Sensing Shear Forces During Food Manipulation: Resolving the Trade-Off Between Range and Sensitivity

Hanjun Song, Tapomayukh Bhattacharjee, and Siddhartha S. Srinivasa

***Abstract*— Autonomous assistive feeding systems need to acquire deformable food items of varying physical characteristics to be able to feed users. However, bite acquisition of these deformable food items is challenging without force feedback of appropriate range and sensitivity. We developed custom solutions using two widely-used shear sensing fingertip tactile sensors and calibrated them to the range of forces needed for manipulating food items. We compared their performance with traditional force/torque sensors and showed the trade-off between the range and the sensitivity of the fingertip tactile sensors in detecting potential bite acquisition successes for food items with widely varying weights and compliance. We then developed a control policy, using which a robotic gripper equipped with the fingertip tactile sensors can autonomously regulate the sensing range and the sensitivity to be able to skewer food items of different compliance and detect their bite acquisition success attempts.**

I. INTRODUCTION

Autonomous robotic manipulation systems have the potential to assist people with activities of daily living such as feeding [1]. To develop an autonomous feeding system, a robot needs to acquire a bite using some type of utensil from a plate/bowl and transfer it to a user. However, successful bite acquisition is challenging without haptic feedback for two main reasons: visual occlusion when contact is imminent [2], [3] and the deformability [4]–[6] of food. In a plate full of food items with varying sizes, shapes, orientations, relative placements, and degrees of occlusion, skewering a food item using vision only can be very challenging. Food items are also deformable with widely varying compliance and, consequently, skewering failures are inevitable. Thus, the robotic feeding system not only needs to have appropriate sensing range to skewer with proper forces but also needs to have the necessary sensitivity to distinguish the subtle changes in forces to detect if the skewering attempt is successful. In general, skewering food items during bite acquisition needs a wide sensing range to exert enough force depending on the compliance of food items. For example, skewering a grape and a carrot would require different forces. On the other hand, during the bite detection phase, observing the additional weight on the fork after bite acquisition to perceive success or failure of the acquisition attempt requires high sensitivity to measure the weights of light food items. Therefore, the same system would need to have reasonably high sensitivity (See Fig.1) to observe the weight change after skewering a light item such as grape. Thus, our key insight is that a robot-assisted feeding system should have a sensor with wide sensing range and high sensitivity.

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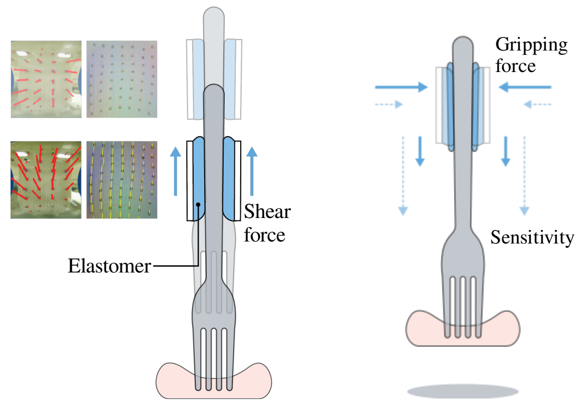
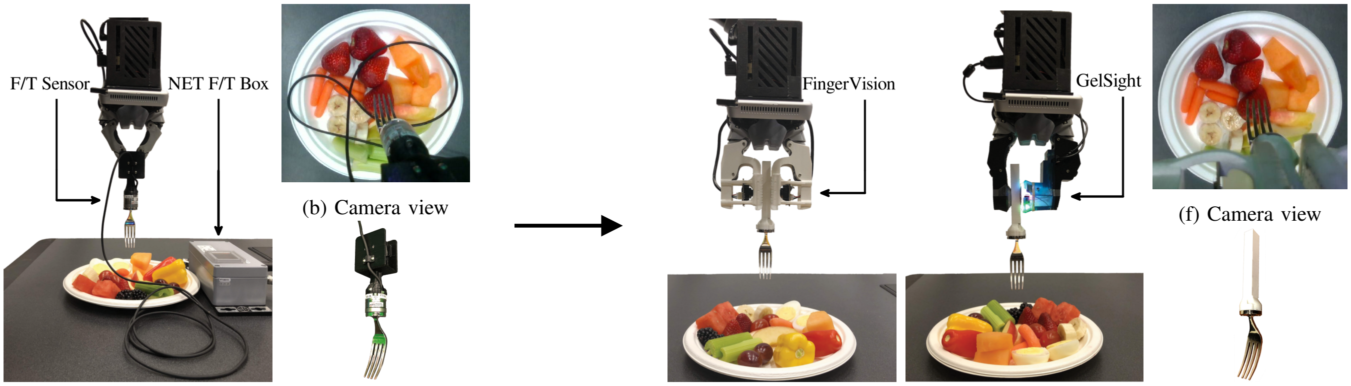


