From Tactile Data to Image Processing, and Application in Robotic In-Hand Manipulation

Van Anh Ho (Ritsumeikan Univ.), Tatsuya Nagatani (Mitsubishi Electric Corp.),
Akio Noda (Mitsubishi Electric Corp.), and Shinichi Hirai (Ritsumeikan Univ.)

I. Introduction

Imitating human touch is still challenging for anthropomorphic robotic hands. Human can perform dexterous tasks basing on not only vision, but also rich information from touch mechanism. Even in some cases with visual occlusion, he/she can easily assess grasped object characteristics, such as friction, roughness, localization, and grip estimation. It thanks to human cutaneous mechanoreceptors which includes four functionally distinct types of tactile afferent [1]. These afferents have particularly high densities in the fingertips, bringing dynamical events, such as skin deformation, direction and spatial distribution of contact forces. Recent research on robotics has kept focusing on creation of robotic hand with human-like sensory systems to perform dexterous tasks, especially tactile sensing system [2]. With advanced technology such as piezo-resistive or capacitive array types, nowadays tactile sensors have better sensitivity, higher spatial resolution, but still far from human afferents. Nonetheless, tactile information has been used widely in robotic hands in many potential applications, such as object recognition, contact states assess. In this paper, we show how to exploit image processing techniques in tactile data information reasoning. It brings the benefits to reduce data processing burden, particularly enriches information of contact states, promises efficient tool to implement robotic tasks.

Conventional applications using tactile sensor attempted to extract efficient force distribution on the contact surface to find out when the contact occurs or is broken, and the location of contact. There are also numerous researches working on object recognition using machine learning techniques, incorporating with uncertainties in measurements. Pezzementi *et al*. [3] make use of tactile image to obtain local surface information during object exploring, combining those patches to build an object. Authors in [4] also utilize tactile images of objects, taking advantage of "Bag-of-Features" in vision to propose a recognition method. Most of approaches use small-sized, coarse resolution tactile sensor, therefore obtained data merely brought discrete and insufficient information about contact condition. With increasingly developing technology, it is promising to create sensor with high resolution. At that time, it would require a different look of tactile sensor, with more advanced and convenient processing method, to bring rich and reliable information for recognition and control. Our method, as treating tactile data as an image, bases on good resolution sensing array, conveying multiple modalities of a physical contact: pressure, contact shape, localization, and stick-slip.

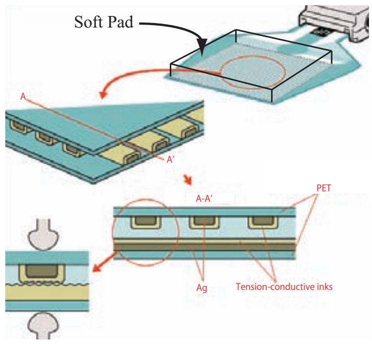

Fig. 1. Nitta® tactile sensor with the soft pad. This image was edited from the original one in [5]

II. Method

A. Tactile Sensor

In this research, we utilized a Nitta® I-SCAN50 tactile sensing system [5]. It is constructed by a grid of tension-sensitive electro-conductive ink lines (Fig. 1). The working principle is quite straightforward: when no load applies at one intersection, there is a light contact between inks, resulting high resistance of inks; when a force is applied to the sensing sheet, conductive inks are pushed to make a strong contact, causing the resistance to drop dramatically. By scanning intersection nodes, information about pressure distribution can be obtained. This sensor consists of 44×44 *tacels* (tactile elements), with $44\,\mathrm{mm} \times 44\,\mathrm{mm}$ in square size, and $1\,\mathrm{mm}$ in row/column spacing. A soft pad with similar square size and $2\,\mathrm{mm}$ in thickness covers the sensing area to form a complete soft tactile fingertip. This tactile system was afterward attached on a robotic finger through a Nitta® 6-DOF (degree-of-freedom) force/torque sensor. We set up the systems on a dual robot arm with grasped object between end-effectors, so that they are able to work in cooperation to imitate a robotic parallel gripper.

