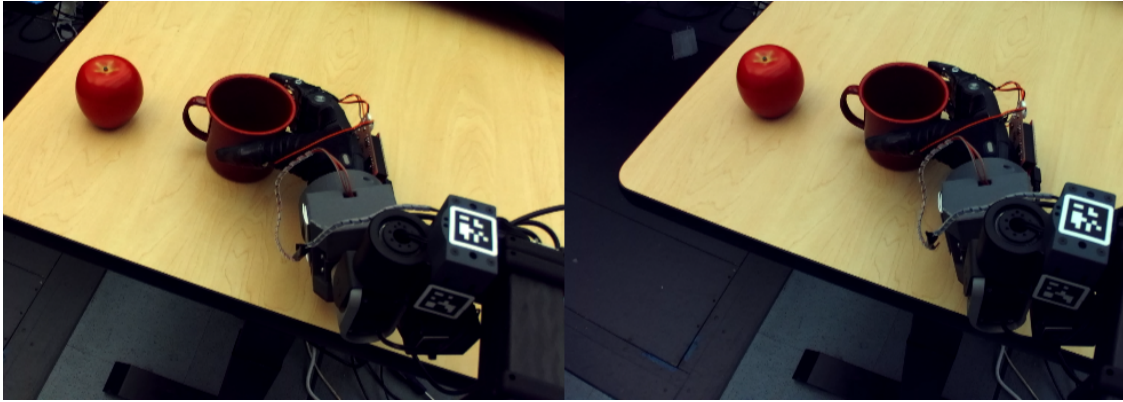


Figure 4.3: Single video feed from the ZED Mini binocular camera that shows images from the left and right cameras.

stimulation to the operator. The system provides visual and haptic feedback to a human operator in the form of binocular video and five surface electrical stimulation haptic feedback channels. The virtual reality headset live-streamed the robot's perspective and tracked the operator's movements, enabling intuitive hand and head gestures for controlling the robot avatar.

Sensa's immersive visual feedback was provided through the ZED Mini's high-resolution binocular video, in order to give the operator better depth perception. The ZED Mini's 1080p mode with 30 frames per second (FPS) and a resolution of 3840 x 1080 was used as a network bandwidth compromise between resolution and FPS. To create the illusion of depth, the single video feed with both the left and right camera feed (Figure 4.3) was separated into two feeds, each visible to only one eye. However, this setup caused double vision (diplopia). The double vision is caused by the differences between the perceived distance forced by the images' horizontal displacement and their true distance away from the camera. To fix this issue, a remote controller that allows the operator to move the video feed horizontally was added to help the operator converge on objects of varying distances.

Interactions with the end-effector were enhanced by surface electrical stimulation-based haptic feedback. The electrical stimulation was spatially and temporally synchronized with visual feedback and each sensory location could be independently varied in intensity according to the pressure exerted on an object. The TASKA hand was a research version with a force sensitive resistor (FSR) in each fingertip for tactile sensing. However, because each built-in sensor only covered a small portion of each fingertip, additional FSRs were added to the middle phalanges of each finger to increase the contact area. The operator wore a custom, lightweight haptic glove to convey haptic feedback proportional to the pressure exerted on the TASKA hand’s sensors (Figure 4.4).

The haptic feedback consisted of five channels of surface electrical stimulation, one for each finger, with the option to substitute palm feedback in place of one of the fingers. Stimulation was produced by a portable investigational medical-grade neurostimulator [11]. The cause of the five channel limitation is the limited number of external inputs of the neurostimulator. The neurostimulator applies controlled electrical pulses through small electrodes placed at specific locations on the hand and fingers to elicit the sensation of touch at the fingertips. The electrical stimulation was described as a feeling of touch on the fingertips, and the perceived intensity of the touch scaled with the level of stimulation delivered. The haptic feedback provided sensation modalities such as pressure and paresthesia that matched the location and pressure of the contact with the robotic hand. This haptic feedback helps the operator interact with objects, discriminate the compliance of the objects, and apply appropriate forces to enable successful object manipulation [34].