(a) Sensing shear force with fingertip tactile sensors (b) Sensitivity changes based on gripping force

Fig. 1: Sensing shear force when skewering a food item using fingertip tactile sensors. Due to the non-linear stress-strain relation of the elastomer, sensitivity of the sensor is adjustable by trading off with the sensing range.

One of the most common choices of sensors for haptic feedback with a fairly wide sensing range and high sensitivity is to use industrial force/torque (F/T) sensors such as ATI Nano25 F/T sensors. One approach to integrate these sensors in a robotic feeding system is to instrument the fork with these sensors as shown in Fig.2(a) and Fig.2(c) [7]. However, these sensors are expensive and present obvious challenges such as the presence of wires which can interfere with the feeding motion and the camera view as illustrated in Fig.2(b) [8]. Another approach could be to put these sensors under the food plate, but doing so will result in force feedback that is dependent on the position of a food item on a plate, which is again not ideal. Additionally, using traditional fingertip tactile sensors which sense normal forces are not appropriate for tool-based food manipulation because contact with a food item happens through a fork and measuring skewering forces requires the measurement of shear forces at the fingertips. Thus, our solution is to use low-cost customizable shear-sensing tactile sensors on the robot fingertips.

Finding low-cost shear-sensing tactile sensors with wide sensing range and high sensitivity is challenging. There have been a lot of developments in tactile sensing technologies in the recent past [9], [10]. Some of these tactile sensors are designed or scaled down to be attached to a robotic fingertip [11]–[19]. Among those fingertip tactile sensors, most provide pressure distribution or contact normal



(a) System with F/T sensor (b) Camera view (c) Forque (d) FingerVision (e) Fingertip GelSight (f) Camera view (g) A fork

Fig. 2: Suggested solutions to replace F/T sensor in the Forque (Instrumented fork). The cost and wiring related issues of the F/T sensor can be resolved by using fingertip tactile sensors, such as FingerVision and Fingertip GelSight sensors.

forces [14], [18], [19] and few of them are able to measure shear forces [11]–[13], [15], [16], [20]–[22]. In this paper, we focus on the FingerVision [15] and Fingertip GelSight [22] sensors because they are not only able to measure shear forces, but are also affordable, customizable, and relatively easy to fabricate. FingerVision (See Fig.2(d)) and Fingertip GelSight (See Fig.2(e)) sensors use cameras and elastomers. They can estimate shear forces by tracking markers on the elastomers when the elastomers are deformed by the shear forces. Some advantages of these types of tactile sensors are that they are economical, customizable, and easy to fabricate. However, they have higher latency (100-200ms), lower accuracy and reliability, and more restricted sensing range and sensitivity when compared to industrial F/T sensors. For food manipulation applications, it is crucial to have sensors with wide sensing range and high sensitivity. Even though the sensing range and sensitivity of these elastomer-based tactile sensors are restricted, the non-linear stress-strain relation of hyperelastic materials [23]–[26] allows us to selectively improve either sensing range or sensitivity of these sensors by controlling gripping forces [19], [27], as illustrated in Fig.1. Therefore, by developing a control policy that intelligently adapts gripping forces, we can use these sensors for food manipulation applications.

Our contributions are listed below:

1) We customized two low-cost shear sensing fingertip tactile sensors for feeding tasks.
2) We investigated the trade-offs between sensing range and sensitivity when measuring shear forces with the tactile sensors for manipulating food items.
3) We developed a control policy to regulate the sensitivity and the sensing range of these fingertip tactile sensors by adapting gripping forces.