B. From Tactile Data to Image Processing

Assuming that there is an object grasped by fingertips, we have an imprint on the tactile sensor soft pad. Depending on applied load each tacel has different 8-bit value, resulting a 44×44-dimension array of tactile data as illustrated in Fig. 2. Wherever the load is applied, the corresponding node will

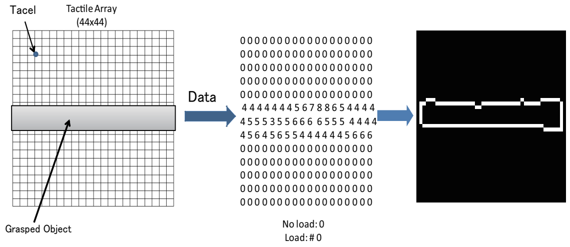

Fig. 2. The similarity between a tactile data and a grayscale image.

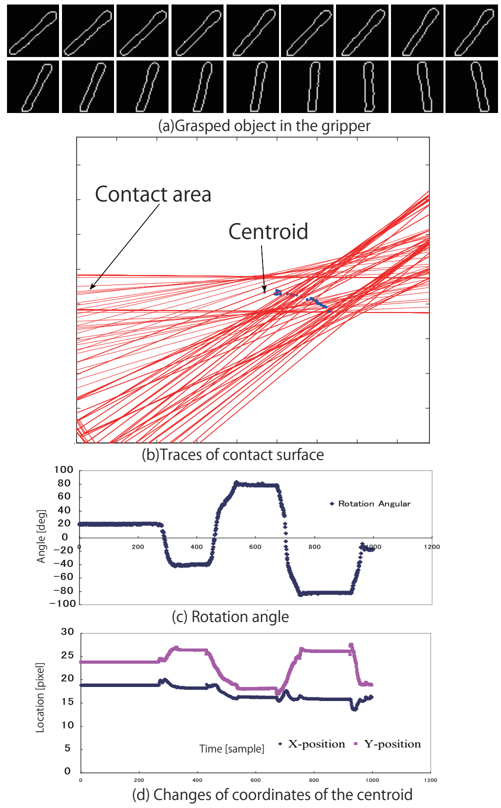

Fig. 3. Localization.

output non-zero value. In several cases, the sensor suffers positive error (nonzero at no-load state) due to noise of the measurement and process. We found that the obtained array shown in Fig. 2 *looks akin* to a *grayscale image*. This image has a size of 44×44, in which each pixel corresponds to a tacel; each pixel has a 8-bit value equal to that of the tacel. In addition, this image has a *background* consisting of zero-valued pixels; and *foreground* which is formed by nonzero valued pixels. As a result, a tactile array can be transformed totally to a real grayscale image, known as *tactile image*. Hence, every action on tactile data will be considered as processing on images. In the next section, we perform several examples to see how potential it is in object manipulation tasks.

III. Some Examples

A. Localization

In the image processing technique, we are able to localize not only position of the contact, but also its orientation by exploiting image moment definition:

$$M_{pq} = \sum_x \sum_y x^p y^q I(x,y), \tag{1}$$

in which $x, y, I(x,y)$ are coordinates of each tacel in the image coordinates, and its intensity, respectively. Here p is the x-order and q is the y-order, whereby *order* means the power to which the corresponding component is taken in the above sum [6]. In this case, M_{00} would be the contact area; and the centroid of the contact area is computed as followings:

$$\begin{bmatrix} x_0 \\ y_0 \end{bmatrix} = \frac{1}{M_{00}} \begin{bmatrix} M_{10} \\ M_{01} \end{bmatrix}. \tag{2}$$

