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Robust Haptic Recognition by Anthropomorphic Bionic Hand through Dynamic Interaction

Koh Hosoda and Tomoki Iwase
Dept. of Adaptive Machine Systems, Osaka University
2-1, Yamadaoka, Suita, Osaka, Japan
hosoda@ams.eng.osaka-u.ac.jp

Abstract— **This paper describes learning of robust haptic recognition by Bionic Hand, a human-like robot hand, through dynamic interaction with the object. Bionic hand is a human-like hand that has soft skin with distributed receptors and is driven by artificial pneumatic muscles. At the beginning of learning, it utilizes the result of physical interaction with the object: thanks to the hand compliance, regrasping will leads object's posture to stable one in the hand. This result can be successively used as object classification for learning dynamic interaction between the hand and the object by a recurrent neural network. We conduct experiments and show that the proposed method is effective for robust and fast object recognition.**

I. INTRODUCTION

Ability of human's hands is prodigious. By using hands, we can recognize and manipulate objects adaptively and stably. Such ability is acquired through experience during his/her development. Researchers have been trying to reproduce such ability by robotic hands, but yet, their ability is far less than that of humans. Existing robot hands do not have sufficient manipulation/sensing skill.

A human has distributed receptors all over his/her hand, and gather information on the object through dynamic interaction. When he/she moves the fingers and the palm, stimuli from the receptors will change and they provide rich information about the object. Recognition ability of the robotic hands may be increased as well by utilizing such distributed receptors and dynamic interaction.

Historically speaking, research on the robotic hand mainly focused on pinching manipulation, grasping the object by fingertips, since the mathematical analysis is relatively easy (e.g. [1]). Therefore, robot hands had their sensors at the fingertips [2], [3], [4]. However, such structure of a hand obviously limits the ability to manipulate and to recognize the object.

There are several studies aiming at object recognition by utilizing complicated tactile pattern obtained from multi-contact [5], [6], [7], [8]. Kawasaki et al. developed a robotic hand covered with a force-sensitive resistance array [5]. They investigated static sensor image when the robot grasps an object. Natale et al. implemented a sensor array to the palm of the robotic hand and distinguished the object by static sensor patterns [6]. Takamuku et al. realized object recognition by a static pattern in a stable posture after regrasping [8]. Watanabe et al. used a 2D finger with distributed switches and developed a method to distinguish softness and radius of cylinders [7]. To the best of our knowledge, this was the only work that utilized dynamic change of sensation. However, since the interaction between a cylinder and 2D finger was very limited, they did not effectively utilize dynamic change of sensation.

In this paper, we describe learning of robust haptic recognition by Bionic Hand, a human-like robot hand, through dynamic interaction with the object. The hand has distributed tactile receptors, and performs regrasping motion without dropping the object. The sensation is used to train a recurrent neural network to memorize the dynamic receptor pattern. Experimental results demonstrate that robust, stable, and fast object recognition is performed by the proposed method.

This paper is organized as follows. First, we introduce the idea how a regrasping scheme and a recurrent neural network can be utilized for haptic object recognition. Then, the technical detail of the proposed learning scheme is described. Finally, experimental results are shown to demonstrate robust, stable, and fast object recognition by the proposed method.

II. ROBUST HAPTIC RECOGNITION UTILIZING REGRASPING SCHEME

A. Regrasping scheme

When a human grasps an object, and is not sure what he/she is grasping, he/she regasps the object without dropping it and tries to figure out what it is. Takamuku et al. claimed that such regrasping leads the object to a certain stable posture by dynamic interaction between the compliant hand (shown in Figure 1) and the object, and as a result, the obtained sensation at the posture also becomes stable and can be utilized to classify the objects [8]. This paper extends this idea that the hand can learn to recognize the object *during* the dynamic process: no need to wait until the object moves to a stable posture.