II. METHODS

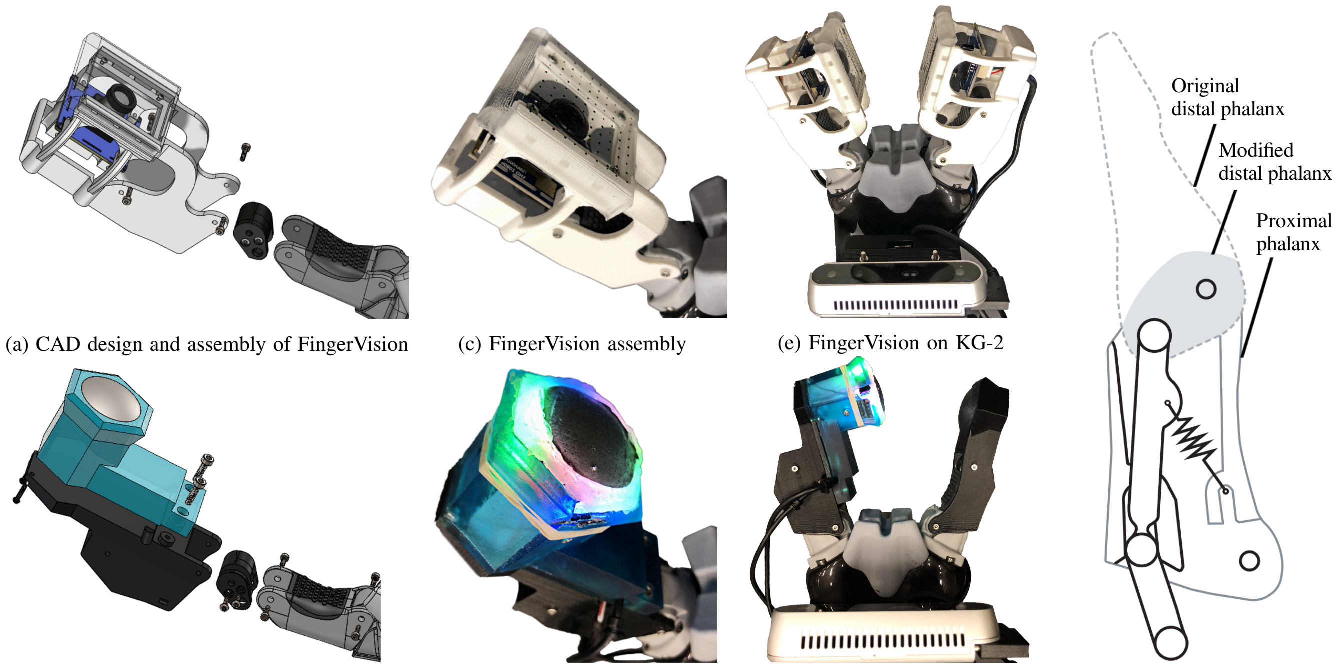
We modified FingerVision and Fingertip GelSight sensors to fit the Kinova gripper (KG-2) and calibrated the forces to get absolute force measurements in Newtons. Calibration is necessary to map the data from the sensors to physical units [28]. We assume that the shape of the fork handle is fixed and therefore any variations in the calibration due to contact area [22] are considered negligible.

A. Hardware Setup

To mount fingertip tactile sensors on each of the fingers of KG-2, we analyzed the mechanical structure and mechanism of the finger and identified the most suitable way to attach them. Fig.3(g) shows a schematic of the mechanism of the finger. KG-2 has two 2-degree-of-freedom (DOF) underactuated fingers [29] and each finger is composed of a proximal phalanx and a distal phalanx. To attach the fingertip tactile sensors to KG-2, we modified the design of FingerVision and designed an adapter for Fingertip GelSight as shown in Fig.3(a) and Fig.3(b), respectively. We mounted the fingertip tactile sensors on the proximal phalanges rather than the distal phalanges of the fingers of KG-2 to provide less backlash and a higher and more stable gripping force. Furthermore, we replaced the distal phalanges with a shorter version to remove the potential for collision between the distal phalanges and tactile fingertip sensors when fingers are actuated as shown in Fig.3(g), Fig.3(a), and Fig.3(b). Fig.3(c) shows modified FingerVision assembled with the proximal phalanx of the finger of KG-2. Fig.3(d) shows Fingertip GelSight assembled with the adapter and the proximal phalanx of the finger of KG-2. Fig.3(e) and Fig.3(f) show the actual implementation of each case. In the case of Fingertip GelSight, we designed a dummy Fingertip GelSight for another finger and attached it as shown in Fig.3(f). We also designed a fork handle to be compatible with the mounting holes of the F/T sensor and the fork tip. We designed the fork handle to have a flat rectangular contact surface and 12mm of thickness which makes the two fingertip tactile sensors parallel when they are holding the fork handle. We 3D printed the fork handle in white as shown in Fig.2(g) because FingerVision works best with white objects.