Using this idea of image moment, we also can estimate the orientation of the contact area, through central moments:

$$\mu_{pq} = \sum_x \sum_y (x-x_0)^p (y-y_0)^q I(x,y). \tag{3}$$

The eigenvectors of the covariance matrix derived by using the second order central moments correspond to major and minor axes of the image intensity, thus the orientation θ can be extracted from the angle of the eigenvector with the largest eigenvalue by the following equation:

$$\theta = \frac{1}{2} \arctan\left(\frac{2\mu_{11}}{\mu_{20} - \mu_{02}}\right) \tag{4}$$

To illustrate this example an experiment was conducted, in which the gripper held tightly a rectangular object; then this object was moved arbitrarily, but maintain the contact, to imitate the in-hand manipulation task. Fig. 3(b) illustrates the trace of the contact area during the movement of the object in the gripper. We also can obtain values of the object's orientation angle (Fig. 3(c)), and the coordinates of the centroid in the tactile image (Fig. 3(d)). Consequently, given the tactile data one can easily localize the grasped object's position and orientation using above idea of image moments.

B. Contact Shape Recognition

Research beforehand used discrete information through a specific number of tactile images during an object exploring task to realize/discriminate object. Usually, obtained tactile images were coarse, thus few information about the object could be assessed. Therefore, it required complicated teaching/learning method to assist the object recognition process [3][4]. Naturally, richer, clearer, and reliable information after each touch would decrease the complication of learning algorithm, as well as uncertainties, and accelerate the realization process in real time application. By exploiting our method with edge detection technique, one can expect better description of contact area, also partial shape of the grasped object (Fig. 4).

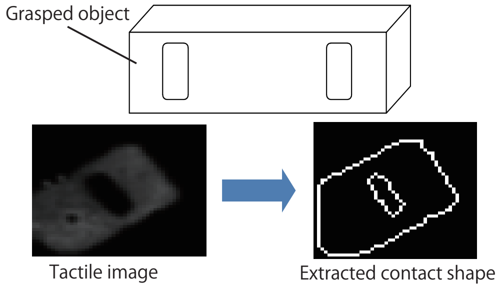

Fig. 4. Contact shape detection in term of boundaries.

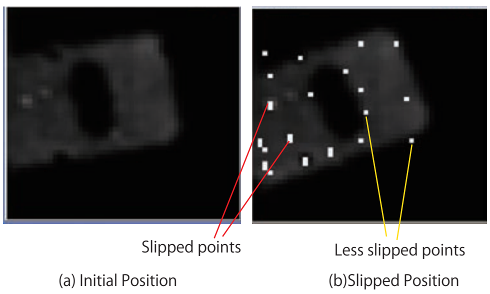

Fig. 5. Slip detection.

C. Slip Detection Method

One of the most difficult tasks for tactile sensor is to detect slips occurring on the contact surface with object. Tactile sensors typically bring information about only perpendicular force component of applied load. Therefore, tangential traction cannot be measured via change of normal force, resulting complications in slip detection. One might judge the slip through movements of the entire contact surface. However, micro slips, which dominates the pre-slip stage of soft object or non-uniform contact pressure distribution [7], cannot be attained easily.

Our approach focuses on tracking featured points on the contact area using image processing, to detect the incipient/overt slip of the object. Featured points are easy-to-track ones, which are usually corners, end-point, etc. Then, optical flow of these points is extracted using Pyramid Lucas-Kanade algorithm [6]. For example, the grasped object in (Fig. 5(a)) was moved and rotated at the same time. Trajectories of featured points are marked with white lines (Fig. 5(b)), showing that points away from the instantaneous center of rotation (of this movement) travel further than the closer ones. As a result, we are able to realize not only points where the slips happen, but also direction of the slide. It is expected to be more efficient to detect the slip when the contact area is more complicated than uniform one, such as contacting with sphere or ellipsoid objects.

IV. A Case Study

In this section, we attempt to estimate force/torque (F/T) acting on the robotic fingertip at various posture of grasped object given information from tactile sensor. A model will be proposed for the tactile sensor, and the estimated force/torque wrench will be compared to the real ones from 6-DOF F/T sensor.