We adopt a regrasping scheme without dropping the object (Figure 2). Since the hand moves its fingers two by two, it can keep grasping the object while its posture gradually changes. Thanks to the interaction between the soft hand and the object, the object moves to a certain stable posture, as demonstrated in [8]. During the process, contact state dynamically changes: number of contact points (surface), contact position, slip condition, etc. But, finally, the hand

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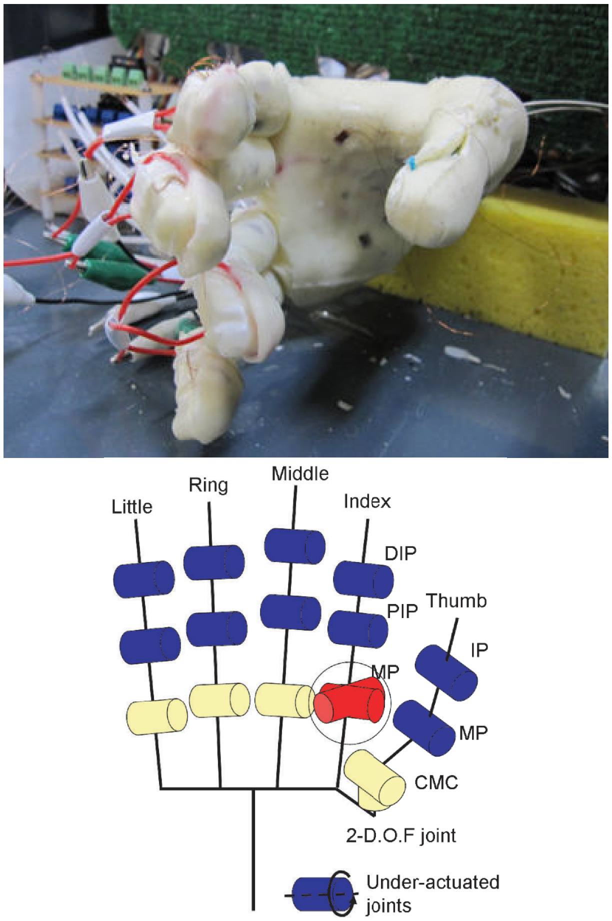


Fig. 1. A robotic hand covered with soft skin. It has human-like skeleton structure (similar structure of [9], but we add another DOF to the index finger, totally 17 DOF) and driven by 18 pneumatic artificial muscles. Inside the silicon skin, 25 strain gauges are embedded as receptors distributed over the fingers and the palm. It also has many PDVF and thermo receptors, but are not used in this paper.

can get a sensor pattern corresponding to the posture, which is relatively stable when it grasps the same class of objects. In the sensor space, we can classify the objects and calculate the value to *represent* their class.

As a result, the hand can distinguish the object class after regrasping, and now the problem is how it can be possible *during* regrasping manipulation. To realize this, we propose to use a recurrent neural network with object classe nodes. The representative value of each object is fed to the neural network described below.

B. Leaning haptic recognition through dynamic interaction

During regrasping the object, sensory flow comes from the receptors embedded inside the soft skin. Since the object posture leads to a certain stable one, we can expect a recurrent neural network to learn the trajectory in the sensor space. We adopt a Jordan-type recurrent neural network [10] that has context nodes and put another two nodes that represent the object class (Figure 3). The structure is similar to RNNPB (recurrent neural network with parametric bias) proposed by Tani and Mori [11], but the object class is obtained by

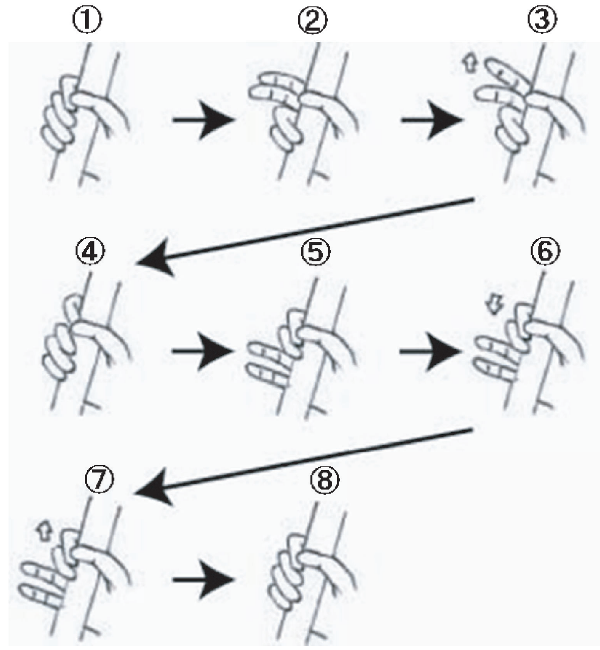


Fig. 2. Regrasping motion. The hand regrasps the object without dropping it. It moves fingers two by two. Dynamic interaction between the soft hand and the object will lead it to a certain posture even when the initial posture is not the same (demonstrated in [8]).

