

A Review of Tactile Information: Perception and Action Through Touch

Qiang Li, Oliver Kroemer, Zhe Su, Filipe Veiga, Mohsen Kaboli and Helge Ritter

Abstract—Tactile sensing is a key sensor modality for robots interacting with their surroundings. These sensors provide a rich and diverse set of data signals that contain detailed information collected from contacts between the robot and its environment. The data is however not limited to individual contacts and can be used to extract a wide range of information about the objects in the robots environment as well as the robots own actions during the interactions.

In this paper, we provide an overview of tactile information and its applications in robotics. We present a hierarchy consisting of raw, contact, object, and action levels to structure the tactile information, with higher-level information often building upon lower-level information. We discuss different types of information that can be extracted at each level of the hierarchy. The paper also includes an overview of different types of robot applications and the types of tactile information that they employ.

The paper concludes with a discussion of tactile-based computational framework and future tactile applications which are still beyond current robot’s capabilities.

Index Terms—Tactile Sensing, Interactive Perception, Tactile Controller, Grasping, In-hand Manipulation, Whole Body Manipulation, Locomotion, Tool Manipulation, Human Robot Interaction

I. INTRODUCTION

Touch is an important sensing modality for robots physically interacting with their environment. Tactile sensing provides robots with a rich set of diverse signals based on contacts between the robot and its environment. These signals provide the robot with information about the objects in its environment as well its interactions with these objects, e.g., if an object begins to slip or if the robot has achieved a sturdy foothold. This information is crucial for performing a variety of tasks in a robust and reliable manner, including dexterous manipulation, locomotion, and human-robot interactions.

However, to use tactile sensing, robots first need to extract the relevant information from the sensor signals. We present an overview of the different types of tactile information that can be extracted from tactile signals. This information ranges from low-level forces at individual contact points to feedback for selecting complex actions based on previous interactions. We propose structuring the information in a hierarchy consisting of contact-, object-, and action-level information.

Qiang Li is with CITEC, Bielefeld University,Germany.
 Oliver Kroemer is with Carnegie Mellon University (CMU), USA.
 Zhe Su is with the University of Southern California (USC), USA
 Filipe Veiga is with Computer Science and Artificial Intelligence Laboratory (CSAIL), Massachusetts Institute of Technology (MIT), USA.
 Mohsen Kaboli is with IAS, Technical University of Munich (TUM) and the BMW Research,Germany.
 Helge Ritter is with CITEC, Bielefeld University,Germany

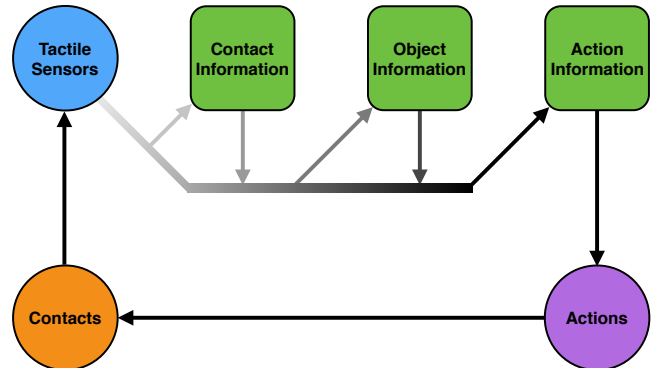


Fig. 1. Perception-action loop for tactile information extraction and control.

Higher-level information tends to build on the information extracted from lower levels as illustrated in Fig. 1. While the contact level contains information from individual contact sites, the object level contains information regarding objects as a whole, often acquired from multiple contacts. The action level refers to information pertaining to the robots actions used to interact with the environment, which often builds upon contact- and object-level information. As a contact-based sensing modality, actions are also important for extracting useful information from the interactions. All three of these levels build upon the sensor-level tactile signals. For each level of the hierarchy, we describe the different types of information that are commonly extracted at that level. We also explain how robot applications employ tactile information from across the different levels.

A number of previous tactile review papers focused on the sensor’s hardware [1]–[4], and discussed specific application domains, e.g., grasping and in-hand manipulation [5]–[7]. Recently Luo et al. [8] showed the newest progress on tactile perception. Akihiko and Christopher [9] reviewed the progress on tactile manipulation and put the highlight on the vision-based tactile sensors and its applications. In this paper, we propose a computational framework to structure tactile perception and actions. We highlight the different types of tactile information and propose a hierarchy for structuring the information. We also explain how various robot applications employ tactile information from across the hierarchy.

The paper is organized as follows. An overview of tactile signals is introduced in Sec. II. Then we explain in detail tactile information at each level of the hierarchy in Sec III through V. In Sec. VI, we briefly discuss analytical and data-driven methods for computing the tactile information. In

Sec. VII, the applications are discussed with regard to how tactile information is used in rich tactile-based tasks, including tactile exploration, grasping, in-hand manipulation, tool manipulation, locomotion and human robot interaction. We conclude the paper with a discussion of open challenges and future research directions for tactile perception and control.

