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FULL PAPER

Recent Progress in Tactile Sensing and Sensors for Robotic Manipulation: Can we turn tactile sensing into vision?

Akihiko Yamaguchi[a*] and Christopher G. Atkeson[b]

[a] *Graduate School of Information Sciences, Tohoku University, Miyagi, Japan*
[b] *The Robotics Institute, Carnegie Mellon University, Pennsylvania, United States*

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This paper surveys recently-published literature on tactile sensing in robotic manipulation to understand effective strategies for using tactile sensing and the issues involved in tactile sensing. It consists of a brief review of existing tactile sensors for robotic grippers and hands, review of modalities available from tactile sensing, review of the applications of tactile sensing in robotic manipulations, and discussion of the issues of tactile sensing and an approach to make tactile sensors more useful. We emphasize vision-based tactile sensing because of its potential to be a good tactile sensor for robots.

Keywords: Tactile sensor, Tactile behavior, Robotic manipulation, Robotic hand

1. Introduction

In human object manipulation, tactile perception plays an important role in addition to visual perception [1]. Do robots benefit from tactile sensing? Recent robotic systems are equipped with good vision systems. Many cameras including RGB, depth, and RGB-D are often used in robotic application. On the other hand, although there are products of robotic hands where tactile sensors are embedded, such as BarrettHand [2], PR2 [3], and ReFlex Hand [4], it will be hard to say that tactile perception and programming robots with tactile sensing are popular. Why is this?

Although there exists much work on tactile manipulation including machine learning-based approaches (e.g. [5–8]), the use of tactile perception is not considered as essential in robotics. Or, robotics engineers seem to be finding ways to avoid using tactile sensors. For example in work on learning robotic grasping with deep learning [9–11], robots learned grasping with visual input only; tactile sensing was not used. In another study of dexterous in-hand manipulation where a Shadow Dexterous Hand equipped with tactile (touch) sensors on the fingertips was used, the researchers did not use the tactile sensors [12]. These implementations were possible because there were consistent relations between the state before grasping (visual scene of the object and the gripper), including the manipulation parameters, and the outcome of manipulation. Such consistent relations can be learned by neural networks or other machine learning methods.

In the context of learning robotic manipulations from human demonstrations, Yang *et al.* proposed a method referred to as teleoperation training [13]. Manipulation of clothes was demonstrated to the dual-arm robot (Nextage from Kawada Robotics co.) by teleoperating it with a head mount display. In this research, tactile sensing was not used; tactile sensors were not

*Corresponding author. Email: info@akihikoy.net

attached on the robots, and the teleoperators did not have tactile feedback. The robots used vision as the input.

In order to understand effective strategies of using tactile sensors in robotic manipulation, we survey recently-published research on tactile sensing for robotic manipulations. The focus of this survey is on tactile sensing for robotic manipulation. Rather than surveying on wide range of tactile sensors, we review off-the-shelf tactile sensors that can be purchased or easily fabricated. For the review of tactile sensors, refer to surveys such as [14]. This survey emphasizes an approach of vision-based tactile sensing for robotic manipulation. Taking the recent progress in cameras and computer vision offers the advantages of high resolution, ease of fabrication and wiring, affordability, and reliability.

The rest of this paper consists of: Section 2: We briefly review existing tactile sensors for robotic grippers and hands. The purpose of this section is knowing what tactile sensors are available to non-experts in tactile sensor development. Section 3: We review what modalities are available through tactile sensors. We focus on sensing slip. Section 4: We review applications of tactile sensing in robotic manipulation. We focus on grasping with tactile-enabled robotic hands. Section 5: We discuss two things in this section. One is the issues in introducing tactile sensors to robotic hands. The other is the open source approach of tactile sensor development as a possible solution to these issues.

2. Brief Review of Tactile Sensors for Robotic Hands

We briefly review the examples of tactile sensors available in robotic hands and grippers.

2.1 *Commercial Tactile Sensor*

The dual arm mobile robot PR2 developed by Willow Garage Co. [3] has a parallel jaw gripper whose fingers have tactile sensors. The tactile sensor on each finger is a capacitive type, consisting of 22 sensing elements. We can obtain a pressure value per sensing element. This tactile sensor was manufactured by Pressure Profile Systems Inc. A capacitive tactile sensor is an array of sensing elements each of which is a capacitor made from two metal plates and a dielectric medium. Applying force on a capacitor changes the distance between the plates, which results in a change of capacitance. From the measurement of the capacitance change, we can obtain the pressure. It is considered that implementing a high spatial resolution is difficult with this approach. There are some applications of capacitive tactile sensors made by Pressure Profile Systems Inc. to robotic hands [15]. An example is the robotic hand with three fingers, BarrettHand developed by Barrett Technology LLC [2]. It optionally has a 6-axis force and torque sensor, fingertip torque sensors, and tactile sensors. The fingertip torque sensor measures torque of the fingertip joint with a strain gage. The tactile sensor has 96 sensing elements in total on the fingers and the palm, that is developed by Pressure Profile Systems Inc. Another example is TWENDY-ONE of the Sugano Laboratory in Waseda University [16–18]. Each hand has 241 capacitive sensing elements by Pressure Profile Systems Inc.