B. Force Calibration

We designed the calibration process for FingerVision and Fingertip GelSight sensors to convert raw sensor values, which are based on the displacement of markers in pixels, to absolute force measurements in Newtons. Previous calibrations for Fingertip GelSight sensors [22] were done for a small range of shear forces. However, food manipulation applications demand a larger range. Calibration for FingerVision sensors was left to the users as discussed in [15].



(a) CAD design and assembly of FingerVision (c) FingerVision assembly (e) FingerVision on KG-2

(b) CAD design and assembly of GelSight (d) Fingertip GelSight assembly (f) Fingertip GelSight on KG-2 (g) KG-2 mechanism

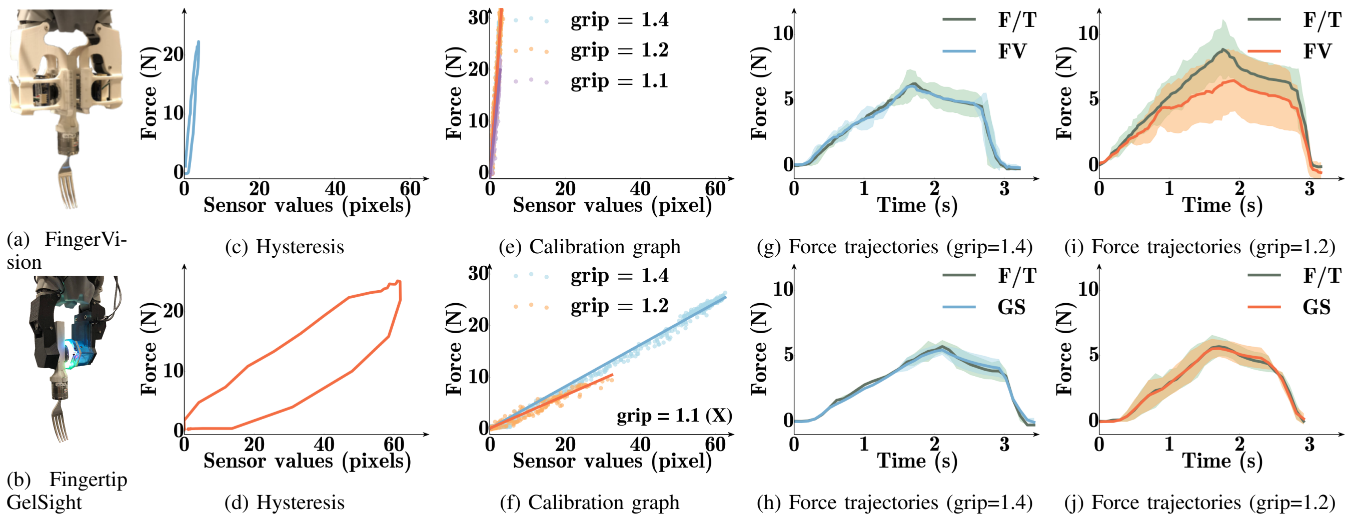
Fig. 3: Hardware design process to attach FingerVision and Fingertip GelSight sensors to KG-2 fingers.

Force calibration is essential to generalize the data from the fingertip tactile sensors and to specify their characteristics, such as range, sensitivity, and hysteresis in physical units. Relevant to the food manipulation task, we specifically calibrated the shear forces for a range of 0-30N and obtained the sensitivity for different gripping forces. We expect that different gripping forces may result in different sensitivities because of the hyperelastic characteristics of elastomers. We set the range of shear forces based on the data [30] from our previous human subject tests for food manipulation [8].

1) Calibration Setup: We attached the fingertip tactile sensors to the KG-2 as described in Section II-A and placed the fork vertically between the robot fingers as shown in Fig.4(a) and Fig.4(b). In between the fork handle and the tines, we added an ATI Nano25 F/T sensor to obtain true force measurements. We had the fingertip tactile sensors grab the instrumented fork vertically as shown in Fig.4(a) and Fig.4(b) with the maximum gripping force. The robot arm was mounted on a wheelchair [31] and we placed the wheelchair in front of a desk. We processed the images of the tactile sensors at 30Hz for FingerVision sensor and 10Hz for FingerTip GelSight sensor using our on-board computing installed on the wrist, and transmitted force data through wireless communication.