II. SENSOR-LEVEL TACTILE SIGNALS

A robot with the sense of touch can acquire information about its surroundings through physical interactions. The sensors are located under the surface of artificial skin [10], [11], [3] and provide the robot with a wide range of signals. In this section, we briefly discuss common types of sensory signals that will form the basis of the computational framework proposed in this paper. We also discuss tactile sensor coverage—how sensors are distributed on the body and how spatial resolution are often selected depending on the given task and the sensors' placement on the robot.

A. Normal and Tangential Force

The most common type of tactile signal is the contact force. Although the tactile sensors are based on the different physical principle, the output (tactile image, voltage) from the raw sensor measurement can be "calibrated" as contact force. Traditionally, the contact force is divided into two components: normal force and shear or tangential force. Normal force is the component orthogonally applied to the contact surface, and tangential force is the component applied across the surface, e.g., friction. Most tactile sensors are able to measure normal force [12], [13]. Some sensors can however directly measure the full 3D force [14]–[18]. The majority of tactile sensors are composed of arrays of sensing elements [3], [19]–[21], and each element in the array is known as a *taxel*. Each taxel provides a local force estimate corresponding to its activation. In addition to contact force, the contact torque may also be estimated by the sensor array [22], [23] using a trained neural network.

B. Vibration

Mechanical vibrations are another fundamental type of tactile signals that is often used to detect contact or slip events between contact surfaces [24]–[26]. When we use a hammer to strike a nail [27], we can feel the vibration via our skin's mechanoreceptors [28]. A robot can similarly detect vibrations using a dynamic tactile sensor. Vibration signals from tactile sensors can be used to detect whether slip occurs between the sensors and the directly contacted object or between a grasped object and another object. This is possible because the vibrations in the latter case propagate additionally through the grasped object and the tactile patterns perceived by the sensors in the two situations are therefore different [29]. Like the fast afferents in human skin, vibration-based sensing is not as useful in static contacts situations, as motion is required to induce vibrations [30].

C. Thermal

Thermal tactile sensing allows a robot to measure the temperature of an object via touching [31], [32]. It mimics the thermal sensing of humans, which are able to perceive temperatures between 5° and 45° [33]. Thermal sensing can also be combined with heating elements to allow the robot to estimate the thermal conductivity of an object [21]. The differences in thermal conductivity can then be used to distinguish between different object materials [34], [35]. For example, metals transfer heat faster than most plastics and rubbers. Determining the thermal state of the contacted object is also very important to decide the next actions. e.g. a robot can estimate a cup's temperature to autonomously reason whether it is safe for serving. In the teleoperation scenario, thermal sensing can help the operator to judge the types of remote objects [36].

D. Pretouch Proximity

Pretouch is the ability to detect objects and their surfaces before contacting with them. A pretouch sensor can provide a robot with the relative geometrical relation to an object [37], which is valuable for the robot's planners [38], [39] and controllers [40], [41], [42]. With the distance, the robot can roughly estimate the object's shape and position before making contact. Depending on the underlying technology, the pretouch sensors may also provide additional information such as color and optical flow [43]. Pretouch sensors can also provide the robot with better predictions regarding when the contact will be made and thus prevent the robot from making contact at high speeds. The principle technology of pretouch sensors varies, and they can be based on cutaneous infrared [44], audio [45], or optical sensing [46]. In this manner, pretouch sensing blurs the line between different sensor modalities.

E. Sensor Coverage

Besides the type of tactile signals, another important characteristic of tactile sensing is the distribution of sensors throughout the robot's body. Body parts covered with high spatial resolution tactile sensors can be used for contact recognition and fine motor control, while parts with lower resolution of sensing can be used for simple contact detection and control. Most tactile skin designs for robots are inspired by the human



Fig. 2. A Shadow Dexterous Hand (left) that has been covered with a tactile skin (middle) in order to provide tactile information at several locations (highlighted green regions on the right rendering).

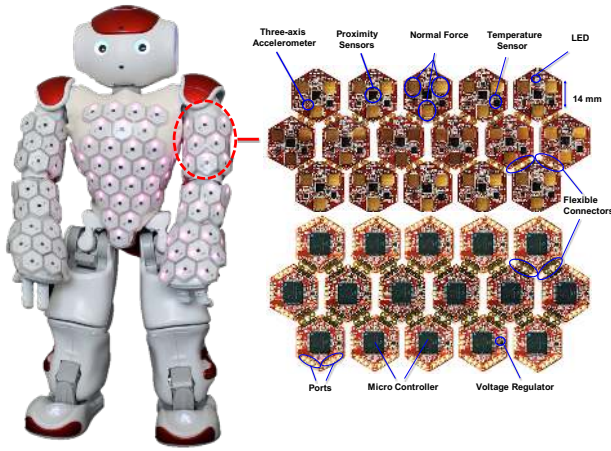


Fig. 3. The NAO humanoid robot covered with a multimodal artificial robotic skin that provides vibration, temperature, force and proximity information [47].

tactile perception system, in which neuroscientists have found that the sensitive tactile receptors are unevenly distributed in the whole body. For example, hands have higher tactile spatial resolutions than other parts to facilitate dexterous manipulation [48].

Many robots’ hands are equipped with tactile sensors, especially at the fingertips [23], [49], [50]. An example of a robot hand with tactile sensors on the finger tips phalanges and palm [51] can be seen in Fig. 2. High spatial and temporal resolutions provide hands with rich tactile information for performing complex tasks, e.g. exploring unknown objects, tool use, and in-hand manipulation.