The examples of resistive tactile sensors by measuring the change of resistance caused by pressure or deformation are strain gage, force-sensing resistors, pressure conductive elastomer [19], and pressure sensitive ink [20]. There are commercial products of those sensors such as the Inastomer from Inaba Rubber Co. [21].

A three-finger robotic hand ReFlex Hand [4] developed by RightHand Robotics Co. provides a tactile sensor TakkTile [22]. TakkTile is made with miniature barometric sensor chips consisting of micro electromechanical systems (MEMS) pressure sensors [23]. The sensor is covered with rubber; the pressure sensor senses the pressure applied to the rubber surface. They developed a unique manufacturing technology: in order to remove the little amount of air in the MEMS pressure sensor during pouring liquid rubber into the mold, vacuum degassing was used, which was necessary to increase the sensitivity.

Similar to human tactile sensors that have multiple modalities, combining multiple modalities would be useful in robotic applications. For example BioTac from SynTouch Inc. mimics some of the physical properties and sensory capabilities of the human fingertip and gives robotic hands more human-like tactile sensing [24]. It can measure pressure distribution at 19 points, 3-axis force, micro vibration, and temperature. SynTouch provides interfaces to commercial robotic hands such as BarrettHand (Barrett Technology, Inc.) and Shadow Dexterous Hand (Shadow Robot Company Ltd.). BioTac has a structure in which a core unit consisting of impedance electrodes, pressure sensor, and thermistor is covered with an artificial skin made of an elastomer; conductive fluid is filled between the core unit and the skin. A drawback of this sensor is its expense; it is more expensive than many commercial robotic grippers.

Some researchers use a force and torque sensor mounting on fingertips of robotic hands. Some small ones are commercially available that are suitable for mounting on fingertips. For example an optics-based force sensor OptoForce (OnRobot A/S [25]) is mounted on each fingertip of a Robotiq Three-Finger Adaptive Gripper in [26]. Small force sensors ShokacChip and Schokac-Cube are distributed by Touchence Inc [27]. These sensors are small and not difficult to install on robotic grippers, however they do not form images of the force or pressure distribution.

2.2 *Vision-based Tactile Sensor*

When we try to introduce good quality (high-resolution, multi-modal) tactile sensors to robotic hands, a vision-based approach would be practical since non-experts might be able to manufacture such sensors with adjustments to their robots. Because of the recent progress in imagers, circuits, and algorithms for computer vision, turning tactile sensing into a vision problem has the advantages: (1) achieving high resolution (superhuman resolution) is not difficult, (2) the sensor structure can be simple and manufacturing is not difficult, (3) wiring is not problematic by using the established network infrastructure, (4) buying the ingredients is affordable, (5) the sensing device (camera) is becoming smaller, cheaper, reliable, and better in resolution and speed, due to the markets of smart phone and endoscopic surgery, and (6) physically robust since the sensing device and the skin can be isolated. Regarding (5), there is an example of embedding a small camera on a human fingertip [28].

The research of vision-based tactile sensor has decades of history. An initial attempt was measuring the frustration of total internal reflection within a waveguide on a sensor surface caused by contact [29–32]. The research trend has shifted to measuring displacement of markers placed on the sensor surface where cameras are used to capture the video and computer vision is used to detect and track the marker movements [33–42]. A reason for this trend is that it is easy to acquire a higher spatial resolution estimate of the force field, and measuring the marker displacements is robust since displacements are proportional to the external force. The resolution of the contact force field depends on the camera resolution and the marker density. Recently high resolution sensors have been proposed, such as TacTip [41]. The dynamic range of the force measurement can be controlled by changing the hardness of the elastic material. For example using softer elastomer as the as the skin, the sensor becomes more sensitive to smaller force.