To address latency, the system required a way to stream high-resolution video with low latency over the internet. WebRTC (Google LLC, Mountain View, CA) provides peer-to-peer real-time communication for the web. With WebRTC, the system achieved imperceptible

latency on a local network and < 1 second latency over the internet when streaming from Los Angeles, California to Cleveland, Ohio (Figure 4.5). The low latency communication of positional data and haptic intensity was achieved using the NeuroReality™ Platform, a communication software designed at CWRU for teleoperation purposes.

Positional information about the operator's head, hand, and fingers was used to allow the operator to have intuitive control of Sensa. The Quest 2's inside-out tracking provided the position and orientation of the operator's right hand and head. In manipulation mode, the operator's head, wrist, and hand motions are mimicked by the robot. In driving mode,

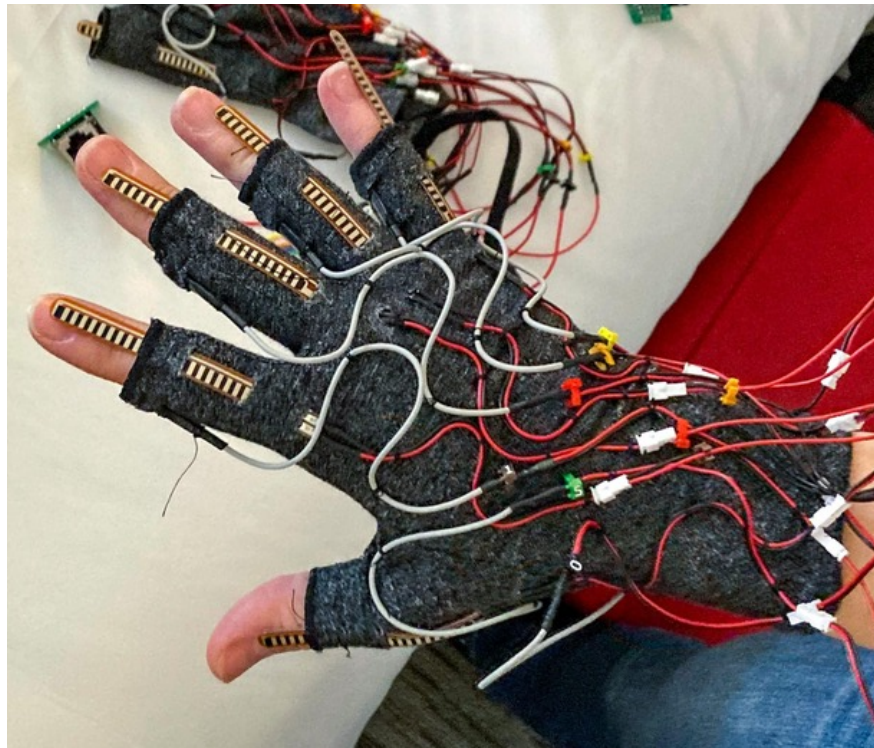


Figure 4.4: Surface electrical stimulation glove with electrodes and bend sensors for all five fingers. An extra optional electrode was placed on the palm for feedback purposes. The operator wears a white glove on top of the surface stimulation glove to improve hand tracking performed by the Quest headset.

