FingerVision for Tactile Behaviors, Manipulation, and Haptic Feedback Teleoperation

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This paper introduces a vision-based tactile sensor FingerVision in order to attract haptics researchers to use FingerVision. We describe the overview of FingerVision and its applications including tactile behaviors and robot manipulation. We also discuss the use of FingerVision for teleoperation with haptic feedback under learning-from-demonstration context.

Keywords: FingerVision, Tactile sensing, Tactile behaviors, Robot manipulation, Haptic feedback teleoperation

1. Introduction

This paper introduces a vision-based tactile sensor FingerVision and its applications in order to attract haptics researchers to use FingerVision. FingerVision was proposed in (1) by Yamaguchi and Atkeson. Its concept is combining proximity vision and tactile sensing. Unlike other vision-based tactile sensors such as (2)~(15), the cameras inside FingerVision can see the outside of the sensor through the skin, which increases the sensing modality. The structure of FingerVision is simple, consisting of elastic and transparent skin, frame, and cameras. Markers are attached on the skin surface for detecting skin deformation. The features of FingerVision are summarized as follows:

(1) Multimodal: It can sense force distribution, slip, object pose, texture, and other information obtained from *proximity vision* (computer vision for nearby objects). The remarks are that: (1.1) Slip can be detected regardless the reactive force from objects. It can sense slippage even when the object is too light to sense force (e.g. origami crane). (1.2) Cameras can sense objects before collision. With this feature, we can create safe interactive robots that are aware of nearby humans.
(2) Easy to manufacture: Because of its simple structure, its fabrication is easy.
(3) Low cost: The most expensive component is the camera. Other components are inexpensive.
(4) Physically strong: External force applies to the skin and frame, and does not reach the camera. Thus it is physically strong. Even if the skin is damaged, replacing it is inexpensive.
(5) The sensing elements (cameras) do not have to cover the whole surface: Using wide-angle lenses (fisheye lenses), we can make the camera allocations sparse.
(6) Processing software could be common, which enables efficient development.
(7) Sensor parameters are adjustable: We can adjust the dynamic range of force (hardness and thickness of the skin), size (small cameras miniaturize the sensor size), spatial resolution (camera resolution, marker allocation, etc.), and temporal resolution (high speed cameras for high FPS).
(8) Other types of sensors can be used: For example thermal cameras.

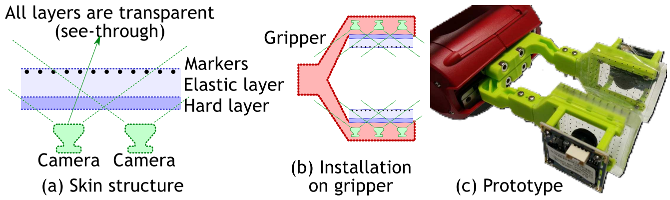

Fig. 1. Conceptual design of FingerVision (a, b) and its prototype installed on Baxter electric parallel gripper (c).

In (16), we demonstrated that FingerVision makes it easy to program some tactile behaviors such as gentle grasp, holding without slip, natural handover, and in-hand manipulation. Especially because of its sensitivity of slip, it was possible to make a grasp adaptive controller which adjusts the grasp to avoid slip during picking up an object [17]. With this controller, the robot with a parallel gripper where the FingerVision sensors are installed could pick up a range of deformable and fragile objects, such as vegetables, fruits, origami arts, raw eggs, and potato chips.

We encourage many researchers reproduce FingerVision for their own devices. For this purpose, FingerVision is open source [18].

In the rest of this paper, we summarize the sensing technology of FingerVision, its applications to tactile behaviors and manipulation, and we discuss the use of FingerVision for teleoperation with haptic feedback under learning-from-demonstration context.