GelSight is one of most popular vision-based tactile sensor, which was developed by Johnson and Adelson in [43]. It consists of a transparent elastomer covered with a reflective skin. The surface texture and shape of an object can be observed by pressing the object surface on the reflective skin (the observation is made from the elastomer side). It could reconstruct the textures of a cookie, a decorative pin, a human fingerprint, and a twenty dollar bill (it is not flat!). GelSight was installed on a finger of a Baxter robot for robotic manipulation tasks [44] where they used GelSight for localizing an object on the finger. In order to estimate the shear forces as well as normal and torsional load, markers were placed around the surface (reflective skin) of the sensor [45]. Similar to other work of vision-based force estimation, they applied computer vision to detect and track the markers. It was also possible to estimate incipient slip [45]. For better robotic manipulation, a version of GelSight with a slenderized fingertip was developed by introducing mirrors around the fingertip, named GelSlim [46]. The finger was designed to be physically durable; it could survive more than 3000 grasp trials.

Much of the above work covers a transparent elastic material with an opaque skin in order to remove the effect of the background on the computer vision processes. In contrast, Yamaguchi and Atkeson proposed the FingerVision sensor which is not covered with an opaque skin [42]. It means the camera can see through the materials. Markers are placed on the surface. Tracking the marker movements with computer vision estimates the external force distribution. Additionally, it provides visual information of nearby objects (proximity vision). Analyzing the visual information gives different modalities, such as high-resolution slip [47], object texture (it could recognize a QR code on the object), and object pose. It should be emphasized that many other slip sensing methods are estimated from other modalities (e.g. vibration, pressure distribution), while FingerVision directly measures the movement of an object. Another interesting point is that even humans do not have such tactile sensation that can see through the skin. FingerVision is available as open source [48] so that researchers can reproduce the sensor. Models for 3D printers are designed for Robotiq and Baxter grippers.

Another approach of vision-based tactile sensing was proposed in [49]. They developed a vision-based tactile sensor with a compound-eye camera consisting of an array of lenses and an imager. Such a camera can sense RGB images and infrared images at the same time. They placed a compound-eye camera under an acrylic plate which was used as a waveguide for infrared light. Contact on the acrylic plate can be detected based on *frustrated total internal reflection* [50] from IR images. Since the other RGB imagers see through the acrylic plate, the sensor can sense nearby objects by stereo vision. This sensor was used in robotic grasp control [51]. The benefit of this approach is that it can sense the contact with vision, i.e. it does not depend on the amount of force from the object. Similar to the transparency of the skin of FingerVision, this approach can be combined with many other ideas such as a vision-based slip detection. A drawback of this approach is that it depends on the optical qualities of the object as reported in [50]. We would need to investigate what objects this approach can sense the contact on. Another difficulty would be the availability of compound-eye cameras.

Similar to vision-based tactile sensors, there is an approach of using proximity sensors (range finders and distance sensors). For example, a tactile sensor consisting of range finders covered with transparent elastic material is proposed in [52]. The idea is that the deformation of the transparent material can be estimated from the measurement of the distances between the range finders and a nearby object. Normal contact forces are computed from the deformation. If there is no contact with the object, this sensor simply gives the distances to it. A similar idea is implemented on a hi-speed robot hand where proximity sensors are used to measure the distance to any objects, and contact. In [53], tactile sensors with a more dense array of proximity sensors were developed, which was used to sense the distance to an object and the surface shape. In [54], fingertips with high-speed and high-precision proximity sensors were developed. They were installed on a high-speed robotic gripper, which was able to catch a fragile object (a paper balloon). In [55], they developed sensing fingers with proximity sensors based on their previous work [56, 57]. Originally the fingertip had a tactile sensor consisting of an array of proximity sensors (Net-Structured Proximity Sensors [56, 57]) that senses the distance to an object. In addition, new proximity sensors are added to the fingernail of each finger for measuring the distance to a support surface such as a table [55].

3. Modalities of Tactile Sensing

There are various modalities of tactile sensing, including contact (on/off), pressure or force distribution, slip, vibration, temperature, and object properties such as texture and hardness.

Providing pressure distribution seems to be most common. Some sensors provide a 3-axis force distribution. Examples of other modalities sensed by tactile sensors are: micro vibration (e.g. BioTac [24]), temperature (e.g. BioTac [24], TakkTile [22]), and proximity [52].

3.1 *Sense of Slip*

As well as force distribution, sense of slip is important in object manipulation. Much research has investigated the role of slip sensation in human manipulation. An important early work on the role of slip in human grasping is [58] which describes a holding behavior where grip force is increased when slip is detected. In addition to launching the field, this work eventually led to the design of the BioTac sensor [59]. Recent papers following up on this work include [60], which discusses how to hold very light objects, and [61], which discusses how grip force is increased during arm movements. More information is available in [62, 63].