2) Calibration Procedure: We recorded the sensor values and force measurements from the F/T sensor while the robot was pushing the instrumented fork vertically on the table until the force measurements reached around 30N. We computed the sensor values by averaging the pixelated vertical displacements of every marker on the FingerVision and Fingertip GelSight sensors. We repeated this procedure 20 times for three different gripping forces using three different ROS position parameters: 1.4, 1.2, and 1.1. After the data collection, we synchronized the values from fingertip tactile sensors to the force measurements from the F/T sensor based on linear interpolation. The hysteresis as shown in Fig.4(c) and Fig.4(d) is mainly caused by the latency of the cameras. We removed the hysteresis by subtracting the latency of each fingertip tactile sensor from the time stamps of the data. We measured the average latency by giving step forces and found that FingerVision has around 120ms of latency and Fingertip GelSight has around 130ms of latency.

3) Calibration Results: Fig.4(e) and Fig.4(f) show the plots of synchronized data from FingerVision, Fingertip GelSight, and F/T sensors when vertical forces are applied to the fork with three different gripping forces. We obtained a linear relationship between the data from fingertip tactile sensors and the force measurements from F/T sensor using linear regression. The unit of the slope is in N/pixels. We defined sensitivity of the sensor as the slope of force data. The sensitivity of each gripping force for each fingertip tactile sensor is 10.837 N/pixel and 7.450 N/pixel for FingerVision when the gripping parameters are 1.4 and 1.2. Fingertip GelSight has 0.404 N/pixel and 0.317 N/pixel when gripping parameters are 1.4 and 1.2, respectively. From the calibration results, we found that lower gripping force improves the sensitivity of the shear force sensing for both the fingertip tactile sensors. Interestingly, we see that Fingertip GelSight has higher sensitivity than that of FingerVision, but has narrower sensing range. This result comes from the different hardness of elastomers, where the harder elastomer of the FingerVision sensor gives lower sensitivity but the wider sensing range and softer elastomer of the Fingertip GelSight sensor gives higher sensitivity but a narrower sensing range. Fig.4(g) shows a calibrated force trajectory while skewering watermelon with the FingerVision sensor when the gripping parameter is 1.4 and Fig.4(i) shows a calibrated force trajectory when the gripping parameter is 1.2. Fig.4(h) and



(a) FingerVision (b) Fingertip GelSight (c) Hysteresis (d) Hysteresis (e) Calibration graph (f) Calibration graph (g) Force trajectories (grip=1.4) (h) Force trajectories (grip=1.4) (i) Force trajectories (grip=1.2) (j) Force trajectories (grip=1.2)

Fig. 4: Calibration process and force trajectories when skewering watermelon for each fingertip tactile sensor with two different gripping forces.

Fig.4(j) also show the force trajectories while skewering watermelon with the Fingertip GelSight sensor when the gripping parameters are 1.4 and 1.2, respectively. Based on the calibration, we verified that FingerVision and Fingertip GelSight sensors are able to provide reasonable range and sensitivity of shear forces when skewering food items.

C. Theoretical Background

The elastomers used in the FingerVision and Fingertip GelSight sensors are categorized as hyperelastic materials like most polymers such as rubbers, sponges and other soft flexible materials. Hyperelastic materials have highly non-linear stress-strain relation and they get stiffer under compression [32]. Therefore, larger the gripping force, stiffer is the elastomer of the sensor and thus higher is the Young's modulus, E. This, in turn, increases the shear modulus, G, given by

$$G = \frac{E}{2(1+\nu)} \tag{1}$$

where ν indicates Poisson's ratio, which is constant for elastomers at around 0.5 [33]. This affects the shear strain and thus the displacement of the markers which directly correlates with the sensor input. Therefore, by changing the gripping force, the displacement of the markers can be changed which, in turn, changes the sensitivity and the sensing range.

III. EXPERIMENTS

We designed experiments in which a robot skewers six different food items using a fork and fingertip tactile sensors with different gripping forces. We collected force trajectories of each food item and showed how accurate the fingertip tactile sensors are. In addition, we also verified that the fingertip tactile sensors are sensitive enough to detect if a bite acquisition attempt is successful. Lastly, we designed a control policy that can adjust the sensing range and sensitivity by intelligently controlling gripping force.