Tactile sensors can also be embedded in other robot body parts, such as arms [52], [53], torso (Fig. 3), legs [54] and feet [55]. Contact information on these parts are closely associated with tasks involving whole-body manipulations, human robot interaction and locomotion. The density of the sensing elements is coarser on these parts because the sampling and processing of large areas of taxels is challenging from a hardware design and communication perspective [3]. The tactile sensors in load bearing parts of the body are often designed in a more robust way to withstand the larger forces needed to grasp heavy objects [56] and support the robot’s weight [57] during walking tasks. Tactile sensors are normally located on the surfaces of regularly shaped links. However, flexible and stretchable sensors have been developed to cover body parts with complex shapes and curved surfaces, [58], [59], as well as the robot’s joints [60].

III. CONTACT-LEVEL INFORMATION

The basic function of tactile sensing is to provide a robot with information about the contact sites, such as local geometries, forces, material properties, and contact events (Fig. 4). In this section, we discuss the type of contact information and how the contact information is extracted from raw tactile signals. This information forms the basic building blocks for the object-level information (Sec.IV) and is widely used for controlling the robot (Sec.V).

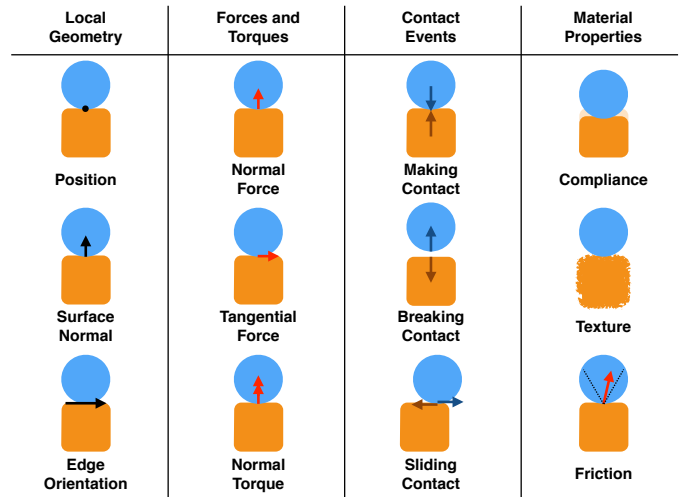


Fig. 4. Examples of different types of contact-level information that can be extracted from the sensor-level tactile signals.

A. Contact Geometry

Tactile sensing is widely used to estimate the local geometry of a contact area including the contact position, normal, and curvature. Many tactile-related tasks rely on precise measurements of the contact position and normal direction, e.g., to compute grasp stability and manipulability [61]. Given a calibrated sensor array [62], the contact position in the tactile sensor frame is computed as the pressure-weighted center of the activated taxels and then mapped to the robot’s Cartesian frame using the robot’s forward kinematics [63], [64]. Using the same principle, the contact normal direction is estimated as the pressure-weighted normal direction of the activated taxels. The position and normal provide a first order approximation of the local surface patch, with the normal direction defining the tangent plane at the contact point.

Tactile sensors can also be used for estimating higher surface derivatives at the contact point, e.g., the surface curvature [65], [66]. Given a tactile sensor with high spatial resolution, the contact surface curvature can be measured based on the relative movement between the sensor and an unknown object when sliding or rolling occurs [65]. For sensors with lower resolutions, the contact surface can be approximated with a second order polynomial equation [61], [66]. The curvature at the contact point is approximated by a local parameterized surface matrix that can be estimated through active tactile exploration.

Tactile image processing is another way to extract contact geometry of a small region. Machine-learning [67], [68] and traditional image based approaches [63], [69]–[71] are widely used to estimate the contact position or feature position for different types of object by detecting salient structures such as edges, corners and small protrusions. For example, a pronounced curvature on an object’s surface will appear as a line in the tactile image. The slope of the line, relative to the tactile sensor, can be estimated by the principle component of the image blob [72]. The 3D direction of the edge is then estimated by combining the line’s slope with the robot’s

forward kinematic model.

B. Force and Torque

Contact forces and torques are directly measured by several tactile sensors [12], [20], [21], [43], [67]. Some sensors only provide the normal force while others also provide tangential forces to give the full 3D force vector. Estimating forces at contacts is important, as it is the transfer of forces that allows the robot to physically interact with objects in its environment. When employing a point contact model, the contact force can be estimated from the contact pressures of all activated taxels [20], [63] or from the sensor's overall deformation [43], [67].

Different approaches have been proposed for mapping raw tactile pressure values to the contact forces and torques [73]–[75]. One example is to model the mapping as a linear function [76], [77]. The drawback of this approach is that it does not work well for sensors that have strong hysteresis or damping properties due to the skin material [2]. For such skin materials, other advanced machine learning algorithms are more suitable. For example, locally weighted projection regression and artificial neural networks can be used to learn the nonlinear relation [25], and Gaussian processes can be used to compensate for the nonlinear hysteresis effects of sensors [78]. Finite element methods have also been used to model the nonlinear functions and learn the model parameters [73].