Many attempts have been made to develop slip sensors. An early approach used a mechanical roller to detect slip [64]. An approach to use acoustic signals (acoustic emission) caused by slip was explored in [65]. A popular approach is using the vibration caused by slip [66–71]. Some vibration approaches used accelerometers [66, 67, 70]. In [26, 45, 72, 73], they analyzed an observed force (and torque) to detect slip. For example in [73], high-pass filtered normal force was used to detect slip. In an optics-based tactile sensor [31], slip is detected as a binary flag when the change of normal force is greater than a threshold. In [26], slip was detected by measuring the increasing rate of change of tangential force.

There are approaches to create a mechanism for making slip-detection easier. In [66], a soft skin covered with nibs which produce small vibrations was introduced into a fingertip. Two accelerometers were embedded in the fingertip. A similar structure of nibs was introduced into an optics-based tactile sensor [31]. In [69], a gripper consisting of two elastic fingers was developed where strain gauges are embedded at the bottom of fingers. Slip on the fingers is detected by the strain gauges as vibration.

Detecting slip with a distributed sensor array is also a popular approach [74–77]. In [77], a 44x44 pressure distribution is converted to an image, and slip is detected by image processing. In [78], a multi-sensor fusion approach was proposed where they combined stereo vision, joint-encoders of the fingers, and fingertip force and torque sensors. In [76], they developed slip detection using center-of-pressure tactile sensors. In [79], they trained hidden Markov models to predict slip. According to their experimental results, the method predicted a slip before a slip actually took place. Some researchers use the BioTac sensor [59]. In [80], two BioTac sensors were used and several strategies to detect slip were compared experimentally. BioTac sensors were also used in [81], where they developed three types of tactile estimation: finger forces, slip detection, and slip classification. They compared machine learning methods to estimate finger forces. They considered two approaches to detect slip: a force-derivative method and a pressure-vibration-based method. They used neural networks to classify the slip category, linear or rotational, from time-varying BioTac electrode values. A similar slip prediction approach was explored in [82, 83] where they used random forest classifiers to classify the tactile data from a BioTac into slip and non-slip classes. They investigated the generalization ability of learned classifier over the objects including unseen ones.

Slip detection methods have been developed for vision-based tactile sensing. In [84], a method to detect slip of an object by tracking the dotted markers placed on the object was introduced. Since they need to place markers on the object, the applications may be limited. In [39, 85, 86], slip was estimated from the "stick ratio". The stick ratio is a ratio of areas of stick and contact regions; the ratio is one when there is no slip, it becomes smaller than one when there is incipient slip, and when the ratio becomes zero, it is considered as total slip. In [39], the stick ratio was estimated from the displacement of dotted markers. In the work of GelSight [45], an entropy of shear (marker) displacement distribution was used to detect slip by thresholding the entropy. It could distinguish the shear (no slip), incipient/partial slip, and total slip. In [87], a slip detection method for TacTip was developed where they used the difference of position of each marker between consecutive frames as the input, and trained a support vector machine to classify the tactile signal into slip or static classes.

The marker displacement was used to detect slip in the above vision-based tactile sensors [39, 45, 87]. In contrast, direct analysis of video was used in the work of FingerVision [47]. Since FingerVision can see through the skin, the movement of object against the sensor is directly shown in the video. Thus, computer vision methods for analyzing the video, such as optical flow and background subtraction, are applicable to detect the movement. In order to distinguish the movement of a foreground object and the background, a color histogram-based object detection was introduced in [47]. Since this approach does not depend on the marker displacement which requires a certain amount of load, it was possible to detect slip of very lightweight objects such as origami arts and dried flowers.

4. Tactile Sensing in Robotic Manipulation

4.1 *Grasping*

Grasping is a most basic and popular application of tactile sensing. A grasping behavior may be decomposed into grasp planning and execution of a planned grasp or grasping behavior. Since tactile sensing is not available in grasp planning, much of tactile grasp research focuses on the use of tactile sensing during grasp execution. Using tactile sensing in grasp execution is expected to reduce uncertainty, such as the pose estimation error of an object [88], unknown content of a container, and friction coefficient of the object. Using tactile sensing aims to increase the success ratio and the stability of grasp. It is achieved by controlling the grasp parameters such as a grasp pose, width, and force to hold an object. Grasp execution with tactile sensing is sometimes referred to as grasp adaptation or adjustment. There are many attempts. One axis to understand such attempts is the intervals (control cycle) of executing grasp adjustments for tactile observation. When the interval is short, the adjustment is continuously performed. Such an adaptation tries to locally find a better grasp around the current grasp. Some criteria are proposed to evaluate a grasp, such as grasp stability and slip amount. When the interval is larger, sometimes it is referred to as re-grasp. After executing a grasp, tactile sensors can be used to assess (evaluate) the result of grasp, which may be used to improve the grasp planning.