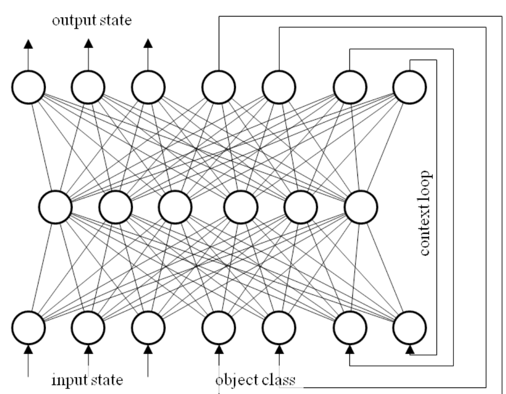


Fig. 3. Jordan-type recurrent neural network with object class nodes.

the resultant sensory state by regrasping (described in detail below) while parametric bias is self-organized. Trained by the object class, learning time becomes dramatically short and learning becomes stable as well. The network is trained by the BPTT (Back Propagation Through Time) method [11].

III. Experiment

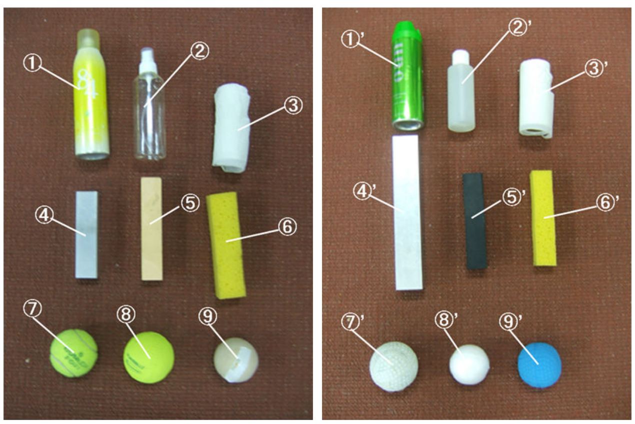
A. Objects used for experiments

We prepared three classes of objects: cylinder, prism, and ball. Each class consists of three objects for learning and three for evaluation (Figure 4). Dimensions of the object is shown in Table I.

TABLE I

DIMENSION OF OBJECTS

		dimention		
shape	number	diameter/width(mm)	height(mm)	weight(g)
cylinder	1	49.8	200	43.4
	1’	53.1	180	57.6
	2	47.7	172	33.1
	2’	43.7	135	106.4
	3	43.1	112.9	13.9
	3’	48.4	112.9	25.3
prism	4	30.0	126	111.3
	4’	40.0	242	280
	5	29.8	150.5	47.8
	5’	30.5	151.3	185.1
	6	38.6	152.5	7.4
	6’	31.0	150.3	4.8
ball	7	63.7	-	55.7
	7’	71.9	-	134
	8	69.5	-	28.9
	8’	59.7	-	2.9
	9	62.2	-	30.3
	9’	66.7	-	35.4



(a) Objects for learning (b) Objects for evaluation

Fig. 4. Objects used for experiments. We prepared three classes of objects: cylinder (top), prism (middle), and ball (bottom). Three objects from a class are used for learning, and three others are for evaluation. Totally, 18 objects are used for the experiments. Note that They are not only different in shape and size but in stiffness, weight, and friction.

B. Experiment 1: Object recognition after regrasping

First, we conducted experiments to confirm the effect of regrasping. We handed objects to the robot at 0[s], and waited until 3.5[s] before grasping was stabilized. Then, we let the robot regrasp twice, each sequence took 7.5[s]. We got the signal from receptors and classified the objects. We applied principal component analysis to pick two main components out of the sensor measurement. The result is shown in Figure 5. We conducted 15 trials for each object in Figure 4(a) and 5 trials for each in Figure 4(b), totally 180 trials, which means 180 points in the figure. We also plot standard deviation ovals for convenience (they are not used for the following experiments). We can see that the ovals separate from each other as the hand repetitively regrasps.

In Figure 6, we show within-class variance and within-class between-class ratio. We can see that the ratio grows as number of regrapsing increases. While within-class variance

TABLE II

CORRECT RATIO AFTER 350,000 LEARNING STEPS

	known(Fig. 4(a))	unknown(Fig. 4(b))
cylinder	95.6 %	80.0 %
prism	95.6 %	93.3 %
ball	100 %	86.7 %
total	97.2 %	86.7 %

of cylinder monotonically decreases, that of prism does not. Variance of ball even increases. We suppose that this could be the result that we prepare objects of different stiffness, for example, hard gum ball (7) and a sponge ball (9)’. We did not have such large difference within the cylinder class.