C. Contact Events

Contact events refer to discrete changes in the contact state between two objects, which include making, breaking, sliding and rolling contacts. Contact events often correspond to sub-goals and errors when interacting with the environment. For example, breaking and making contact between a foot and the ground is the goal of each step in a walking task, while a sliding foothold is usually considered to be an error.

The transition between contact and no contact is a near-instantaneous event that results in a discontinuous interaction model. It is therefore important that the robot can detect the events quickly and reliably. A common way to detect the contact is to compare the measured tactile signals with a given threshold [60], [79], which is estimated from previous contact experiences. Another method is to use dynamic tactile sensors [80], which compute the vibration features to distinguish contact from no contact. Using this approach, it is possible to detect the contacts not only between the robot's skin and the environment but also between a grasped object and the environment [81].

In addition to transitions from no contact to contact, the robot may also experience the change from a static contact to a sliding contact. Since lots of approaches assume no slip and slip often corresponds to errors and is difficult to control, robust detection of slip is a crucial research topic. In practice, gross sliding is usually preceded by an incipient slip event, wherein only some low-pressure regions of the contact patch begin to slide [80]–[83]. That is to say, the outer regions on a fingertip begin slipping while the central region, where more pressure is applied, does not slip [63],

[84]. Hence, detecting incipient slip is a key capability for avoiding gross sliding from happening. Incipient slip can be detected with high-frequency tactile feedback (normally $> 1\text{kHz}$) using frequency-domain analysis approaches [79], [80], [83], [85]. Other approaches include learning from data and using image processing techniques, e.g., using a Hebbian network [86], using optical flow from a fingertip camera [87], or using random forests to predict slip from multi-modal tactile information [88].

Robots can additionally differentiate between different types of slip, e.g., determining whether the gross sliding is rotational or translational [24], [25], [43], [71], [89]. For such classification, neural networks are trained to classify time-series tactile pressure data or visual features for vision-based tactile sensors [25], [89].

D. Material Properties

The interactive nature of touch allows a robot to estimate object's material properties which may not be easily extracted visually. Researchers have defined 15 different properties to present the object's surface [90], and these properties can be reduced to 5 important dimension, namely stiffness, friction, surface texture thermal conductivity and adhesion. Stiffness can be measured by the robot pressing into the object with a specified contact force and measuring the resulting displacement of the contact point [91]–[94]. Similarly the coefficient of static friction can be estimated by measuring the normal and tangential forces when incipient slip occurs [95], [96].

Texture information is useful for differentiating among materials, as well as detecting blemishes and smooth surfaces. To achieve good classification result, a robot will often slide the tactile sensor across the surface and observe the resulting vibrations and time series signals [97]. Classifiers, such as kNN, ANNs, and SVMs, can then be trained to classify the different textures [98]–[101]. Better classification performance can be achieved by employing multiple sliding motions with varying velocities and directions [102].

Thermal conductivity is another useful material property. While the temperature of an object is estimated by a thermal sensor, the thermal conductivity of the material is estimated by the transfer rate of thermal energy [21], [103]. Given that materials conduct heat at different rates, the detected transfer rate can also be used to classify different materials [35], [104].

IV. OBJECT-LEVEL INFORMATION

Many tasks involve interacting with or manipulating unknown objects. To perform these tasks reliably, the robot needs to estimate the state and properties of the manipulated objects. Tactile sensors can be used to acquire a wide range of object-level information via raw sensor values or by combining contact-level information during interactions. [Inspired by human exploration actions for determining object properties \[30\], we illustrate several common actions to extract necessary object-level information in Fig. 5.](#)

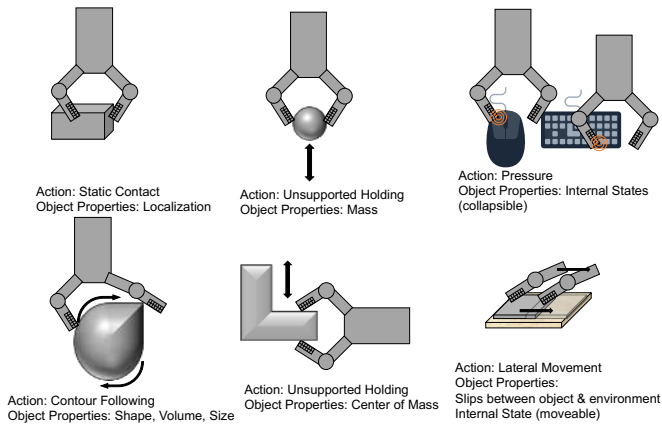


Fig. 5. Several actions for which different types of object-level information are necessary for the actions execution.

A. Object Localization

A robot needs to accurately estimate the pose of an object in order to precisely manipulate it to a desired location. Localizing an object using tactile feedback only is not a trivial task. Approaches are commonly based on filtering theory [105]–[108]. These approaches use the measured contact positions and normal of the object as input, and probabilistic models of the object’s pose are then updated over time to capture the uncertainty of the estimation over multiple interactions [107].

In addition to accuracy, the efficiency of estimation is also important especially for tactile exploration tasks. To this end, optimization approaches can be used to select informative actions and explore the most uncertain pose space [109]–[112]. It is often assumed that the object is static and not affected by the exploration [105], [109], [110], [113]. Researchers have also proposed methods for tracking an object’s pose while it is being moved [106], [114].