4.1.1 Heuristic Grasp Adaptation Strategy

Designing control strategies or policies is an approach of grasp adaptation. In [88], an integrated manipulation system consisting of a robotic arm and a three-finger robotic hand was presented. An external vision, finger torque sensors, and tactile sensors on fingers and palm were unified. They demonstrated the usefulness of the unified system through some experiments, including a task of aligning the lid over the canister and screwing on it. The tactile sensors were used to compensate the error of estimating poses of objects caused by the uncalibrated stereo vision. In [89], a grasp adaptation was developed with tactile sensors on the PR2 robot.

Similarly, a human-inspired grasp strategy was developed for grasping a range of objects without breaking them [73]. A study of grasp strategy of humans [1] was considered in their method. The PR2 robot with the tactile sensors on the fingertips was used. These tactile sensors provide an array of pressures, while humans use slip sensation in grasping [1]. In [73], they estimated slip from the pressure array as mentioned in Section 3.1.

In [90], a grasping strategy of 3-finger 8-DoF robotic hand with biomimetic tactile sensors were developed. They used contact detection on each link of the fingers to create the motion of fingers to adapt the shape of grasp.

4.1.2 Grasp Adaptation with Slip Detection

Using slip sensation to adapt grasp is a popular approach. A simple control strategy, increasing the grasping force when slip is detected, works robustly in many situations if the detection of slip is accurate. Examples include [66, 76, 85, 91, 92]. In much of this work, slip was estimated from other modalities such as vibration, force, and center of pressure, as mentioned in Section 3.1.

Slip detection for an optics-based tactile sensor was used in grasp adaptation [31] where grasping force of a robot hand was controlled to avoid slip. An experiment of grasping a paper cup was conducted, where water was poured into the cup. It was demonstrated that the robot adapted the grasp against the increasing weight of water without breaking the paper cup.

[81] created a behavior to gently pick up objects where they combined finger force estimates, and slip detection and classification. As mentioned in Section 3.1, machine learning was used to detect slip from the tactile reading of the BioTac sensors.

A grasping strategy with slip detection was studied in [26] where multiple-finger grippers were considered. In the experiments, they used a 3-finger robotic hand (Three-finger Adaptive Robot Gripper from Robotiq Co.) where OptoForce sensors were attached on the fingertips. This paper explored grasp adaptation to deformable objects with dynamic centers of mass, such as containers with liquids.

In [82], they trained a classifier of slip and non-slip classes from the BioTac reading, and applied the estimation in stabilizing the grip. They considered a situation where a single finger with BioTac on a 7-DoF robot pushed an object against the wall. The control strategy was rather simple: when the robot predicts slip, it increases the force in the direction of the contact normal. They extended this method in [83] where an improved slip classifier was used. They were able to stabilize a deformable plastic cup where the finger pushed one side and a human pushed the other.

Grasp adaptation with FingerVision was explored in [47, 93]. As mentioned in Section 3.1, slip was directly detected with FingerVision by analyzing the video from the cameras. As the result, it could detect slip of very lightweight objects such as origami and flowers. Because of this feature, the grasp adaptation with FingerVision could adapt grasp to a range of objects including lightweight ones. In [47], they demonstrated that the grasp adaptation with FingerVision works with origami cranes and flowers. In [47], they extended the grasp adaptation control for a wide variety of objects including deformable and fragile objects such as vegetables including tomatoes, mushrooms, and zucchinis, fruits, raw eggs, and cupcakes.

4.1.3 Grasp Adaptation with Estimating Friction Coefficient

A grasp adaptation strategy which included estimating the friction coefficient was explored in [94], which was referred to as a slipping control algorithm. They attempted to estimate the friction coefficient at the contact points of a grasped object from the observation of a tactile sensor (an optics-based force and torque sensor was used). Then the estimated friction coefficient was used in slipping control. The same grasp adaptation strategy was used in [95].

4.1.4 Grasp Adaptation with Grasp Stability Estimation

Constructing a grasp stability estimator from tactile reading is also a popular approach in grasp adaptation. A grasp stability estimator can be used to trigger grasp adaptation control, as well as to plan a better grasp.