2. FingerVision

FingerVision is a vision-based tactile sensor consisting of elastic and transparent skin made with silicone, frame made with 3D printed support and acrylic, and cameras. Fig. 1 shows the conceptual structure. Markers are placed on the surface of the skin for detecting skin deformation to estimate

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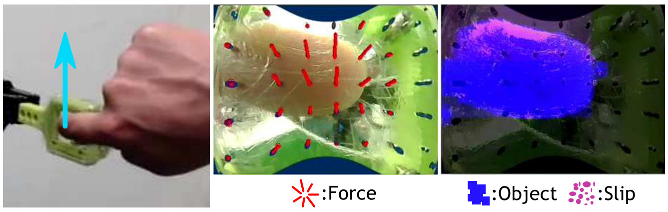


Fig. 2. Example of sensing when pushing the sensor by finger. Force distribution, slip, and object (finger) are detected.

external force distribution. In the prototype of FingerVision (Fig. 1(c)), we use Silicones Inc. XP-565 that has A-16 Shore hardness as silicone, black micro plastic beads of 1 mm diameter for markers, and ELP Co. USBFHD01M-L180 USB camera with fisheye lens. The thickness of silicone is 4 mm, the markers are allocated on 5 mm grid, and the thickness of acrylic is 2 mm. The camera stream is taken at 320x240, 30-60 FPS.

The raw measurement from FingerVision is image sequence as usual cameras. We use several different computer vision methods for estimating force distribution, slip, and object pose. Estimating force distribution is achieved by tracking the markers whose movement tells us the deformation of the silicone skin. Estimating slip and object pose are done by directly analyzing the camera stream. We refer to such computer vision for nearby objects as proximity vision.

2.1 Force Estimation By Marker Tracking For tracking the markers placed on the surface of the elastic skin, we use a blob tracking method. It consists of two processes: calibration to detect initial marker positions, and tracking the marker displacements. In the both processes, the camera image is rectified for compensating the distortion caused by fisheye lens, and then converted to a black and white image by thresholding black color as the markers are black. In the calibration, we cover the sensor with white sheet in order to avoid detecting noise from background. A blob detection method implemented in OpenCV (`cv::SimpleBlobDetector`) is used. The calibration takes less than 1 second. Marker tracking is done independently per marker. We assume a small region around a marker at its previous position, and apply the same blob detection method of OpenCV. If the marker movement is unexpectedly large, we reject the result since it would be noise. We also compare the size of blob to distinguish the noise. The obtained marker displacements are converted to 3-dimensional force estimates. Refer to (16) for the details of force estimation. Fig. 2 shows an example of marker tracking where the red bars highlight the marker movement.

2.2 Proximity Vision We directly process the camera stream for proximity vision. Although we could use many of computer vision algorithms for proximity vision which would increase the sensing modality, we implement two algorithms: nearby-object detection and slip estimation. The object detection is useful to estimate the pose (position and orientation) and size of grasped object or nearby object, and is also used to distinguish the background and object movement. Slip is estimated by a background subtraction method with the mask of detected object. We also considered optical flow, but background subtraction was better in some cases where the object does not have sufficient texture. In the calibration stage, we build the background model. An object model is we adaptively and dynamically constructed. Both the background and the object models are represented as color histograms. As the background subtraction method, we use an implementation of OpenCV (`cv::BackgroundSubtractorMOG2`). With this implementation, the strength of slip at each pixel is estimated which does not have the direction of slip. Refer to (16) for the details of slip and object detection. Fig. 2 shows an example of detecting nearby-object and slip.

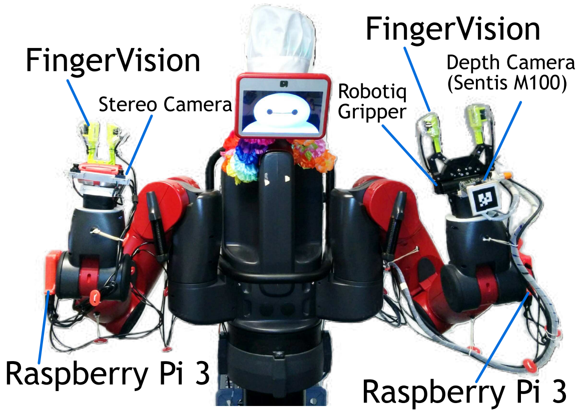


Fig. 3. Baxter system with two grippers where FingerVision is installed on each finger. Raspberry Pi is used to stream the camera data to Ethernet network.

