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Shape Classification using Tactile Information in Rotation Manipulation by Universal Robot Hand

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1. Introduction

Recently, a variety of humanoid robots have been developed to help humans by working in human environments (Kaneko, 2002). However, these robots can not work as well as humans, because many robotic elements still require advanced research and development. One of these elements is a dexterous robot hand. For humanoid robots to be able to do various jobs in environments designed for humans and to use the same tools that humans use, those hands must have the same size and number of fingers and a tactile sense similar to those of the human hand. It is necessary to develop dexterous robot hands. Examples of multi-fingered robot hands developed includes the Utah/MIT Dexterous Hand (Hollerbach & Jacobsen, 1996), which has four four-jointed fingers driven by pneumatic actuators with tendon cables and a full tactile sensing suite using a capacitance sensor suitable for contact control (Johnston et al., 1996). Other examples are the Gifu Hand (Mouri et al., 2002) having 20 joints with 16 degrees of freedom (DOF) and the KH Hand type S (Mouri et al., 2005) having 20 joints with 15 DOF. These lightweight hands have six-axis force sensors and distributed tactile sensors consisting of a pressure sensor sheet with conductive ink. Despite the obvious importance of tactile sensors, they have not been actively used to recognize objects. Among the few studies achieving effective dexterous movement using tactile sensors, Pribadi (Pribadi et al., 1989) and Allen (Allen & Mechelman, 1990) focused on the sensing of global object shapes and fitting these shapes to object models. Okamura proposed detecting features based on definitions using a hemispherical fingertip having a tactile sensor (Okamura & Cutkosky, 2001). Despite their important results, these methods require extensive investigation but do not use distributed tactile sensor very effectively. By the way, Klatzky researched haptic exploratory procedures by the human hand (Klatzky & Lederman, 1990). In this research, exploratory procedures are classified into eight motions, i.e., lateral motion, pressure, static contact. They are important to obtain object's attributes. Especially "contour following", which can obtain object's outer shape in a manipulation, is necessary to manipulate an object dexterously. However, this procedure has not been realized in a robot hand's manipulation.

To obtain object's shape while a robot hand manipulates an object, we propose a shape classification. It uses the five-fingered robot hand, called Universal Robot Hand, which has distributed tactile sensors. Universal Robot Hand rotates an object, and tactile sensors measure pressure distribution once every 10 ms. A kurtosis is calculated from each pressure distribution, and dynamic programming (DP) matches the time-series kurtosis pattern with reference patterns and outputs valuated values. The evaluated value is classified based on a given threshold. Experiments demonstrated that three symmetrical objects are classified accurately.

2. Universal Robot Hand and Rotational Manipulation

2.1 Universal Robot Hand

Each of Universal Robot Hand's five four-jointed 3-DOF fingers is 333.7 mm long (Fig. 1) and Table 1. Each Joint is driven by a miniaturized DC motor and a reduction gear (Harmonic Drive Systems, Inc.) built into each link, and also has a joint torque sensor and a rotary encoder. Joints 3 and 4 drive at equal ratios, like a human finger. Tactile sensors are attached to the ventral sides of links.

Universal Robot Hand's three-layer tactile sensor consists of urethane gel (Exseal Co.), pressure sensitive rubber (Inaba Rubber Co., Ltd.) and an electrode pattern sheet (Fig. 2). This simple arrangement provides high productivity and easy maintenance. The urethane gel has a hardness of ASKER-C 15 and 2.5 mm thick. When an object comes in contact with this sensor, the force and shape of the contact surface deform the urethane gel. This deformation creates a pressure distribution in the pressure sensitive rubber. The rubber has about 0.5 mm thick and contains electrically conductive particles. When the pressed rubber

Fig. 1. Universal Robot Hand

Joints	4
Actuators	3
Actuator driver	DC micro motor
Angle range (deg)	- 10 ≤ Joint 1 ≤ 10 0 ≤ Joint 2-4 ≤ 90
Maximum joint velocity (rpm)	29
Maximum joint torque (Nmm)	110