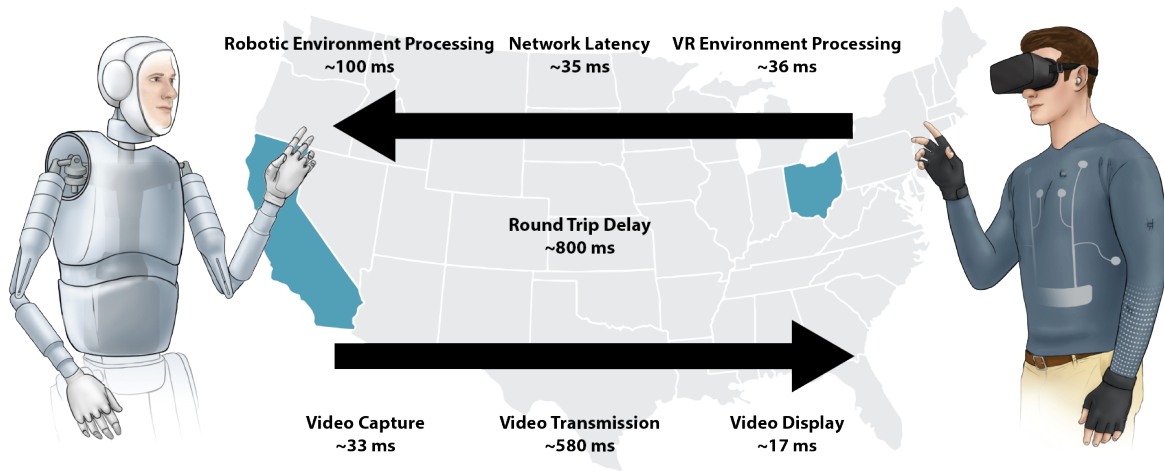


Figure 4.5: Round trip latency, shown in terms of the system components. Hardware and software latencies for each process along the teleoperation paths were calculated based on the slowest refresh rate in each process. The Cleveland to Los Angeles network latency was measured using the functionality of the NeuroReality Platform. Round trip latency was calculated based on the time difference between when the operator’s hand moved and the robot’s hand moved in the incoming video at the operator site.

the operator controls the translation of the robot using intuitive hand gestures and rotation of the robot using head movements.

While this tracking methodology allows for an all-in-one, portable setup, the performance is impaired by occlusion of the hands from the headset’s line of sight. During system testing, whenever the operator’s hand was not within the sensing range of the cameras, the headset failed to obtain accurate finger positions and hand poses. This hand tracking limitation was addressed at the finger level by adding bend sensors (Figure 4.4) to the glove over the metacarpophalangeal joints (Flex sensors 2.2; Sparkfun, Niwot, CO). The bend sensors provided a 1-DOF flexion/extension measurement of each finger at the metacarpophalangeal joint. To mitigate differences between operators, the flex sensors were calibrated at the be-

ginning of each session and were used only as a backup for the Quest-based hand tracking information when parts of the hand were occluded from the Quest’s view. When the difference between the Quest and bend sensor position estimates exceeded a threshold, the Sensa system used the bend sensor measurements in place of the Quest measurements. This implementation allowed for steady finger control even when parts of the hand were not visible to the Quest system.

4.4.4 Recipient Experience

A teleoperated system that provides social assistance must bridge the gap between the operator and the recipient through real-time, verbal, and non-verbal human-like communication.

4.4.4.1 Implementation

In order to enhance human-to-human connection, Sensa included anthropomorphic features and human-like communication capabilities. The anthropomorphic hand allowed the recipient and the operator to engage in human connection gestures such as nods and handshakes. Sensa was also equipped with a stereoscopic camera, a microphone, and a speaker so that the operator could communicate with the recipient via visual and auditory cues.

To improve the social connection between the recipient and the robot, an anthropomorphic end-effector and head analog were chosen. The ZED Mini camera (Figure 4.6) was placed on the Stretch RE1’s head to simulate the operator’s eyes in appearance and function. In addition to the implementation of the ZED Mini binocular camera, the pan and tilt degrees of freedom of the head were enabled such that the operator’s head movements were

mapped to the robot’s camera. This setup allowed the robot to perform head gestures such as nodding. The camera together with the VR headset allowed for visual communication between the operator and the recipient. Also, the TASKA hand end-effector mimics a human hand and allowed the robot to perform human-like gestures such as handshakes (Figure 4.7). To provide audio communication, the Stretch RE1’s onboard microphone and speaker captured and transmitted audio from the robot to the recipient. The Quest 2’s microphone and speakers provided audio communication to the operator. Visual and audio communication were synchronized by the WebRTC transmission protocol.



Figure 4.6: ZED Mini mounted on the Stretch RE1’s head. The ZED Mini was used to simulate the operator’s gaze and to provide stereoscopic vision to the operator.