B. Shape

The shape of an object refers to its global geometry. Shape information is often needed to plan interactions with objects. For example, a robot with a two fingered gripper needs to find opposing surfaces of an object for grasping. The shape can be reconstructed by measuring the positions and normals of surface patches [115]. Employing tactile sensing is especially useful for estimating the object’s shape in visually occluded regions [116]–[118]. The tactile sensors can thus play a complementary role to vision sensors for updating the object’s model.

By touching the object at one single location, tactile sensors only estimate the local shape of relatively small regions, so multiple contacts are needed in order to obtain the global shape. This procedure is time consuming, and extensive efforts have therefore focused on optimizing touch sequences to reduce the uncertainty of the estimated shape and improve the model as quickly as possible [119]–[121]. The shapes are often represented by Gaussian processes to model the uncertainty [120] or by fitting geometrical models to the tactile point clouds [112].

C. Mass and Dynamics

While an object is grasped or manipulated, it acts as an additional payload for the robot. The mass and CoM are then required for the accurate dynamics model of the new system composed by the robot arm and hand plus the grasped object [61]. When grasping an object, the robot should place its hand near the object’s center of mass to avoid large torques. Conversely, the robot can estimate the center of mass by slightly lifting the object and observing the torques. Correctly estimating the mass and center of mass, allows the robot to avoid improper contact force by using the estimated information to adapt the grasp force.

The estimation of the object’s mass and CoM requires an interactive control procedure. Different action strategies and learning approaches have been proposed for estimating them and also the object’s inertial matrix [122]–[126]. While grasping a heavy object, a robot can estimate the object’s mass parameters based on the force and torque measurements from the wrist [122], [127]. For light objects, tactile estimates of the fingertip forces during simple lifting actions can be used to localize the center of mass of unknown objects [123], [124]. For an object that is too large to grasp, a robot can estimate its mass parameters by tipping it and stabilizing it in a different posture [125], [128].

D. Contents of Containers

The interactive nature of touch allows tactile sensing to estimate properties of objects that would otherwise be latent. In addition to the mass properties of an object, a robot may also determine the contents of container objects. For example, a robot may determine if a non-rigid container is full or empty, as well as open or closed, by squeezing it and observing the resulting tactile signals [129].

In addition to squeezing action, a robot can shake a container to estimate the amount of material inside or the material properties of the contents [102], [130], [131]. One example approach estimated the viscosity of a liquid within a container by using a learned Gaussian process model and selecting different shaking behaviors to actively acquire the best estimate [130].

V. ACTION-LEVEL INFORMATION

For most applications, robots need to execute sequences of actions to finish more complex tasks [132], e.g., grasping, transporting, releasing for pick-and-place tasks or executing a sequence of steps for walking tasks. Tactile sensing can be used to compute action-level information for performing and monitoring the complex task at all stages (see Fig. 6). Action level information may be computed from contact-level [25], [79], [88] and object-level [106], [114], [123], [124] information as well as directly from tactile signals [26].

A. Action Selection and Initialization

Tactile data from previous actions and interactions can be used to select the next action and initialize its parameters. Robots can use previous actions to explore the objects and

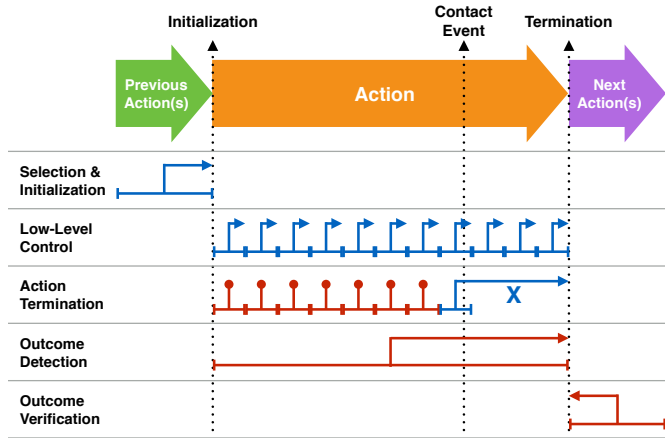


Fig. 6. The large arrows at the top show a sequence of actions’ execution. In the lower part, horizontal baselines indicate the time window when the tactile information is being extracted. The arrows indicate the time point when the action is monitored and the action is performed or adapted. **Action selection and initialization** uses tactile signals from the previous interaction to select and set the parameters of the current action. **Low-level control** uses the sensory data from each time step to select the next low-level control input during the action execution. **Action termination** monitors the action at each time step and either continues the action (red) or terminates it (blue) if a specific contact even has been detected. **Action outcome detection** then determine if the executed action was successful, or which type of error occurred, based on the tactile signals acquired during the action execution. **Action outcome verification** uses an additional action to generate more tactile signals to determining the outcome.

extract object-level information, then use the updated object model for initializing the current action [106], [115], [133].

The exploratory actions themselves are selected to acquire additional information based on the current belief for the object’s properties [110]. For example, when the robot has acquired a partial 3D model of an object based on previous tactile feedback, then the next grasp should be selected to explore locations where the model is still uncertain [118], [120]. Similarly, the robot may select other exploration parameters e.g. different normal forces and velocities for a series of finger sliding movements in order to better recognize an object [97].

