2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)
October 25-29, 2020, Las Vegas, NV, USA (Virtual)

Tactile Event Based Grasping Algorithm using Memorized Triggers and Mechanoreceptive Sensors

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***Abstract*— Humans perform grasping by breaking down the task into a series of action phases, where the transitions between the action phases are based on the comparison between the predicted tactile events and the actual tactile events. The dependency on tactile sensation in grasping allows humans to grasp objects without the need to locate the object precisely, which is a feature desirable in robot grasping to successfully grasp objects when there are uncertainties in localizing the target object. In this paper, we propose a method of implementing a tactile event based grasping algorithm using memorized predicted tactile events as state transition triggers, inspired by the human grasping. First, a simulated robotic manipulator mounted with pressure and vibration sensors on each finger, analogous to the different mechanoreceptors in humans, performed ideal grasping tasks, from which the tactile signals between consecutive states were extracted. The extracted tactile signals were processed and stored as predicted tactile events. Secondly, a grasping algorithm composed of eight discrete states, Reach, Re-Reach, Load, Lift, Hold, Avoid, Place, and Unload was built. The transition between consecutive states is triggered when the actual tactile events match the predicted tactile events, otherwise, triggering the corrective actions. Our algorithm was implemented on an actual robot, equipped with capacitive and piezoelectric transducers on the fingertips. Lastly, grasping experiments were conducted, where the target objects were deliberately misplaced from their expected positions, to investigate the robustness of the tactile event based grasping algorithm to object localization errors.**

I. INTRODUCTION

Dexterous object manipulation is one of many key features that distinguish humans from all other living animal species. Although it is usually taken for granted in humans, an object manipulation task is an extremely sophisticated act, since the synthesis of several sensorimotor systems is required [1]. Thus, robots have only successfully replaced humans in environments where the human and robot workspaces are separated, where the robot workspaces are completely modeled or predictable [2].

Researchers have focused on using visual sensors to address the problem of using robots in uncertain environments. The rapid development of camera-based and deep learning approaches allowed robots to use object localization or segmentation techniques to recognize and localize objects [3]. The localization information, along with the target object's properties, such as stiffness and weight, are estimated from

*This work was supported by the Korea Institute of Machinery and Materials (KIMM) in 2020 [NK224G, Development of core machinery technologies for autonomous operation and manufacturing].

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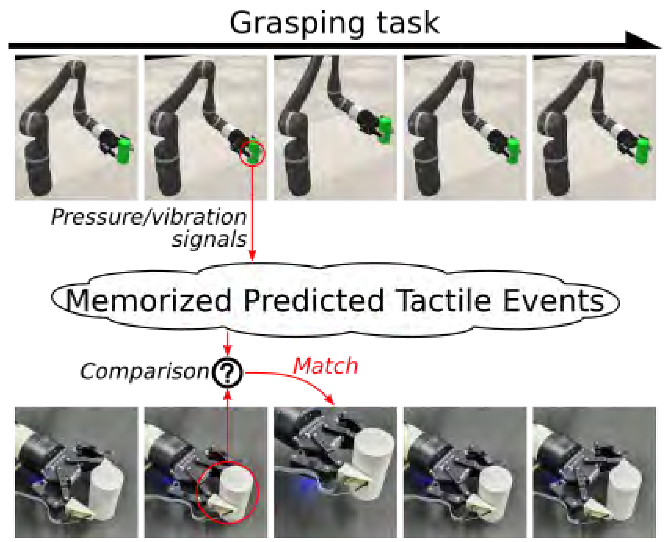


Fig. 1. Extraction of predicted tactile events from a simulated grasping task and using the memorized predicted tactile events for state transition trigger in the tactile event based grasping.

object recognition results and used to plan and execute object manipulation actions [4]. Although the grasping method based on visual data seems ideal, its performance can be deteriorated for several reasons. First, there is a substantial possibility that the object localization is not accurate, due to light conditions and wrongly calibrated cameras [5]. Secondly, as the manipulator approaches the target object, the object's occlusion from the camera's field of view amplifies the problem of imperfect object localization, hindering the manipulator from performing corrective actions using only visual information. Lastly, there are inevitable errors in the robot's physical model or control, which lead to positional errors during the control of the manipulator. This error is sometimes large enough to cause failures in delicate grasping tasks [6].