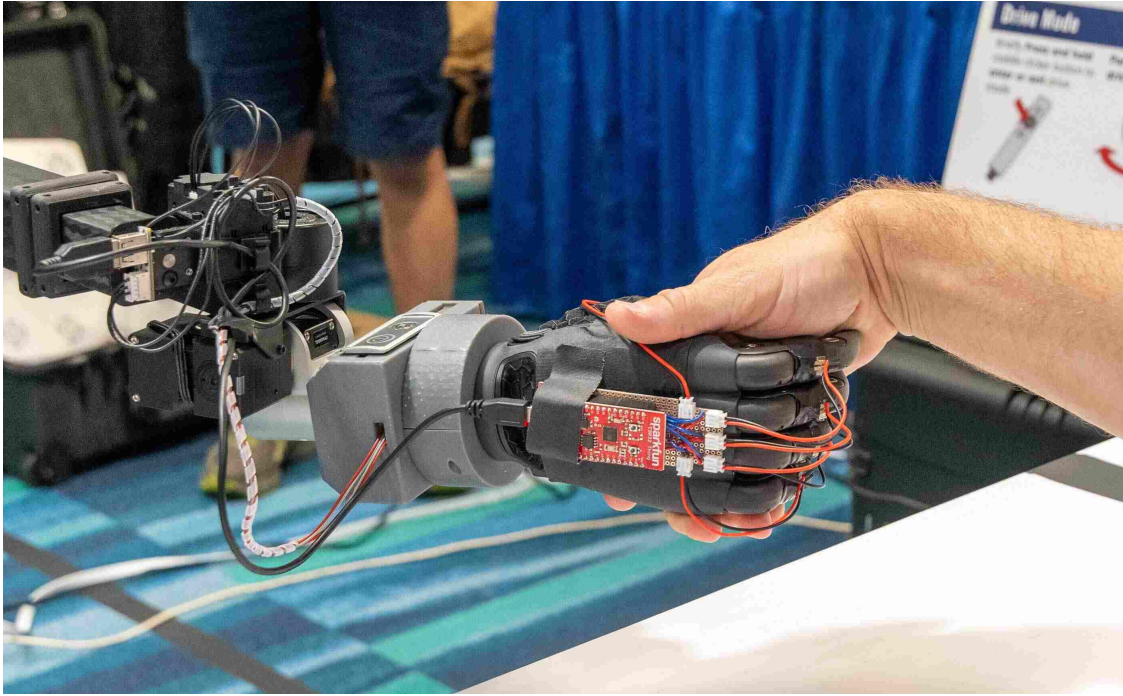


Figure 4.7: The operator and recipient engaging in a handshake through the teleoperation system.

4.4.5 Safety

Ensuring recipient safety is paramount for human-robot interactions in environments such as the home. The causes of accidents can be categorized into three groups: human error, workplace design, and robot design [47]. In the context of in-home assistive robots, developers can address these risks by designing the robot system to be intuitive, adaptable to unknown/unstructured environments, and robust to performance errors. Types of accidents can be further grouped into pinch and impact injuries [47]. Pinch injuries typically result from a part of the individual's body being trapped between moving parts of the robot or between the robot and the environment. Modern robotic manipulators such as the JACO (Kinova, Inc., Boisbriand, Canada) and the UR5e (Universal Robots, A/S, Barcelona, Spain)

are designed with smooth and rounded surfaces all along the arm. Joints are also spaced such that the possibility of pinching is minimal. Impact injuries are caused by the robot colliding with the individual or striking the individual with a tool. Impact injuries can be reduced by improving the robot's perception of its surroundings through additional sensors. Assistive robots are often equipped with laser rangefinders and cameras to help them navigate their environment and identify objectives. These considerations are important for choosing a robot platform and developing the robot's control software.

4.4.5.1 Implementation

The Stretch robot was designed with stability and safety in mind. The robot weighs 23 kg, which exceeds safety guidelines for a single person to lift [79], but is light enough for two people to lift or a single person to roll using the wheeled base. The robot's predictable Cartesian motions allow for safe human-robot interactions, with the only pinch points being between the lift joint and the head of the robot as well as between links along the telescopic arm.

Several safety features were implemented to protect Sensa and those interacting with the robot. In order to prevent injury to the recipient, collision avoidance was implemented using the horizontal LIDAR sensor. If an object was detected to be within 0.25 m in front of the robot, the robot would come to a stop. The Stretch robot comes with an emergency stop feature, which is activated by a push button on the head of the robot. An additional software-based emergency stop was implemented for the operator's use. Due to the increased grip strength of the TASKA hand, a force threshold of approximately 7 N was set for each finger. If grip force exceeded this threshold, the finger would be unable to flex further and was only permitted to extend. Force and velocity thresholds for the arm and lift joints were

also implemented in order to avoid injury or damage during a collision with a recipient or another object in the environment. To date, after over 150 hours of teleoperation, the Sensa robot has never collided with anyone unexpectedly and has never caused any injuries.