Action selection is also used for recovering from failed grasps and other actions. When a robot’s grasp attempt fails, the robot can use the data from the failure to extract latent object properties and adapt the grasp for the next attempt accordingly [134], [135]. The resulting regrasping strategy thus has a higher likelihood of succeeding by exploiting the tactile information to select the next grasp.

B. Tactile Feedback for Low-level Control

Once a robot starts to execute an action, it can employ continuous tactile feedback to control the interaction by computing suitable motor commands [136]. For this computation, contact-level information [25], [79], [88], object-level information [106], [114], [123], [124] or raw tactile signals [26], [137] are required.

Tactile servoing uses feedback from tactile features to control the pose of the robot end-effector and maintain a certain amount of pressure while interacting with objects with various material properties [72], [77], [123], [138]–[140]. This

approach allows the robot to explore the unknown object, actively extract object’s features [141], [142] and cope with the geometry and material uncertainties of the contacted objects. It is also useful for tracing the edges of objects [72]. In servoing tasks, action and perception are tightly coupled as the robot needs to continuously adapt its actions to the current tactile signals.

In addition to continuous servoing control, the robot may also compute actions to respond to certain contact-level events, e.g., incipient slip. Reacting to these events requires quick reflexes. In many cases, incipient slip detection triggers an increase in the normal force exerted by the controller [24], [83]. Rather than waiting for the slip event, the robot may also learn to predict these events in advance using tactile sensing [25], [88].

C. Action Termination

Action termination allows a robot to determine if the current action should be continued or terminated, such that the robot can then switch to another action. Terminating an inappropriate action early allows the robot to reduce the negative effects of colliding with objects or other errors, as well as avoiding errors when a goal is reached earlier than expected.

To perform action termination, the robot continuously monitors the tactile signals and learns a binary classifier. Given the model classifier and the current tactile data, the robot can determine if the action should be continued or terminated [143]. Another way to decide whether an action should be terminated is to learn a model of the expected sensory signals [144]. The robots compare the predictive output of this model to the actual sensor values during the action execution [140], [145]. The action is then terminated if the deviation from the expected model output is too large.

D. Action Outcome Detection

Actions are not guaranteed to always succeed, even when robust tactile feedback is used in the control loop. Therefore, it is important for the robot to determine that the goal is reached, and no error occurred during execution. Outcome detection can be formulated as a classification problem where the classifier has a binary output indicating if the action was successful or not [146]. The robot may also attempt to determine the specific type of error if one occurred. The outcome classification may also be achieved with a probabilistic approach that computes the probability of a successful outcome [135]. For the input, the robot may use the entire time series tactile signal from the action execution. However, often only the final frame is used as it tends to be highly informative for determining the outcome [147], [148].

Outcome detection has been used for evaluating grasp stability. In this case, classifiers or probabilistic models are used to determine if a grasp was successful before attempting to lift the object [135], [146]–[150]. Rather than continuing the planned sequence of actions, a detected failure may trigger a regrasping action or a replanning strategy [135]. Outcome detection can thus serve a similar role to action initialization, but for the subsequent action.

Outcome detection is also important for providing the robot with additional information for future executions of the action. The robot can use outcome detection as feedback for learning actions from experience [151], [152]. Successful outcomes give greater rewards and thus encourage similar action executions in the future.

E. Action Outcome Verification

Many outcomes are ambiguous given only the observed tactile signals during the action execution. A robot therefore needs to use interactive perception to disambiguate these situations. By applying an additional action, and observing the resulting tactile signals, a robot can estimate more reliably the outcome of the previous action. For example, a robot may attempt to perturb a screw sideways to verify that it was correctly inserted into a hole [153]. A robot may also attempt to lift an object to verify that a grasp was successful [134]. Similar with direct outcome detection, the outcome verification can be posed as a classification problem. However, the input data is provided by the tactile signals from the following actions. Outcome verification requires extra time and effort to perform the subsequent action, and it may change the state as a result, but it also provides useful information for determining the outcome.

VI. TACTILE COMPUTATION: ANALYTICAL AND DATA-DRIVEN MODELS

Tactile computation approaches can generally be divided into two groups—analytical or data-driven.

Analytical approaches exploit physics-based models to compute tactile information [66], [80], [96], [107], [120], [127], [77]. From the descriptions of tactile information in Sec III through V, it is clear that many of the processed signals have a clear physical meaning. Higher-level information, such as object properties and action commands, are computed from the raw tactile signals or from contact information by accumulating interactions and using physical models. By utilizing the principles of physics to create models of the environment, human operators can easily understand the robots' perception procedure and its decision-making processes. However, these models normally rely on structured interactions and accurate feedback signals. If precise information of the interactions is not available and more complex tasks are being considered, simplified assumptions about the interactions must be taken to facilitate the design of the models.