In [96], in order to adapt grasping an object whose pose is observed with uncertainty, a grasp adaptation was developed with tactile feedback of the BarrettHand. An SVM classifier was learned to estimate grasp stability from tactile data, which was used to determine if the adjustment action is executed. The SVM classifier estimates if the grasp is stable or unstable, whose input is the grasp features represented by a bag-of-words model of the valid contacts obtained from the tactile sensing data. The training dataset was constructed with the GraspIt! simulator where the stability was determined by thresholding the epsilon and the volume qualities that measures the grasp robustness against disturbances (i.e. less-fragility) and the grasp strength respectively.

In [97], a grasp adaptation to handle uncertainties of object properties such as the weight and the contact frictions was proposed. It was designed for a three-finger robotic hand with BioTac sensors on the fingertips. The grasp adaptation consists of an object-level impedance controller, which is triggered by a grasp stability estimator. The grasp stability estimator was learned from successful (stable) grasp example. It is a one-class classifier (Gaussian Mixture Model was used) predicting if the current grasp is stable from an input of grasp features. The grasp features consist of the grasp stiffness and the rest length defined in the virtual frame of an object, and the tactile reading. This grasp stability estimator was also used in the object-level impedance controller where the goal is adapting the grasp stiffness and the rest length so that the grasp becomes stable.

An adaptive grasping method was proposed in [98] that finds a stable grasp on a novel object. It consists of two estimation models: a grasp stability estimator from tactile data, and a predictor of tactile data from the current data and an adaptive action. By combining them, an adaptive action that improves the grasp stability can be found by an optimization.

Grasp stability estimation is also used in triggering re-grasp. In [7], a re-grasping strategy was studied where the quality of grasp is estimated from the tactile sensing, and the re-grasp is executed when the grasp is unstable.

Calandra et al. used the GelSight embedded 2-finger parallel gripper to predict grasp success [99]. Later they extended the method for adapting grasp by re-grasping an object [100]. In both papers, a deep, multimodal convolutional neural network was constructed that predicts the outcome of a grasp (grasp success probability). The input of the network is multimodal: images from an external RGB camera and the GelSight cameras. In the re-grasping setting [100], grasp adjustment actions are also used as input. The neural network was trained with 9000 [99] and 6450 [100] grasp trials with the Sawyer robot. The trained neural network was used to predict the grasp success [99], and select the most promising re-grasp action [100]. A similar re-grasping strategy was explored in [101] where GelSlim was used.

4.1.5 Complete Grasp Process with Tactile Sensing

A complete process of grasp planning with machine learning and grasp execution with tactile sensing was explored in [102]. The grasp planning was achieved with deep neural networks that estimate a stable grasp from an input image. A BarrettHand was used with the Universal Robots UR5 robot to execute the planned grasp. The tactile sensors of the BarrettHand were used to correct the training dataset of the neural networks. The dataset consists of pairs of input and output variables, where a label of stable or unstable grasp is necessary as the output. The tactile sensors were used to assess the grasp. In the grasp assessment, a swinging motion was performed to test the stability of the grasp. The tactile reading during the motion was used to compute the assessment value. If the assessment value is above a threshold after the swinging motion, that grasp is recorded as a stable grasp.

4.2 *Other Robotic Manipulations*

We briefly explore the use of tactile sensors in robotic manipulations other than grasping. There are several different uses of tactile sensing, such as: detecting events (touch on finger [31], slip [31], and touch on grasped object [32, 42, 47]), estimating pose and location of touched objects [8, 44, 47, 77, 103], using the tactile data in part of the state of reinforcement learning [5, 6, 8], and exploring the workspace without vision [104, 105].

4.2.1 Detecting Events with Tactile Sensors

In [31], tactile sensors were used in opening a cap of a bottle by twisting it, where the tactile data was used mainly as triggers of actions. For example, events of contact (touch) and slip were used as triggers.

In [42], a cutting fruits task was implemented where a knife was held by a FingerVision-enabled gripper. The tactile data was used to determine when the knife reaches the cutting board. Such an event would be difficult to detect with external vision due to occlusion.

In [32, 47], robots with tactile-enabled robotic hands were used in handover tasks which are often considered in human-robot interaction. In both studies, tactile signals were used as a trigger to activate the handover motions. In [32], the tactile sensors were used to detect a tapping force applied to the bottom of the grasped object which triggers the handover motion. In [47], the tactile sensors were used to detect touch events on the grasped object where both force change and slip were considered as the events. When grasping an object tightly, force change is easier to detect than slip, while when grasping an lightweight object gently, slip is easier to detect than force change.