4.5 Future Improvements

4.5.0.1 Manipulation Capabilities

While our hardware modifications to the Stretch RE1 improved its function as an avatar, further software improvements could be made. The robot avatar was controlled by the operator through direct teleoperation, where each operator action was directly mimicked by the robot with no AI assistance. Due to limited depth perception and nonzero network latency, even simple tasks such as picking up an object were not always trivial for the remote operator. Autonomous teleoperation assistance could be integrated to improve task performance and efficiency by implementing shared autonomy techniques [25]. Based on the operator’s control inputs, the robot could predict their intent and provide seamless assistance by modifying the robot commands to reduce the cognitive burden on the operator.

4.5.0.2 Operator Interface

Sensa is currently limited by Meta’s image recognition-based hand tracking. The custom Sensa system mitigates hand tracking issues at the finger level using the flex sensors, but rotation and position of the hand are still susceptible to these limitations. A recent update (v39) on the Quest’s application programming interface improved the robustness of the hand tracking, which resolved the issue of spontaneous unintended changes in wrist rotation.

Our calibration procedure could also be improved to streamline the operator setup. The

visual calibration for determining the operator’s convergence angle could be automated using eye tracking. During calibration of the haptic feedback, operator-specific thresholds for stimulation are determined through a lengthy process of verbal questioning. This method was time-consuming and had to be repeated for every use since the wearable interface could shift between donning-doffing instances. The process could be automated by creating an interaction-based calibration system that allows the operator to quickly calibrate visual and haptic feedback from within the VR environment and save their profiles for a personalized recalibration process.

One of the main challenges of using the avatar system was the operator’s depth perception. Additional sensors, such as a camera mounted on the wrist, could be added to improve the performance of tasks requiring fine manipulation. A head camera with higher resolution and field of view would also enable better depth perception and immersion.

4.5.0.3 Recipient Experience

One key component of human communication that Sensa is missing is facial expressions. In social interaction, 55% of the affective information is communicated through facial expressions [73]. A possible solution is to use the operator’s face in a video conference-like manner to transmit this information from the operator to the recipient. To transmit the operator’s facial expressions, a neural network could be used to generate expressive images of the operator based on a facial recognition camera and eye tracking technology.

4.5.0.4 Safety

While force thresholds were enabled to avoid injury during collision, a more compliant behavior of the robot would improve safety. Instead of stopping abruptly upon reaching a force threshold, the robot could be programmed to exhibit compliant behavior in order to avoid large impact forces, as during unexpected contacts. Compliant robot control is commonly used in industrial settings involving human-robot collaboration. Another future improvement for safety could be achieved by anticipating and reacting to collisions through the use of the robot’s onboard camera and internal sensors.

4.6 Conclusion

The Sensa system is a proof-of-concept, teleoperated, service-type social robot designed to address the physical and social needs of assistive technology recipients. The Sensa system addresses the physical assistance needs of recipients through a lightweight, mobile, 13 degree-of-freedom robot. Its teleoperation capabilities allow the operator to assist the recipient with everyday tasks in unstructured environments. The human-safe robotic interface provides an effective platform for a naive operator and recipient to interact with one another.

Sensa allows the recipient and the operator to interact with each other and the recipient’s environment in a natural and immersive manner. The haptic feedback and interaction capabilities of the system allow a human operator to interact with everyday objects in homes, long-term care facilities, and other unstructured environments. The communication capabilities of the Sensa system allows for the operator to have a fluid conversation through bidirectional audio and immersive video. Furthermore, the anthropomorphic features of Sensa, allow for natural non-verbal communication and interactions between the assistive

technology recipient and a remote family member.

In the future, we hope to assess the usefulness and performance of assistive systems such as Sensa through human user studies involving our target population (e.g. individuals with disabilities). These experiments would focus on both objective metrics related to task performance and subjective user experiences from the recipient and operator. The results will help determine which aspects of a teleoperated system play an important role in human-to-human connection. Therefore, the Sensa system represents an important step in moving from proof-of-concept robots to real-world applications.