Another approach is to employ data-driven methods to compute and process the tactile information implicitly [74], [135], [144], [154], [155]. These approaches learn mappings from raw sensory signals, or lower-level features, to high-level [object properties and action commands](#). Supervised, unsupervised, and even reinforcement learning methods can be used to learn suitable features for a variety of tactile tasks. Hierarchical representations, such as neural networks, are often used to learn multiple levels of features. The learned intermediary features are generally not interpretable by humans. Data-driven methods generally do not require a precise model of the interaction and they tend to avoid brittle assumptions. Flexible

representations allow the robot to adapt the learned model to the specific task based directly on data. It is often easier to provide data from contact-based interactions than to predefine an accurate analytical model.

VII. APPLICATIONS OF TACTILE INFORMATION

Rich tactile information provides lots of possibility for performing tactile-relevant tasks, which include: tactile exploration, grasping, in-hand manipulation, locomotion, tool manipulation and human robot interaction. [In this section, we summarize the relation among tactile information, computation method and applications in the table I. The table elements can be read as "in X application, X tactile information is studied with X method". We discuss and give examples that how robots can compute and use contact-, object-, and action-level information within these complex task domains.](#)

A. Tactile Exploration

Tactile exploration is an effective way to extract properties of an unknown object through touch [141], [142]. Humans use many exploration procedures to obtain knowledge about objects [30] – lateral motions, pressure, enclosure, contour following, object's part motion tests, and affordance tests. Inspired by these findings, many tactile-based exploration methods have been developed for robots to estimate important parameters including contact level information such as local geometry [66] and material properties [97], as well as object level information such as shape [156], [157] and mass information [123]. [In addition to the analytical approaches, recently some researchers were proposing the data-driven approaches to learn the contact geometry and object's properties \[75\] \[159\] using large tactile dataset.](#)

Another representative application of tactile sensing in exploration is tactile servoing control. [This is mainly computing the action level information to maintain the desired contact pattern defined by contact level information considering single \[72\], \[138\] or multiple contact areas \[158\].](#) In the example of single contact [72], [138], a tactile planar array is assembled on the end-effector of the arm. The desired tactile pattern is the specified contact position and force. The tactile array explores the object's surface by implementing sliding and rolling actions. The goal of the action information is to minimize the deviation of the tactile pattern. This approach can also be used to control a robot hand for exploration [158]. This controller was using multi-contact area on hand and exploring the surface of an unknown object to improve the robot hands grasping capability.

B. Grasping

Grasping is one of the most widely researched aspects of robot manipulation [198], as it provides a robot with control over the grasped objects and it is a common prerequisite for tool usage. [Similar to tactile exploration, tactile grasping is also an important method to extract object properties. Some researchers extracted the contact level information \[81\], \[91\] and object level information \[89\], \[105\], \[110\], \[126\] using](#)

TABLE I
A SUMMARY FOR TACTILE INFORMATION AND COMPUTATION APPROACHES IN APPLICATIONS

	computation approach	Contact level	Object level	Action level
Tactile Exploration	analytical models data-driven	[66], [97] [75]	[123], [156], [157] [159]	[72], [138], [158] [160] [161]
Grasping	analytical models data-driven	[81], [91] [164], [165]	[89], [105], [110], [126] [166], [167]	[162], [163] [134], [168]–[170]
In-hand Manipulation	analytical models data-driven	[171] [154]	[172] [178]	[173], [174], [137], [175], [176], [177] [179], [151]
Tool Manipulation	analytical models data-driven	[180] [29]	[181] [139]	- [182] [183], [143], [153]
Locomotion	analytical models data-driven	[184], [95], [185], [186] [189]–[191]	- -	[187], [188] -
Human Robot Interaction	analytical models data-driven	- -	- -	[192] [193], [194], [195] [196] [197]

analytical methods, and others computed them with data driven approaches [164]–[167].

Tactile sensing has also been used for analytical grasp controllers [162], [163], and for data-driven grasp synthesis, grasp outcome detection, and re-grasping [134], [148], [169]. Analytical approaches rely on accurate contacts position, normal direction, and force estimates to compute a grasp posture that maximizes the grasp quality metric [158], [199]. For data-driven approaches, the robot uses contact and object information from previous grasps to predict grasp qualities and compute regrasp postures [110], [134], [148], [169], [200].

Once the object has been grasped, tactile feedback can be used to control the contact forces [201], [202] and detect incipient slip [25], [81], [83]. By detecting or predicting incipient slip using tactile data, the robot can automatically increase its grip force to avoid gross slip without having to explicitly estimate the object-finger friction coefficients [203].

C. In-hand Manipulation

In-hand manipulation involves using the dexterity of the robots hand to change the state of a grasped object. For this task, some work focused on the computation of contact and object level information [171], [172], [154], [178], but the majority of work was to study the tactile controllers to relocate the grasped objects. The controllers have been performed with either multifingered robot hand [23], [173], [177], [204]–[207] or grippers [208]–[210].

For local repositioning while maintaining contact, the object is precisely grasped then moved with the robot’s fingertips [173]. Tactile sensing is used to estimate the contact and object information and actively control the contacts between the fingers and the object [174], [176]. Alternatively, tactile sensing can also be used to directly learn a mapping from the contact sensor information to the robotic fingers desired joint velocities [151], [179] in a data-driven way.