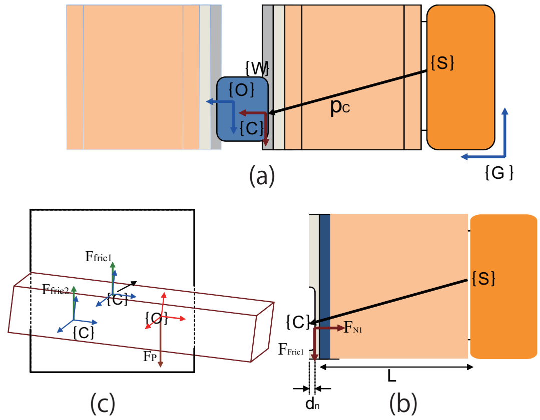

Fig. 6. Geometrical analysis: a) Grasped object with gripper. b) Separation of one finger for analyzing with applied forces. c) External forces acting on object.

A. Estimation Model

Given a known object which is grasped by the gripper with an arbitrary pose as illustrated in Fig. 6(a). One can see in Fig. 6 that $\{O\},\{C\},\{W\},\{S\},\{G\}$ are coordinates of the object, contact location, wrist, sensor location, and the global one, respectively. We will use feedback from tactile sensor to estimate wrench $[F,M]^t$ acting on the position of the $\{S\}$-coordinate (location of F/T sensor). Fig. 6(c) shows the relative position of the grasped object in the gripper. In the $\{W\}$-coordinate, localization of the object is specified by position and orientation of the $\{C\}$-coordinate respect to the $\{W\}$-coordinate, particularly x_c, y_c, z_c, θ_c. While (x_c, y_c, θ_c) can be easily obtained through localization ability of the tactile sensor which is mentioned in Section III-A; contact depth of the object over the soft pad z_c can be estimated by relative position of two fingers of the gripper. External forces acting on the object are contact force, including normal and tangential components, and the gravity force.

To calculate normal force component acting on the contact surface, we exploit the idea of virtual cantilever paradigm proposed in [7], in which the soft pad is virtually divided to infinite number of elastic cantilevers. Normal force distribution can be estimated by calculation of reactive force acting on deformed cantilevers. In this paper the the contact surface is flat, thus cantilevers have the same contact depth d_n (Fig. 6(b)), which simplifies the calculation of the normal force as stated below:

$$|F_{n_1}| = \iint_S \frac{Ed_s}{l} d_n = \frac{E}{l} d_n \iint_S d_s = \frac{ES}{l} d_n, \qquad (5)$$

where E, l are Young's modulus and thickness of the soft pad, respectively; S is contact area which is calculated as zero-order moment M_{00} of the tactile image mentioned in Section III-A.

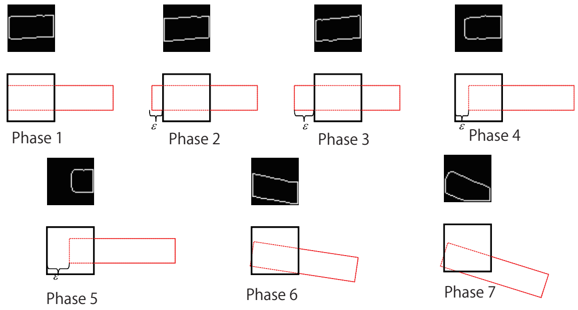

Fig. 7. Postures of the grasped object through phases.