CHAPTER 5

Summary and Conclusion

The work presented in this dissertation has provided new insights into the importance of touch for both humans and robots. For robots working in granular material environments, the sense of touch is crucial since the effectiveness of vision-based approaches is limited. We explore the applications of buried cables and objects in various granular mediums such as playground sand, poppy seeds, and glass beads. For teleoperation operators, the addition of haptic feedback increases confidence during object manipulation and the feeling of embodiment during remote robot operation.

5.1 Contributions

Novel tactile-based proximity sensing framework for estimating the distance to a buried object using granular media jamming: We developed a novel method of sensing the proximity to buried objects by leveraging granular media jamming and the sense of touch. We hypothesized that an increase in tool force would be experienced when the wedge of displaced granular material made contact with a buried object. To model this interaction, we used a theoretical log-spiral soil failure model to estimate the shape of the displaced granular material. The log-spiral model of the failure surface proved to be an effective model for tactile-based proximity sensing of a buried object.

Experimental verification of theoretical soil failure surface in shallow robotic applications: We performed physical robotic experiments in various granular materials to verify our framework for the perception of buried objects. As of now, there are few studies that involve the use of a sensorized hand/gripper in granular materials. While most studies generally involve the use of a load cell above the granular material, our study differs by using a sensorized end-effector such that the data is collected from within the granular material. Our experimental study verifies the model proposed by [Soltanbeigi et al.](#) for shallow granular material environments with real robots.

Novel framework for estimating the orientation and diameter of cables buried in granular material: We developed novel approaches for both estimating the orientation and diameter of cables buried in granular material. The methods for orientation estimation use feature extraction layers based on the heightmap image Hessian and entropy. The method for diameter estimation uses curvature from the heightmap and minimizes the variance of distances between the center line of a cylindrical cable and points on the heightmap. The orientation and diameter estimation methods were evaluated under challenging experimental conditions in which cables were buried in granular material to various extents. We successfully demonstrated the best-performing methods even under the challenging condition of cables fully buried in a non-homogeneous sand mixture.

Developing an immersive and multimodal teleoperated robot: We created an immersive avatar-like, teleoperation system that would enable an operator to seamlessly embody a robot through intuitive full-body controls and multimodal feedback. To achieve this, we designed a virtual reality (VR)-based system that provided visual, auditory, and electrotactile haptic feedback. Natural head and hand movements were used to control the robot in order to facilitate intuitive learning of the controls. The haptic feedback system that relied on

electrical stimulation on the surface made use of electrical signals to activate the sensory nerves located at the bottom of each finger and in the palm region. This system was tested with naive operators who performed tasks such as performing a celebratory toast, completing a children’s puzzle, and describing a museum artifact using tactile feedback.

5.2 Future Work

5.2.1 Autonomous Tactile Exploration within Granular Material

Robots are expected to function independently in unfamiliar, real-life scenarios, such as finding buried objects in search and rescue missions. In situations where robots are required to operate in materials that are not transparent, tactile and proprioceptive feedback can be more useful than visual feedback. However, constructing a comprehensive, tactile-based model for exploration can be challenging due to the fact that tactile measurements are limited in their field-of-view and sparse in number.

In the work of [Jia et al. \[46\]](#), the robot’s ability to haptically explore within a non-homogeneous sand mixture was tested using a sensor model that takes into consideration the unique properties of granular materials. This model also helped to understand the forces of interactions between the robot and its surroundings. The strategy for the robot’s tactile exploration was carefully planned to effectively find and delineate a buried object, while at the same time minimizing any potential physical interactions that could cause damage to the object.

The kernel-based sensor model benefits greatly from being able to detect the current environmental interaction state of the robotic fingertip. This is because estimating the distance between the robotic fingertip and a buried object can enhance the accuracy of the

sensor model. By defining the measurement range based on the actual distance to the buried object, instead of relying on a rupture distance from a granular material failure zone model, the accuracy of the sensor model can be improved. As a result, enhancing the sensor model using the work presented in Chapter 2 could lead to better accuracy in locating, mapping, and characterizing buried objects.