Table 1. Finger specifications

becomes thin, resistance in that region drops. Measuring this electrical resistance enables to be calculated the pressure in the region. Measuring the electrical resistance of the rubber requires two electrodes. One of the two electrodes sends voltage and the other receives it. We designed these electrodes on a flexible multi-layer polyimide board to simplify the sensor structure. Each measurement point is 3.4×1.8 mm and individual points are spaced at 0.2 mm. Each measurement point detects a force range of 0 to 1 N. As shown in Fig. 1, a finger has three tactile sensors. There are 102 measurement points on each fingertip, and the other two parts of the finger have 70 points each. The tactile sensor takes 10 ms to measure one pressure distribution.

Fig. 2. Structure of Tactile Sensor

2.2 Rotational Manipulation

Universal Robot Hand uses thumb and index finger to rotate an object. Two fingers pinch an object at the position to classify the shape. The thumb moves forward and the index finger moves backward simultaneously and vice versa, while the tactile sensor on the index finger measures pressure distributions on the contact surface between the object and fingertip. Assuming that the object does not slip and the object's radius is known, its rotational angle is converted to positioning fingertip and joint angles calculated using the Newton method. Repeating this process generates a rotational manipulation trajectory up to target angles of

the object. The joint angle is used to calculate joint torque with proportional derivative (PD) control. Stiffness control adjusts the torque so that contact force remains almost constant. Universal Robot Hand repeats rotational manipulation and classifies the area's shape repetitively. We call this manipulation repetitive rotational manipulation. Repetitive rotational manipulation is shown in Fig. 3. Fig. 3 (1)-(3) show the thumb moves forward and the index finger moves backward, then the octagonal cylinder is rotated clockwise.

Fig. 3. Rotational Manipulation using Thumb and Index Finger

3. Pressure Distribution Quantification

We propose a pressure distribution quantification prior to shape classification. A tactile sensor measures the pressure distribution based on the contact shape and total contact force (Fig. 4). Environmental conditions such as temperature and humidity are assumed to be constant. When the total contact force is constant, the pressure distribution depends entirely on the contact shape, i.e., if it is convex, pressure distribution exhibits sharp convexity and, if flat, gentle convexity.

Fig. 4. Pressure Distribution Quantification

Based on these assumptions, the contact surface is quantified as follows: As shown in Fig. 4, the Axes of coordinates are set to the pressure distribution, with average distribution

defined as average x axis pressure for the yp-plane. Kurtosis γ is calculated from average distribution as follows:

$$\gamma = \sum_{n=1}^N \frac{p_i(c_i - \mu)^4}{N\sigma^4}$$

where $p_i(i=1..N)$ is the average distribution pressure, $c_i(i=1..N)$ pressure weighting coefficients, N average distribution length, μ average, and σ standard deviation. Kurtosis is a statistical parameter quantifying distribution sharpness. If distribution becomes sharp, kurtosis becomes high, and vice versa. Kurtosis is suitable for contact shape classification because it expresses pressure distribution sharpness in a single value.

Although kurtosis can quantify the static contact shape, single kurtosis cannot classify shapes changing during rotational manipulation, which requires time-series pressure distribution. We therefore applied our work to time-series pressure distributions in rotational manipulation.

4. Shape Classification

4.1 Proposal Method

Our proposed method of shape classification is shown in Fig. 5. Universal Robot Hand obtains regular pressure distributions. Each pressure distribution is averaged in the direction of finger width to yield an average distribution. Kurtosis is calculated repeatedly, yielding time series kurtosis (Fig. 5). For a prism, kurtosis is high at an edge and low at a face, therefore time-series kurtosis has extreme values for feature contacts. Our method extracts patterns from a time-series kurtosis between the extreme values, as shown in Fig. 5.

Fig. 5 Shape Classification

We call this extracted pattern, kurtosis patterns. DP matching (Uesaka & Ozeki, 1990) evaluates the similarity between a kurtosis pattern and a reference pattern to classify the contact shape. The reference pattern is the kurtosis pattern for a known shape. DP can shrink or stretch patterns, even if the pattern length is different. This allows to change rotational velocities. DP selects the optimal local path for the minimum accumulated distance between former two patterns, then matches and evaluates the two patterns.