A. Experiment Setup

We selected six food items: grapes, cherry tomatoes, apples, celery, watermelons, and hard-boiled eggs, based on their variation in weight. We categorized grapes and cherry tomatoes as light food items (average weight < 10g). Apples and celery were categorized as medium food items (10g $\leq$ average weight < 25g). Lastly, we categorized watermelons and hard-boiled eggs as heavy food items (average weight $\geq$ 25g). We used the fork equipped with the F/T sensor to obtain not only the sensor data from the fingertip tactile sensors, but also the ground truth force measurements when skewering food items.

B. Experiment Procedure

There were two phases in this experiment: the bite acquisition phase and the bite detection phase. Furthermore, we designed a control policy that utilized the non-linear strain-stress relation of the elastomer.

1) Bite Acquisition and Bite Detection Phases: The robot skewered six different food items five times each with two different gripping forces. We selected the two gripping forces based on the closing position of the gripper with 1.4 as the high gripping force and 1.2 as the low gripping force. For FingerVision, the noise of the sensor is about 0.012 pixel and this affects the minimum sensing threshold. $1/100$th of pixel noise originated from the computation method for the sensor output explained in Section II-B.2. If the sensor value went over the threshold in the bite detection phase, it was able to tell that a food item was on the fork, and this was marked as a successful trial. We expected that if the robot was gripping the fork with high gripping forces, fingertip tactile sensors would sense the heavy food items but not the medium and light food items due to the low sensitivity. On the other hand, we predicted that the robot would be able to detect even medium and light food items with increased sensitivity by lowering the gripping force. Finally, after counting the successful bite prediction trials for each gripping force, we tested the reliability of the sensor by hitting an empty plate five times to see if the sensor could detect that no food was skewered.

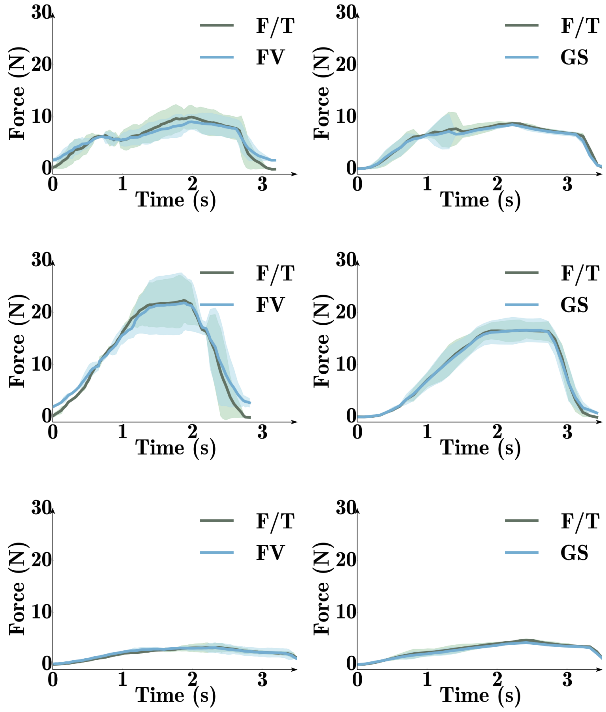


Fig. 5: Force trajectories when skewering grapes (top), apples (middle), and eggs (bottom) with ATI Nano25 F/T (F/T), FingerVision (FV), and Fingertip GelSight (GS) sensors.