5.2.2 Haptic Shared Autonomy Teleoperation System

The unpredictability of home environments poses a significant challenge to fully autonomous algorithms that were designed for structured conditions. Human intervention is usually required to overcome these challenges. One such strategy is *shared autonomy*, where the human and robot, each with their different capabilities and limitations, work together towards a common goal. The human leverage experience, context, and human creativity to provide high-level decisions. The robot leverages perception and autonomy algorithms to assist with lower-level control. For example, a human operator could select a target object to be grasped from a cluttered environment while the robot plans the end-effector’s digit placement and grip responses.

Existing studies in the literature on shared autonomy have demonstrated its effectiveness in improving task performance [25, 44, 114, 117, 115] (Fig. 5.1). However, it can often be difficult for operators to understand how and why their commands are being modified by the autonomous system, resulting in reduced *transparency* of the robotic system. This can lead to disagreements between the human and autonomous commands. Reduced transparency can also negatively affect users’ satisfaction and willingness to use robots [54].

In order to enhance transparency, a *haptic shared control* model was developed [96, 89, 8] (Fig. 5.1). In this setup, AI provides assistance solely through haptic cues instead of

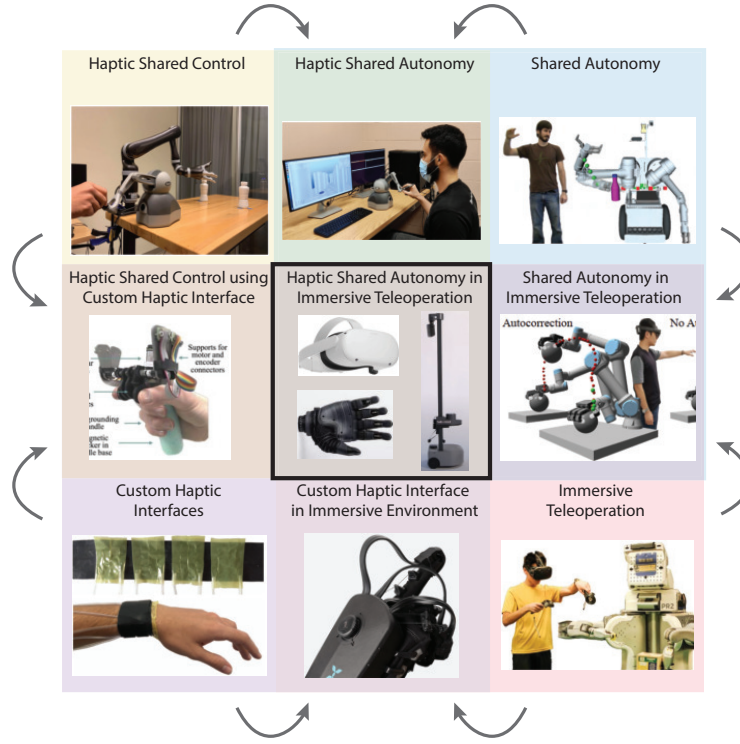


Figure 5.1: Diagram of existing literature [86, 130, 25, 113, 114, 90, 83, 132]. The gap filled by the proposed future work is highlighted in the center.

overriding the human’s direct control. However, this can also be a disadvantage of haptic shared control systems for certain applications. For example, for unmanned aerial vehicle teleoperation, it has been shown that operators still crash even when provided with haptic cues and retain full control authority [57, 129].

Recently, a *haptic shared autonomy* paradigm has been proposed in which haptic cues are used to inform the operator of the inner state of a shared autonomy system [130]. The haptic cues are designed to inform the user about how their commands compare to the action proposed by the robot and help prevent the feeling of the robot “having a mind of its own” [44]. For example, haptic cues were provided by a dynamic collision avoidance program in order to assist operators with navigating mobile robots through densely populated

environments [71].

To our knowledge, haptic shared autonomy has not yet been combined with immersive teleoperation (e.g. virtual and mixed reality) [132, 60]. Although traditional shared autonomy has been explored in immersive environments, prior works have not addressed shortcomings related to human-AI agreement and transparency [114]. Building upon the telepresence system from Chapter 4, the use of intuitive haptic cues without impeding natural hand motion is a potential direction for future work. The overall goal would be to design a novel haptic shared autonomy framework for immersive teleoperation that combines (i) haptic feedback from natural physical interactions with the environment, (ii) robot autonomy, and (iii) haptic cues that enhance the transparency of the operator’s commands with respect to robot autonomy.

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