Note that the hand is driven by pneumatic artificial muscles. Its preciseness and repeatability are very poor. Also, it is impossible for us to give an object to the robotic hand in very precisely controlled posture. We rather try to give it in different posture to demonstrate robustness of the proposed method.

We can utilize this result for the next step: learning haptic recognition during regrasping. Representative value, the center of the ovals in this case, is used as the object class in the recurrent neural network (Figure 3).

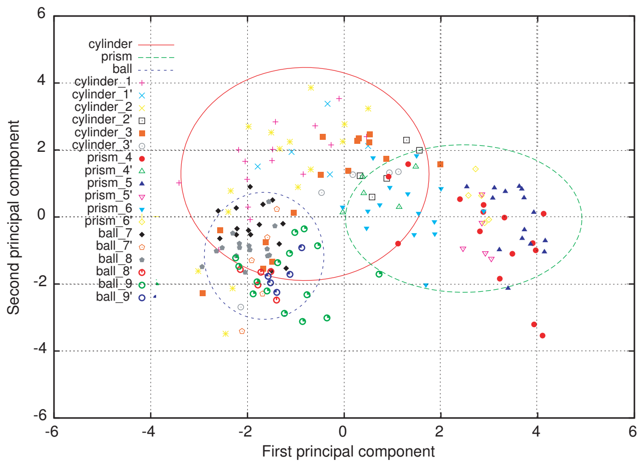
C. Experiment 2: Learning object recognition by neural network

First, we checked the learning ability of the recurrent neural network. In this experiment, we used 25 strain gauges embedded in the hand. Therefore, the dimension of input and output layer was 25. We used 50 hidden layers, 16 context nodes, and 2 object class nodes. As the input for the object class nodes, we used (0.112, 0.869) for cylinders, (0.954,0.558) for prisms, and (0.273,0.095) for balls, which were obtained representative value in the principal component space by the previous experiment.

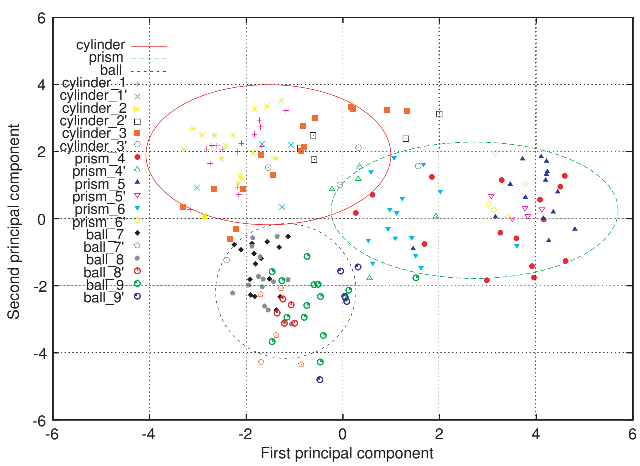
Temporal sequence of stain gauge signals and the object class of 9 objects (Figure 4(a)) were used to train the recurrent neural network. For learning, we feed 18.5[s] long time sequence is sampled in every 0.5 [s]. Initial weights are set randomly between -0.1 and 0.1.

We checked the correct ratio whether the network can detect the object correctly (the object class nodes go within a certain range) when we feed a whole sequence (which means whole 18.5[s]) to it. We use temporal sequences that are used for training for check, and ones that are not used for training as well. We checked 5 learning courses and the results are shown in Figure 7. Correct ratio grows up to 80% after 100,000 learning steps (which means 100,000 sequences are presented to the network). We also show the correct ratio after 350,000 learning steps in Table II.

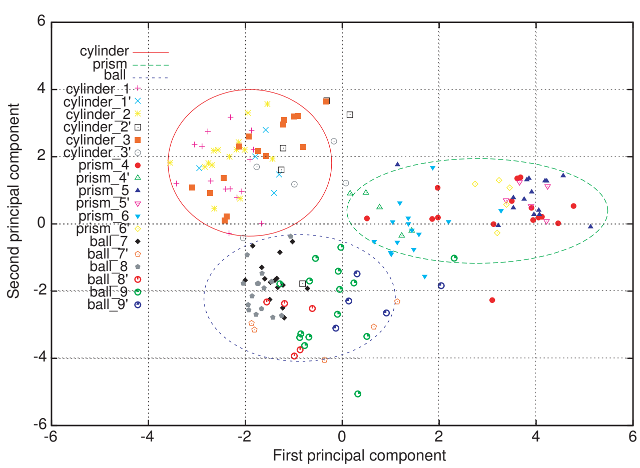
From these results, we can conclude that the neural network can eventually recognize the object class very precisely, even when it is not used for the training (note that it is very difficult to define “class” though). These results demonstrate that the proposed method can perform robust and stable recognition.