4.2 Dynamic Programming

In DP matching, Pattern Z is expressed as a reference pattern:

$$Z = \{z(j) \mid 1 \leq j \leq J\}$$

where j is the number of elements and J reference pattern length. Pattern U is expressed as a kurtosis pattern:

$$U = \{u(i) \mid 1 \leq i \leq I\}$$

where i is the number of elements and I kurtosis pattern length. The local distance between $u(i)$ and $z(j)$ is denoted by $d(i,j)$, define as follows:

$$d(i, j) = (u(i) - z(j))^2$$

Distance accumulated between the reference and input pattern at point (i, j) is denoted by $S(i, j)$. With DP matching, $S(i, j)$ is updated using the following iterative equations:

Initial Conditions ($i=1, j=1$):

$$S(1,1) = d(1,1)$$

($i=1, 2 \leq j \leq J$):

$$S(1, j) = \infty$$

Iterative Equation ($2 \leq i \leq I, j = 1$):

$$S(i,1) = d(i,1) + S(i-1,1)$$

($2 \leq i \leq I, j = 2$):

$$S(i,2) = d(i,2) + \min \begin{cases} S(i-1,2) \\ S(i-1,1) \end{cases}$$

($2 \leq i \leq I, 3 \leq j \leq J$):

$$S(i, j) = d(i, j) + \min \begin{cases} S(i-1, j) \\ S(i-1, j-1) \\ S(i-1, j-2) \end{cases}$$

These equations select the optimal local path for the minimum accumulated distance, Meaning $S(i, j)$ as the minimum accumulated distance between the reference and input pattern shrinks or stretches from 1/2 to 2 times along the time axis. DP output A is defined as follows:

$$A = \frac{1}{T} S(I, J)$$

This normalizes output with the sum of weights. T is the length of matched patterns. We use the evaluated value of similarity between the reference and kurtosis patterns with output A .

5. Experiments

5.1 Experiments at a constant velocity

Conditions for experiments confirming that time-series kurtosis indicated contact shape and classified highly accurately during repetitive rotational manipulations assumed that rotated objects are a cylinder, hexagonal prism, and octagonal prism (Fig. 5). Objects are 15 mm thick, and the inscribed circles of the cross-sectional outer-edge on each object are 35 mm in diameter. Universal Robot Hand rotated the cylinder by 0.63 radian, the hexagonal and octagonal prisms from edge to face. The rotational velocity was constant, 0.15 rad/s.

Fig. 6. Objects

The relationship between kurtosis and time step is shown in Fig. 7. Cylinder kurtosis is almost constant at 2.5. Hexagonal and octagonal prisms kurtosis, however, is a time-series waveform. Local maxima kurtosis of the hexagonal prism are higher than those of the octagonal prism, showing edge sharpness because the hexagonal prism has edges sharper than the octagonal prism. Local minima kurtosis of the hexagonal prism are lower than that of the octagonal prism. These results reflect the hexagonal prism plane length for 20.2 mm and that for the octagonal prism of 14.5 mm. The time-series kurtosis acquired in rotational manipulation therefore reflects object shape accurately.

We calculated the evaluated values using DP. Kurtosis patterns of the hexagonal and octagonal prisms, which range from the local maximum to next minimum values, are extracted from the time-series kurtosis. For the cylinder, kurtosis patterns for 0.63 radian rotation are extracted. The number of kurtosis patterns of each object is 20. The evaluated

values between the kurtosis and reference patterns provided beforehand are calculated. Averages and standard deviations of the evaluated values are shown in Table 2, which shows that the lower the evaluated value, the greater is the similarity between that the kurtosis pattern and the reference pattern. For different objects, the evaluated value averages, as well as the standard deviations, are high. The cause of these high averages is that the kurtosis patterns are not similar to the reference patterns. On the other hand, for the same object, averages and standard deviations are small, because the kurtosis patterns are similar to reference patterns. If threshold is 0.01, the classification results are shown in Table 3. The classification accuracy for the hexagonal and octagonal prisms is 90%, and that for the cylinder is 95%. These classification results are very high, confirming the effectiveness of the proposed classification.