In [90], tactile reading was used to trigger the releasing action of grasped object when placing it on a table. They also used an event detection in a peg-in-hole task where they detected the hole with tactile reading during sliding the peg (a bottle) on a plane.

4.2.2 Estimating Pose and Location with Tactile Sensors

In [103], as an example manipulation with a TacTip, rolling a cylinder with a single-finger robot was explored. It achieved a super-resolved manipulation at sub-millimeter accuracy where the high-resolution tactile sensor was used for localizing the cylinder. Similarly in [47, 77], tactile sensors were used to estimate the poses of objects in the hand, and the estimate was used in in-hand manipulation of the objects.

In [44], pose estimation of a grasped object was used in an insertion task of a USB connector. GelSight was used to estimate the pose of the grasped USB connector, and then it was inserted into a socket.

In [8], a contour-following control was learned with tactile sensors and reinforcement learning. BioTac was used as the tactile sensor on a robotic hand. It demonstrated some manipulations of tracing a string and closing a ziplock bag.

Another example of pose estimation of a grasped object from tactile reading was proposed in [106], which was implemented on a 3-finger robotic hand with tactile sensors.

4.2.3 Reinforcement Learning with Tactile Sensors

Since modeling the contact between robot fingers and an object is not easy, machine learning is sometimes used with tactile sensing. There are examples of using reinforcement learning in order to learn tactile manipulations.

In [5], reinforcement learning of a robotic scraping task was implemented. The state involved data from tactile sensors that sense an array of pressures. In [6], in-hand manipulation skills of a cylinder were acquired with reinforcement learning where tactile data was used as a part of the state vector. They used a ReFlex hand that has tactile sensors made from MEMS barometers. In the work of the contour following of a ziplock bag [8], they converted the tactile reading from BioTac into discrete states (three spatial relationship between the fingerpad and the zipper), which was used as the state space of reinforcement learning.

Since typically the sensor space of a robotic hand with tactile sensors is high dimensional, sometimes researchers manually extract features for the state of reinforcement learning. Instead of a manual feature-set design, an approach to use autoencoders was proposed in [107]. It reduces the high dimensional sensor space into a low dimensional latent space which is used in the state space of reinforcement learning. They tested the proposed method in a simple robotic task of tilting a pole where BioTac was used. In [108], they developed an unsupervised learning method to learn a spatio-temporal representation of a time series of tactile data. In [109], they modeled the manipulation procedure with POMDP (partially observable Markov decision process) in order to represent the latent states, and built a Q-learning to learn a policy with the learned representation. In [110], they built a three-dimensional latent space from a tactile sensor where BioTac was used. Then they learned dynamical models on the latent space for tactile servoing.

4.2.4 Exploring the Workspace without Vision

There is some work to explore a work space in a dark scene, i.e. without vision. In [104], active exploration was developed to search for objects in an unknown workspace with tactile sensing. A similar approach was used in a study of tactile-based grasp learning where touch based object localization called “touch-scans” and tactile based re-grasping methods were developed [105].

4.3 *Tactile Perception*

We briefly review the applications of tactile sensing to perceiving objects and environment. For a thorough review of tactile perception, refer to [111, 112]. The basic idea is pressing the tactile sensors on an object or stroking the surface of an object with the tactile sensors, and estimating the properties such as texture type, hardness, and shape from the tactile data.

In [38], they explored estimating the local shape (e.g. an edge) of an object and the irregularity of the object surface by pressing a vision-based tactile sensor on the object. In [40], a similar approach was explored, where the object shapes were detected in more detail. They used TacTip, and referred to their method as "seeing by touch".

Sensing by stroking or poking a target object is a kind of active perception. In [113], a method to estimate the classes of wood, cork, paper, and vinyl was proposed where the tactile data was observed by stroking the material with a tactile sensor consisting of distributed strain gauges and PVDF films. In [114], the shape of an object was estimated by stroking the surface with robotic fingers with tactile sensors. They used optical tactile sensors. In [115], they used the all modalities of a BioTac sensor and estimated 117 kinds of textures at the precision of 95.4% from tactile data of stroking a texture. In [116], a fingertip with two force sensors, an actively heated temperature sensor, and a microphone was used to categorize objects into six material classes; metal, plastic, wood, glass, ceramic, and fabric. In [117], tactile sensors on a four-finger robotic gripper were used to classify the object into 20 classes. They used machine learning to classify where several different setups were compared, such as using single frame data and time-series data. The tactile sensors are called uSkin, which can sense a distribution of 3-axis force by detecting the magnetic field changes [118].

In [119], they classified grasped objects from tactile reading, which was handled as images. The tactile sensor was Weiss Robotics sensor DSA 9205, a resistive pressure array consisting of 6 x 14 cells.