In order to move the object further [211], robots need use finger gaiting to switch between different grasps while maintaining the object in hand. To this end, the fingers need tactile sensing to detect breaking and contacting with the object to effectively walk the hand around the objects surface. For dexterous hands, researchers have proposed using human-inspired finger gaiting strategies [175]. In order to imitate the human, demonstrations of gaiting behaviors with tactile signals

can be acquired by fitting the human subject’s hands with tactile finger caps [212].

D. Tool Manipulation

Tool usage is a core aspect of many manipulation tasks [213]. A key aspect of employing tactile sensing in tool manipulation is that the task contacts are between an object and the held tool. The contacts are therefore not directly on the tactile sensors, unless the tool is itself instrumented [180].

Tactile sensing can be used to detect contacts on tools, localize tooltips and other important parts of the manipulated tools [29], monitor the progress of tasks and detect manipulation failures. Tactile feedback can also be used to estimate and maintain the orientation and forces at the contact points to perform the compliance control tasks. Tactile sensing can also be employed in a dual-arm setup to estimate the kinematic parameters of a grasped tool (1 D.O.F) [181].

Tactile sensing is also used for controlling and using unknown tools. The main challenge is that no kinematic or dynamic manipulation model can be directly used to compute the tactile action information for a given task. To this end, data driven methods [182] become a valid approach to compute the action command implicitly. There is more challenge interactive control task–multi-stages contact interaction. For example, a peg may slide freely or become jammed during an insertion task. Tactile sensing allows the robot to interactively detect these different types of contact modes [143] and plan recovery actions accordingly [153].

E. Locomotion

Tactile sensing is not only useful for manipulation tasks, but also for locomotion. Ground vehicles and walking robots, such as humanoids, quadruped, and hexapod robots, need to use contacts with the environment to move around. Tactile sensing provides to them with estimates of the state of the robot and the environment terrain [95], [214] during locomotion. For example, wheeled robots can use tactile sensing to monitor their contact with the ground [189]–[191]. Vibration signals from microphones or accelerometers in the wheels can be used for determining the type of terrain.

Maintaining balance is a key part of both standing and walking. To maintain balance, the robot needs to use tactile sensing to estimate its contact locations for support [95], as

well as detect obstacles and other perturbations that may cause it to lose balance [187]. The tactile sensing can also be used for learning a tactile-motor mapping for standing [186]. Walking requires deliberately planning and controlling gaits, which consist of multiple phases [215]. The transitions between phases are often triggered by contact events, such as the heel contacts with the ground. Tactile sensing has also been used to study where to place a foot [188]. By estimating the type of terrain, a robot can generate appropriate gaits and switch to a suitable leg controller.

F. Human Robot Interaction

In addition to interacting with inanimate objects and terrain, robots also need to physically interact with humans. Human robot interaction (HRI) applications span a wide range of different tasks including [intuitive programming](#) [192], putting on clothing [196], handing over objects [216], [safe interaction with collaborative robots](#) [217], [218] and shaving [193]. During these tasks, the robot need to ensure that the interaction forces are safe and adapt to the humans body.

In the context of HRI, contact and object level information is computed with the similar way like tactile exploration and grasping. Recent new progress is focusing on inferring the humans latent state and intentions from sensory feedback [219]–[221]. For example, during a handover, the robot can employ vision and tactile feedback to determine when the human has a suitable grip and is ready to accept the object [194]. Similarly, when performing collaborative tasks such as carrying large objects, the robot measures interactive forces and torques through the force/torque sensor on the wrists for performing the task and react accordingly [195].

In addition to performing tasks, human robot interaction can also be used to teach robots new skills from demonstrations [222]. In this manner, the robot can be directly guided by a human using force controllers [223]. Physical interactive corrections can also be used to refine [robots](#) skill executions through touch [197].

VIII. CONCLUSION AND FUTURE WORK

Tactile sensing is an important sensing modality as it allows robots to estimate properties of objects and interactions, and it provides feedback for adapting the robots' executed actions. In this paper, we discussed the main types of information that can be acquired using tactile signals as well as different types of applications in which this information can be used. We explained how tactile sensing can be used to acquire data related to individual contacts, objects, and skills. These different types of information can be extracted from the sensor signals using analytical techniques or data-driven approaches. The information extracted from these various types of methods can then be used for a wide range of different applications. The proposed categorization of tactile perception approaches is thus applicable to various task domains.

Our review of tactile information focused on the different types of estimation problems that robots must overcome, rather than the specific types of methods used to address these problems. In this manner, we provide a structure for this

research field that can be applied both to past work as well as future research. Although we have made great strides as a research community, none of the presented problems should be considered as solved.

In addition to developments for the individual challenges that we discussed, we also expect to see more approaches that collect contact- and object- level information while performing actions for a given task. Methods for contact- and object-level information currently tend to employ purely exploratory skills, e.g., stroking and prodding [141], [158] or basic manipulations, e.g. simple grasping and lifting [105], [110], [124]. Similarly, action-level methods often assume that object and contact information are already provided or it is fixed and therefore does not need to be explicitly represented [113], [120]. Future work on tactile sensing will also explore deeper how analytical and data-driven approaches can be combined more efficiently. Current methods often focus either on analytical [66], [80] or data driven approaches [135], [154], [179]. By combining these two approaches will allow robots to work efficiently by exploiting their prior knowledge and adapting to novel situations autonomously.

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