(a) At 3.5[s]: just after handing



(b) At 11[s]: after the first regrasping



(c) At 18.5[s]: after the second regrasping

Fig. 5. Experimental result: standard deviation ovals within the classes. Data from the strain gauges (25 dim.) is compressed by the principal component analysis into 2D. The ovals separate from each other as the hand repetitively regrasps.

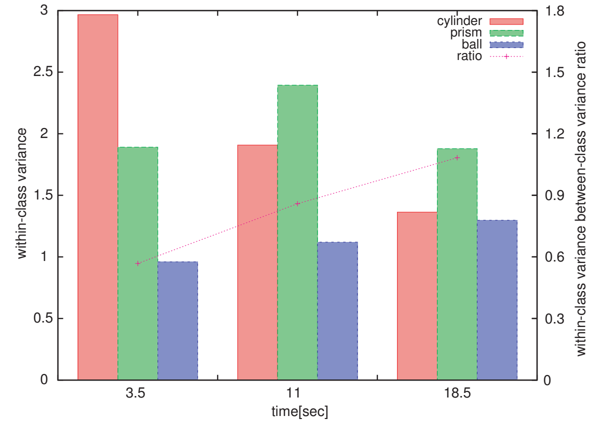


Fig. 6. Within-class variance and within-class between-class ratio. The ratio monotonically increases as time of regrasping increases.

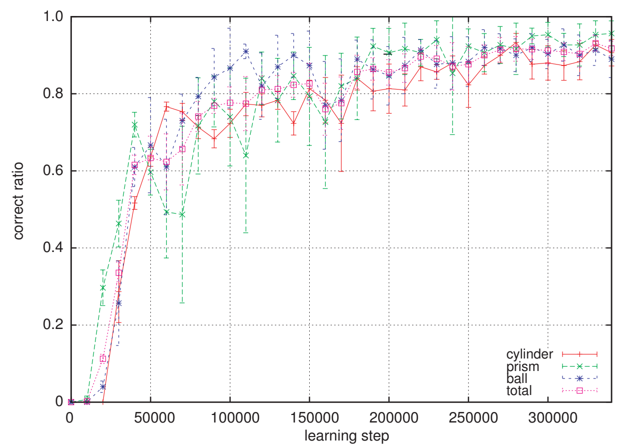


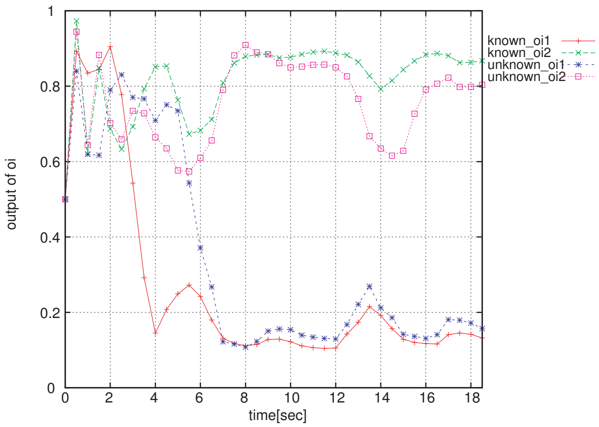
Fig. 7. Correct ratio of detecting objects.

D. Experiment 3: Object recognition during regrasping

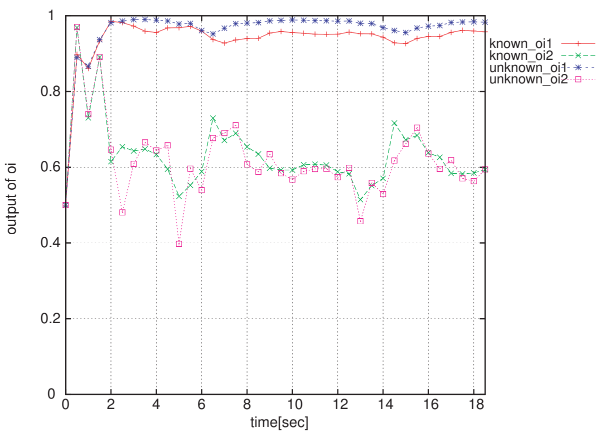
Finally, we confirm the temporal recognition ability of the network. After the training, we expect the network to learn the dynamics of interaction between the hand and the object. As a result, we may not have to wait until the object goes to a certain stable position, but the hand can distinguish it during regrasping.