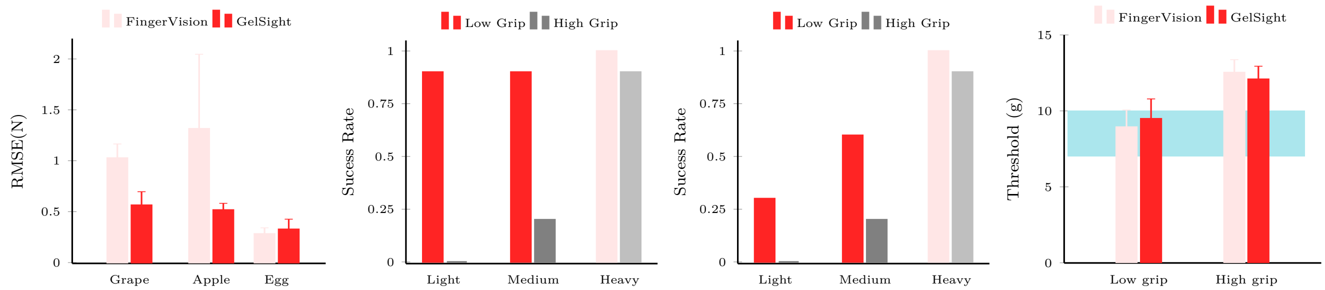
2) Control Policy: Food items are of varying compliance and thus sometimes may require exerting high forces to skewer hard items using a tightly-gripped fork. However, doing so may reduce the sensor sensitivity required to detect whether a lightweight food item was picked up. Therefore, we implemented a control policy that would work for varied food items. We developed this control policy to regulate the range and the sensitivity of the sensor by controlling the gripping force. The idea is to grip the fork with maximum gripping force (gripping parameter of 1.4) to have wide sensing range during the bite acquisition phase, and lower the gripping force (gripping parameter of 1.2) to have better sensitivity during the bite detection phase. We designed this control policy because the grasped fork may be unstable or prone to slipping when the gripping force is low due to the narrow sensing range. We tested this control policy on an empty plate, one light item, one medium item, and one heavy item, with five trials for each. We tried this policy on an empty plate to see if the sensor has enough reliability even after changing gripping force and hitting something.

C. Experiment Results

1) Bite Acquisition Phase: Fig.5 shows the force trajectories from ATI Nano25 F/T, FingerVision, and Fingertip GelSight sensors when skewering grapes, apples, and eggs respectively. The solid lines in the plots show the mean of force trajectories from five trials for each food item and the shaded area denotes the standard deviation of force trajectories. It is evident from the force trajectories that FingerVision and Fingertip GelSight sensors can detect subtle changes of shear forces. For example, we observe a rapid drop of forces when skewering food items that have a relatively hard skin but are soft inside, such as grapes and tomatoes. [30]. This subtle but rapid drop of forces right before 1 second is due to the piercing of the skin by the fork during skewering. This shows that FingerVision and Fingertip GelSight sensors have sufficient sensitivity and response rates to detect subtle changes in forces.

Fig.5 also shows that FingerVision and Fingertip GelSight sensors provide enough sensing range for shear forces to skewer both soft and hard food items. For instance, skewering apples and eggs require around 20N and 6N of vertical force respectively. Note that we observe a fairly large standard deviation of force trajectories from Fig.5, which are comparable to that from F/T sensors. This is not only from the noise in FingerVision and Fingertip GelSight sensors but also from the variation in shape and compliance of food items. Fig.6(a) shows the average root mean squared error (RMSE) and the standard deviation of forces for each food item obtained from FingerVision and Fingertip GelSight sensors with respect to the F/T sensor. Overall, FingerVision sensor has around 0.942N of RMSE and Fingertip GelSight sensor has around 0.469N of RMSE.

2) Bite Detection Phase: Fig.6(b) and Fig.6(c) show the success rates of bite detection for FingerVision and Fingertip GelSight sensors for different gripping forces. It is evident from the figures that with low gripping force, a robot has a higher success rate in detecting whether the bite acquisition attempt was successful for light and medium foods items. The sensor completely failed to sense light food items (grapes and cherry tomatoes) when gripping force was high but the success rate (0.9) was significantly higher (p-value < 0.05) when gripping force was low. This result shows that the weight of light food items ($<$ 10g) is usually lower than the minimum sensing threshold when gripping force is high, but still higher than the threshold when gripping force is low. In general, the minimum sensing threshold is considered to be the noise floor of the sensor and this can be obtained by multiplying the noise and the sensitivity of the sensor. Based on the results from Section II-B.3, the thresholds of the FingerVision sensor are around $12.5g$ and $8.93g$ for high and low gripping forces, respectively. The thresholds of the Fingertip GelSight sensor are $10.47g$ and $9.48g$ for high and low gripping forces, respectively. This shows that the thresholds of the sensors become smaller and stay in the range of the weight of light food items (7-10g, shaded area in the graph) when the gripping force decreases as illustrated in Fig.6(d). Note however, the success rate is comparable for heavy food items (watermelon and egg) irrespective of high or low gripping force. This means that the sensitivity is high enough to sense the weight of heavy food items (25g) for both high and low gripping forces. For medium food items (apple and celery), the success rate of bite prediction is 0.2 when gripping force is high and 0.9 when gripping force is low, and it is statistically significant with the p-value less than 0.05. This significant difference in success rates means that the weight of medium food items, which is between 10-25g, is usually lower than the minimum sensing threshold when gripping force is high. These results clearly show that a robot