As a result, normal force component in the $\{C\}$-coordinate is specified as $F^C_{n_1} = [0\ 0\ F_{n_1}]^t$. There are two components of friction force acting on two contact surfaces of fingers. Due to the symmetry, it is sufficient to calculate one, the other is obtained similarly. In the $\{O\}$-coordinate, we have the following equations:

$$\begin{cases} F^O_{fric_1} + F^O_{fric_2} + F^O_P = 0 \\ |F^O_{fric_1}| = |F^O_{fric_2}| = |P/2| \end{cases} \tag{6}$$

As a result, friction force in $\{C\}$-coordinate:

$$F^C_{fric_1} = T^C_O(-\frac{1}{2}F^O_P) = -\frac{1}{2}T^C_O F^O_P, \tag{7}$$

where T^C_O is the homogeneous transform matrix from $\{O\}$-coordinate to $\{C\}$-coordinate. Consequently, forces acting on the $\{S\}$ is estimated as follows:

$$F^S = T^S_C F^C_{contact} = T^S_C(F^C_{n_1} + F^C_{fric_1}), \tag{8}$$

where T^S_C is the homogeneous transform matrix from $\{C\}$-coordinate to $\{S\}$-coordinate.

To estimate the moments M on the $\{S\}$-coordinate, we simply introduce a vector $p^S_C = [p_x\ p_y\ p_z]^t$ from $\{S\}$ to $\{C\}$ so that: $M = p^S_C \times F^S$. By using a skew symmetric matrix P^S_C we can easily obtain the following relation: $M = p^S_C \times F^S = P^S_C F^S$. Because this analysis is static, friction torque acting on the contact surface can be eliminated. As a result, for each posture of the grasped object and data from the tactile sensor, wrench acting on the fingertip can be obtained as follows:

$$\begin{bmatrix} F \\ M \end{bmatrix} = \begin{bmatrix} T^S_C F^C_n + T^S_C F^C_{fric} \\ P^S_C T^S_C F^C_n + P^S_C T^S_C F^C_{fric} \end{bmatrix}. \tag{9}$$

B. Experiment Results

In this experiment, we changed various posture of the grasped object in sequence as illustrated in Fig. 7. Obtained wrench from F/T sensor was then compared with the calculated results from the aforementioned estimation model. Some representative results are plotted in Fig. 8. One can observe that there are similarity between the estimated wrench and experimental wrench. Slightly small differences come from the uncertainties in experimental setup, data acquisition, and estimation model. As a result, this case study shows that by only using tactile data, and proposed estimation model, we can obtain force/torque acting on the fingertip.

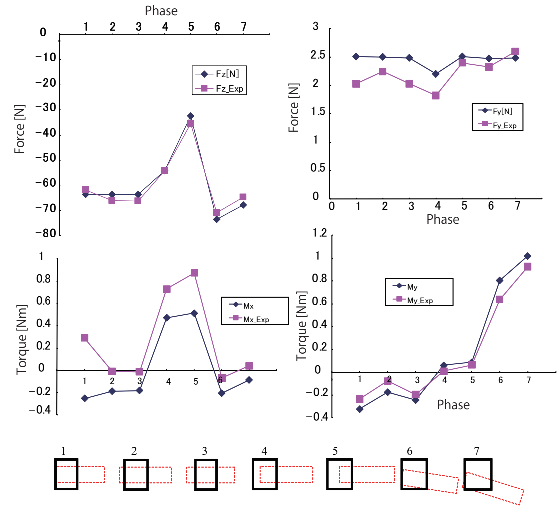

Fig. 8. Comparison between estimated wrench (dark blue dots) and experimental ones (dark pink dots).

V. CONCLUSION

In this paper, we present a concept of using tactile sensors as sufficient tools in localizing, recognizing object in robotic in-hand manipulation tasks. Our approach operates on a moderately high-resolution intensive array data that are obtained from a tactile sensor when a robotic gripper grasps an object. In stead of using tactile data as an array of discrete numbers, we treat it as a grayscale image. By working with successive images from tactile sensor exploiting image processing tools, we are able to extract rich information about the contact condition between an object and the gripper. Experimental results show that from the processed data, one can realize the grasped object's position/orientation, contact shape, as well as the stick-slip condition on the contact surface. We also conducted a model for an object-grasping gripper with tactile feedback in various postures of the object, and a corresponding experiment setup to validate computed results. In the future, we will enhance the tactile system with artificial intelligence to apply in real-time manipulation tasks.

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