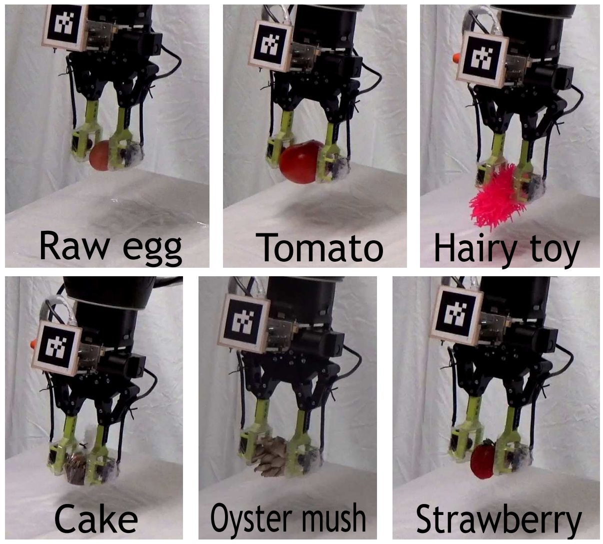


Fig. 5. Examples of grasp adaptation control.

3. Tactile Behaviors and Manipulation

We briefly describe the tactile behaviors and manipulation with FingerVision to demonstrate the variety of its applications. Here we assume that the FingerVision sensors are installed on parallel grippers mounted on a dual-arm robot Baxter (Fig. 3). As the gripper, we use a Baxter electric parallel gripper and a Robotiq 2-finger adaptive robot gripper-85. We designed 3D printed frames for each gripper. Fig. 4 shows an illustration of the tactile behaviors.

Gentle Grasp The purpose is grasping an object with a small force. We use the force estimation to stop closing the

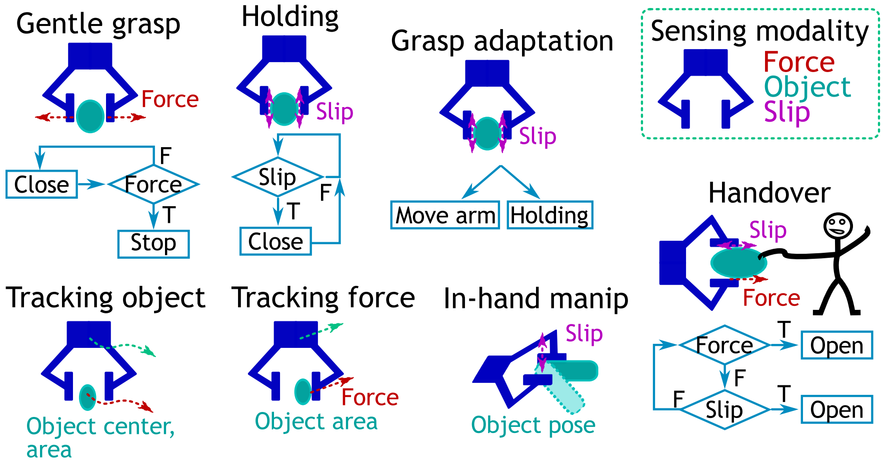


Fig. 4. Tactile behaviors.

gripper.

Holding The purpose is controlling the grasp (gripper width) to avoid slip when holding an object. The strategy is simple: closing the gripper when slip is detected.

Grasp Adaptation In general, the goal of grasping is eliminating slippage of holding object during lifting up. We implement this behavior by combining the lifting up motion and the holding behavior (slip avoidance control) mentioned above. More concretely, we repeat until the object is lifted up: moving the object upward slowly; if slippage is detected, moving the object to the initial height and closing the gripper slightly. Refer to (17) for more details of grasp adaptation control.

Handover The purpose is naturally passing an object to a human. FingerVision is used as a trigger to open the gripper. Both force estimation and slip detection are used as the trigger: if one of them is detected, the gripper is opened. Combining two modality increases its applicability. When grasping an object strongly, force tends to be detected. When grasping a light weight object such as an origami crane, slip tends to be detected.

Tacking Object The purpose is tracking an object between the fingers. We control the robot arm so that the target object locates at the center of the fingers. We use the object detection and the pose estimation. The position on the camera image plane is estimated accurately; we control the robot arm to center the object on the image. For controlling the height of the object from the camera, we use the area of the object on the image. From two FingerVision sensors on two fingers, we obtain two estimates of object areas on the images. By controlling the robot to equalize the areas, the object locates at the center of the fingers.

Tracking Force The purpose is operating the robot by pushing slightly. We use the force estimate and control the robot towards the pushed direction. We also use the object detection as a trigger to activate the control, which increases the safety since the robot does not move when no object is between the fingers. We compared two variations: one uses the force estimate of Baxter (estimation from joint torque sensors), and the other combines the force estimate of Baxter and FingerVision. In the latter case, the robot was operated with smaller force.