(a) RMSE of force trajectories (b) Bite detection for FingerVision (c) Bite detection for GelSight (d) Sensitivity for different grips

Fig. 6: RMSE of the force trajectories, the success rate of bite acquisition for each sensor, and the minimum sensing threshold for each gripping parameter (Low grip means 1.2 and high grip means 1.4). Blue shaded region shows the weight range of light items.

can potentially adjust the sensitivity of sensors by controlling its gripping force, and that the sensor sensitivity with a low gripping force is high enough to detect the weight of food items ranging from lightweight to heavyweight. However, increasing the sensitivity of the fingertip tactile sensors by decreasing the gripping force has the trade-off of reduced force sensing range, and also may constrain a robot from applying larger forces needed to skewer hard food items such as carrots.

For the experiments when the fork tines hit an empty plate and nothing was skewered, the fingertip tactile sensors correctly detected that food was not skewered when the gripping force was high. However with low gripping force, two out of five trials incorrectly reported that food was skewered. This implies that having low gripping force during the skewering phase could result in false detection. This is because the force sensing range decreases as gripping force is decreased, which could lead to unstable gripping while hitting the empty plate. Therefore, we came up with a control policy using which the sensing range and sensitivity can be adapted by intelligently changing the gripping force (See Section III-C.3).

3) Control Policy: Using our control policy, we performed the same experiment of hitting an empty plate, and every time it correctly detected that no food was skewered. We also found out that changing gripping force and hitting the plate did not degrade the reliability of the sensor. For the experiments with food items, we could successfully detect the bite acquisition for every food item (grape, apple, and egg) with 100% success rate. Also, the fork was securely held by the gripper due to the high gripping force while skewering. This control policy can be very useful especially when the robot is skewering a food item that is hard but light, such as a mini carrot, because it requires wide sensing range due to its hardness and high sensitivity because of its light weight.

IV. DISCUSSION

In this paper, we analyzed the characteristics of FingerVision and Fingertip GelSight sensors in terms of sensing shear forces. We identified that sensitivity changes as gripping force changes for the these fingertip tactile sensors. We also showed that this can be a useful feature of the fingertip tactile sensors for food manipulation by proposing a control policy. However, there are some assumptions that may need to be relaxed in real-life applications.

First of all, we assumed that the latency of each fingertip tactile sensor is constant. However, the latency may vary depending on the computing and networking environments. For example, we used 120ms for the FingerVision sensor and 130ms for the Fingertip GelSight sensor. With varying latency, the actual exerted forces could be lower or higher than the force converted with the calibration based on fixed latency. One solution could be to find a way to get real-time latency of the cameras. Another solution could be to develop a prediction model of the fingertip tactile sensors.

Another challenge is that the calibration is not consistent, especially for the FingerVision sensor. That is because the FingerVision sensor is affected by lighting conditions and the color of objects. One possible solution to reduce the influence of lighting conditions is to have an additional layer on the surface of the elastomer that blocks lights entering through the non-contacted area of the elastomer of the FingerVision. A preliminary test of covering the sides using masking tape reduced the noise and error in the sensor values. Using bright-colored objects could also circumvent the problem.

Interestingly, the Fingertip GelSight sensor has higher sensitivity than that of the FingerVision sensor. However, the higher sensitivity sometimes leads to larger hysteresis due to the greater viscosity of the elastomer or a mismatch in marker tracking algorithms which are difficult to fix. In addition, the dome shape of the elastomer of the Fingertip GelSight sensor makes gripping unstable. We had multiple instances when the fork slipped or rotated during skewering. The previous versions of the Fingertip GelSight sensor had flat surfaces which may be more suitable for our application.

Finally, another challenge was to reliably control the movement of the KG-2 fingers. The fingers of KG-2 move radially based on position control. This leads to uneven distribution of forces on the fingertip tactile sensors when gripping force is low. We can resolve this problem by designing our own parallel mechanism gripper for KG-2. In future, we will integrate these sensors with our autonomous robotic feeding system and use real-time force feedback from these sensors to feed users.

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