Fig. 7. Kurtosis vs. Time Step

		reference		
		hexagon*	octagon*	cylinder
hexagon*	AVE	0.00121	0.01262	0.07642
	SD	0.00106	0.00285	0.03566
octagon*	AVE	0.1179	0.00241	0.03566
	SD	0.00571	0.00227	0.00433
cylinder	AVE	0.10297	0.06107	0.00545
	SD	0.01434	0.01093	0.00259

* Prism shape

Table 2. Averages and Standard Deviations of Evaluated Value

	Hexagon*	octagon*	cylinder
Classification Accuracy (%)	90	90	95

* Prism shape

Table 3. Classification Accuracy

5.2 Experiments using Five Different Velocities

The rotational velocity was changed by 0.5, 0.75, 1.5 times, and double original speed, giving 0.075, 0.113, 0.225, and 0.3 rad/s, respectively. The objects shown in Fig. 6 were used. Universal Robot Hand rotated the cylinder by 0.63 rad, the hexagonal and octagonal prisms from edge to face. The relationship between kurtosis and time step of the hexagonal prism is shown in Fig. 8. Corresponding to rotational velocities, time-series kurtosis are shrunk or stretched, i.e., the time-series kurtosis's period of 0.3 rad/s is half that of 0.15 rad/s. Local maxima and minima kurtosis are constant, even if rotational velocities are different. These results mean that time-series kurtosis can reflect the object's shape.

Fig. 8. Time-series Kurtosis of Hexagonal Prism at five different velocities

By the same described in 4.1 and using the same reference patterns, we calculated classification accuracies from 20 kurtosis patterns of each velocity. The results including in 4.1 are shown in Table 4. The classification accuracies of each rotational velocity are high, despite the reference patterns of a rotational velocity 0.15 rad/s. These results show that our proposed method is robust accommodating changes in rotational velocity. Shape classification does not require reference patterns for each rotational velocity, and is confirmed its effectiveness.

	Rotational Velocity (rad/s)				
	0.075	0.113	0.15	0.225	0.3
hexagonal prism(%)	85	90	90	90	85
octagonal prism(%)	85	90	90	85	80
cylinder(%)	90	95	95	95	95

Table 4. Classification Accuracies using Five Different Velocity

6. Conclusion

We proposed a shape classification in rotation manipulation. In this classification, time-series kurtosis is calculated from pressure distributions, and kurtosis patterns are extracted from time-series kurtosis. DP calculates evaluated values between kurtosis pattern and

reference patterns to determine whether to classify a contact shape if the evaluated value is falls below a given threshold. Experiments demonstrated the effectiveness while Universal Robot Hand rotates objects repetitively.

The whole outer shape classification we also proposed in continuous rotation manipulation (Nakamoto et al. 2009) is applicable to manipulation where the robot hand continuously rotates an object in one direction. We plan to combine repetitive and continuous classification that uses repetitive classification in regular processing continuous classification when it cannot classify a shape. This combination is expected to classify shapes robustly. We also plan to downsize the robot hand and improve the tactile sensor.

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Without a doubt, robotics has made an incredible progress over the last decades. The vision of developing, designing and creating technical systems that help humans to achieve hard and complex tasks, has intelligently led to an incredible variety of solutions. There are barely technical fields that could exhibit more interdisciplinary interconnections like robotics. This fact is generated by highly complex challenges imposed by robotic systems, especially the requirement on intelligent and autonomous operation. This book tries to give an insight into the evolutionary process that takes place in robotics. It provides articles covering a wide range of this exciting area. The progress of technical challenges and concepts may illuminate the relationship between developments that seem to be completely different at first sight. The robotics remains an exciting scientific and engineering field. The community looks optimistically ahead and also looks forward for the future challenges and new development.

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