As mentioned before, GelSight is able to detect the texture and the shape of an object surface. It was able to detect the textures of a cookie, a decorative pin, a human fingerprint, a twenty dollar bill, USB connector, and so on [43, 44]. In [120],they developed a method to estimate the properties of clothing including thickness, smoothness, fuzziness, season to be used, textile type, and washing method from the reading of GelSight by pressing it on a cloth. Deep neural networks were used as the classifier where the GelSight image was directly used as the input.

Estimating the shapes of objects by touch (and stroking) is also a popular application of tactile sensing. As mentioned above, in [40, 43, 44, 114], they used tactile sensors to sense the surface shape of objects. In [40, 43, 44], they estimated small-scale surface shapes (textures), while in [114], they estimated relatively larger shapes.

In [121], a method to estimate 3D shape of objects was developed where GelSight was used with an external vision. In their system, a rough 3D shape of object is predicted from a single-view color image with neural networks, and then it is refined by touching regions where the visual prediction is highly uncertain.

In [122], a planning algorithm was proposed to estimate a path to stroke an object in order to reduce the uncertainty of the shape roughly modeled from vision. A similar approach of such a tactile exploration was proposed in [123].

5. Discussion

5.1 *Issues of Introducing Tactile Sensors to Robotic Hands*

Summarizing the survey described so far, we found that there is much work of tactile sensing and many different uses in the applications to robotic manipulations. However, tactile sensing seems to be still experimental in robotics. The following are possible reasons:

- **Difficulty to install on robotic hands**. When installing tactile sensors on robotic hands, we need to place tactile sensors in a limited space, and the finger surface shapes vary including flat and curved surfaces. Robot hands are typically not designed for sensors.

- **Wiring, power supply, and processing**. Installing many tactile sensors increases the complexity of wiring of signals, power supply, and processing circuits.
- **Low durability, fragility**. Many of tactile sensors directly interact with external forces, which sometimes breaks the sensors. If we cover a sensor with elastic material to protect it from large external forces, it will decrease the sensitivity and increase the hysteresis. Note that there are different types of durability, such as external force, liquids, temperature, dirt, and chemical. If repairing the sensor is low cost and easy, low durability might be accepted. However many of tactile sensors are not easy to repair. Low durability would also suffer the use in machine learning due to the change of sensor properties. When a sensor property changes, that change needs to be estimated.
- **Less compatibility with the other tactile sensors**. There are variations of modalities, and spatial and temporal resolutions in tactile sensors. The sensing principles also vary. Due to that, many tactile sensors are not compatible with others. They also decrease the reusability of software.
- **It is unclear what we can do with tactile sensors**. Many robotic manipulations can be implemented without tactile sensors. Grasp adaptation can be also achieved with soft robotic hands without tactile sensors.
- **Disadvantages caused by tactile sensors**.
  - **Maintenance becomes complicated**. We would need periodic calibrations, and repairs.
  - **Programming becomes complicated**.
- **Expensive**. High performance tactile sensors are typically expensive.
- **Asking for the moon**. Some of researchers tend to require tactile sensing capabilities that are hard to achieve. Implementing human-quality tactile sensors is impossible with the state-of-the-art.

These issues prevent the researchers from using tactile sensors, which makes it difficult to accumulate the knowledge of using tactile sensors.

5.2 *Open Source Tactile Sensor Project*

A solution to popularize the use of tactile sensing in robotic manipulation scenarios would be open source projects for tactile sensors. Since there are a lot of robotic grippers and hands, providing tactile sensors for all of them is impractical. In many cases, roboticists wish to customize grippers and hands for their purposes. Making the fabrication, software, and case studies open would be a solution to this issue, which might lead to forming a community for that tactile sensor.

Some tactile projects are available from the Soft Robotics Toolkit [124], which is an open platform of soft robotics. For example TacTip and TakkTile are available through the Toolkit (note that TakkTile is currently a product [22]).

FingerVision is also available as open source [48]. On the project website, its fabrication including CAD models for 3D printing, software including standalone programs and ROS packages, and tutorials are available. There is a community of FingerVision developers where technical knowledge about FingerVision development and applications are shared. Some successors of FingerVision have been developed such as [125].

6. Conclusion

In this paper, we investigated tactile sensors for robotic hands and their applications to robotic manipulations. We found that many different types of tactile sensors were used in robotic manipulations in many different ways. Through this survey, we discussed the issues of introducing tactile sensors into robotic systems. As a possible solution to these issues, an approach of open source tactile sensors was introduced.

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