We used the network after 350,000 learning steps, and present a temporal sequence of known/unknown object. The result is shown in Figure 8. A prism can be recognized within 2[s], a cylinder within 6[s], and a ball within 8[s], almost within second regrasping.

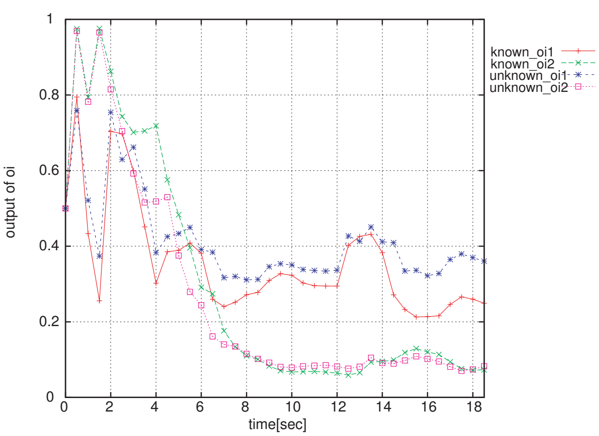
Last but not least, we check the role of the context nodes that are supposed to be important for learning the dynamic time sequence. We plot the correct ratio over time in Figure 9 in three cases: (1) using recurrent neural network with 16 context nodes, (2) using PCA with immediate sensor data, and (3) using recurrent neural network without context node. If we do not use the context node, the recognition ability of the network is almost the same as PCA with immediate sensor values. We can see that the context nodes help to recognize object faster.



(a) tempral sequences for k nown/unknown cylinders



(b) tempral sequences for known/unknown prisms



(c) tempral sequence for known/unknown balls

Fig. 8. Temporal output of object class nodes. Time before converge to be *recognized* is approx. 6[s] for cylinders, 2[s] for prisms, and 8[s] for balls. It may be interesting to note that balls can be easily detected from other two, but cylinders are a bit difficult to be distinguished from prisms.

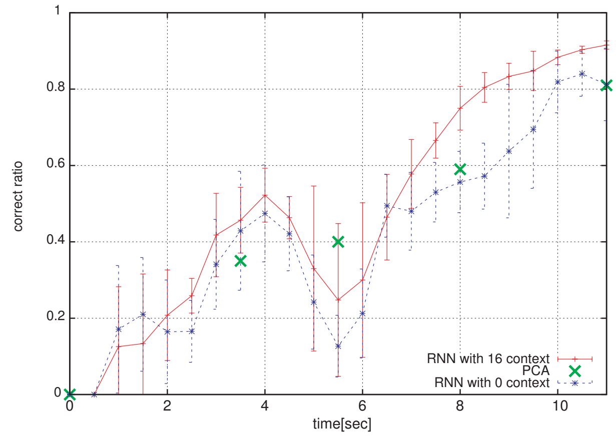


Fig. 9. Time sequence of correct ratio

IV. Discussion and Future work

If the hand grasps the object statically and uses the receptors for getting contact points with respect to the hand coordinate frame, they only provide kinematic information, and as a result, there is no advantage of using tactile sensing over vision except occlusion problems. We can maximize the advantage of using tactile sensing over vision when contact points change dynamically and we get more information on the dynamic interaction between the hand and the object, and dynamic of the object itself, as well. This paper shows such ability of the tactile sensors, and we believe that such sensing modalities will dramatically improve the overall ability of the hand, and eventually, lead to that of humans'.

Again, we like to emphasize that the robotic hand is controlled by pneumatic artificial muscles. Artificial muscles provide essential flexibility to the hand and enable it comply with various objects. Since the hand is driven by compliant muscles, it can (relatively) easily explore the object and can recognize it. Soft silicon skin also plays a crucial role. Uncertainty from such compliance is usually harmful to the existing *stiff* robotic hands consisting of metal and electric geared motors. We suppose that principles for controlling such rigid system is completely different from that for soft and flexible biological system. This may be one of reasons why existing robot hands do not have sufficient manipulation/sensing skill.

The proposed method does not use any visual information for recognition. Humans obviously recognize the manipulated object not only with tactile sensing, but with vision. Then, the next step is how we can combine these two modalities, which is not an easy problem.

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