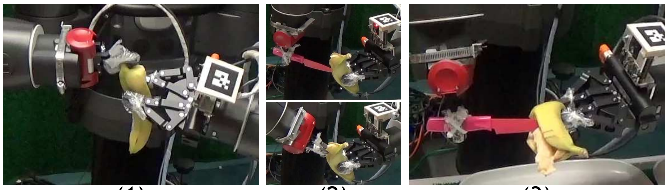
In-hand Manipulation The purpose is changing the orientation of a grasped object without releasing it. This is achieved by repeatedly relaxing and tightening the gripper based on the slip estimate until the target orientation is achieved.

More details of the gentle grasp, holding, handover, and in-hand manipulation are described in (16). Its accompanying video is available on `https://youtu.be/L-YbxcyRghQ/` Fig. 5 shows the examples of grasp adaptation control. Its video is available on `https://youtu.be/0sAkec5bpu4` and `https://youtu.be/uy32t09e704` The video of tacking object is available on `https://youtu.be/TAA4YJqEOqg` The video of tracking force is available on `https://youtu.be/FQbNV549BQU`

4. Discussion: FingerVision for Teleoperation with Haptic Feedback

Haptic feedback teleoperation (e.g. (19)) is an important technology for telesurgery. It should be also useful in other robot manipulations. Manipulation tasks in everyday activity are still difficult problems of robotics. A promising approach to enable robots performing everyday activity is learning from human demonstrations [(20)]. However transferring human skills is not easy due to the difference of embodiments between humans and robots. Kinesthetic teaching [(21)~(23)] makes demonstrations easier but the issues are the lack of haptic feedback and the difficulty of performing a task by moving the robot body. Teleoperation was used in demonstrating manipulation skills [(24)(25)]. In (24), it was referred to as teleoperation training where manipulation of cloth was demonstrated to a robot by teleoperating with a head mount display. In (25), manipulation skills of dexterous robot hands were demonstrated to a simulated robot hand by teleoperating with Mujoco HAPTIX system [(26)], CyberGlove III, and HTC vive tracker. However haptic feedback was not used in these work.

Teleoperating a robot without haptic feedback is difficult especially when there is slippage between the robot hand and the manipulated object. In the experiments of teleoperating the Baxter robot with a joy stick to peel a banana (Fig. 6), we found that the teleoperation is very difficult since the operator could not sense the state of the grasp. As the consequence,



(1) (2) (3)

Fig. 6. Teleoperation of peeling banana with Baxter. Watch: `https://youtu.be/rEeixPBd3hc`

the banana slipped often in the grippers which caused many manipulation failures. This could be improved by installing tactile sensors on the robot grippers and activating the holding strategy to avoid slippage. However such a control does not work when the operator wants to produce slippage on purpose; for example, washing a dish with hand.

Haptic feedback teleoperation for demonstration will increase the variety of teachable tasks and performance of skills (e.g. speed of motions). With a sophisticated haptic feedback, the teleoperators of robots can demonstrate skills as if moving their own bodies, which is easier than kinesthetic teaching. Example tasks are peeling banana, mixing stew, other cooking tasks, washing dishes with hands, and construction of PC (especially handling cables).

4.1 FingerVision for Haptic Feedback FingerVision provides multimodal tactile sensation to robot hands. It could be a useful sensing device to be used in haptic feedback teleoperation.

FingerVision perceives 3-dimensional force distribution and non-directional slip distribution. Humans can sense these modality with their skin, but the sensitivities of FingerVision and human skins are different. FingerVision is sensitive to slippage regardless the object weight; actually it senses movement even when the object is not contacting with the finger. Moreover, FingerVision has other modality such as a pose, an area, and texture of nearby object, which human skin cannot perceive. Thus, the research question is how to create haptic feedback from the sensed data of FingerVision? Ideally we will need a haptic device that gives multimodal sensation with high resolution. Another question is that: can humans adapt to use such haptic feedback to teleoperate robots to manipulate objects better?

It will be also necessary to improve FingerVision for haptic feedback teleoperation purpose. The current qualities of spatial resolution, dynamic range of force, precision, etc. will not be enough in some scenarios.

5. Summary

We described a vision-based tactile sensor FingerVision, and its applications to tactile behaviors and manipulation. We also discussed the use of FingerVision for teleoperation with haptic feedback.

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