Humans can overcome the previously mentioned uncertainties by utilizing tactile sensations and visual sensations to manipulate an object. The tactile sensation inevitably plays a critical role in object manipulation because it is an action that requires direct physical contact with the environment. Many information can be deduced from the tactile sensations, including not only information on the physical properties of the object, such as the shape, weight, and stiffness, but also information on the tactile events that occur as a result of physical interactions between the skin and the environment [7].

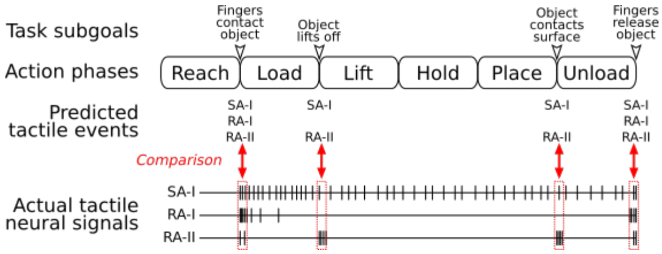


Fig. 2. Human grasping method using tactile events [12].

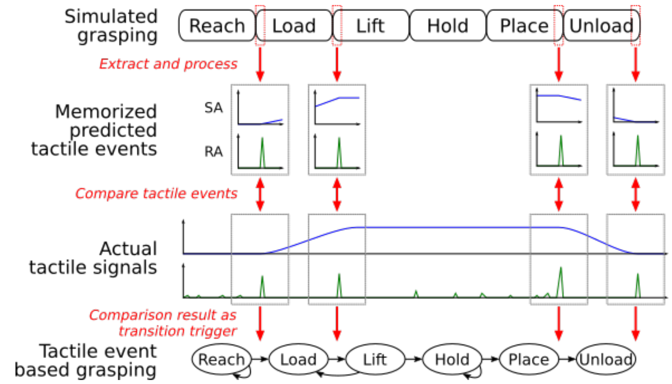


Fig. 3. Overview of the usage of simulated tactile signals as predicted tactile events for the human-inspired grasping algorithm.

Acknowledging the importance of tactile sensation in grasping, many research groups have developed tactile sensors integrated with robotic hands or grippers. The variety of tactile sensors that have been developed is described in detail in [7], [8], [9]. There have been researches to implement robot grasping algorithms using these tactile sensors that resemble the human grasping method. Romano et al. [10] used capacitive pressure sensors and accelerometer to detect tactile events between states in a human-inspired grasping algorithm. Su et al. [11] used tactile signals from BioTac (SynTouch, USA) sensors to detect slip events to drive their grip force controller. In both works, the transition between the states in the algorithm is triggered by a preset threshold, which is heuristically determined by the operator. The heuristic method is applicable in a simple grasping task because the predicted tactile events during a grasping task were made well known through researches introduced by Johansson and Flanagan [1], [12]. This method shows inherent limitations when it is expanded to a more complex object manipulation task because the predicted tactile events are not known by the operator.

This paper introduces the implementation of the tactile event based grasping algorithm using memorized predicted tactile events from extracted from simulations. The graphical summary of our method is shown in Fig. 1. First, in Section II, the human grasping and an overview of the implementation of our tactile event based grasping algorithm is introduced. Secondly, in Section III, the simulation scene settings are described, along with the extraction and processing method of the tactile signals into discrete memorized tactile events. In the latter part of Section III, we describe the components and working principle of our grasping algorithm in detail. Thirdly, the robot system mounted with mechanoreceptive tactile sensors and the grasping experiment, where the target objects' positions are slightly varied to emulate positional uncertainties, with its results are shown in Section IV. Lastly, we conclude the paper in Section V.

II. TACTILE EVENT BASED GRASPING

First, the background of the human grasping method is explained. Then, the overview of our tactile event based grasping algorithm is described in detail.

A. Human grasping

The human tactile sensation is a result of the transduction of mechanical stimuli to neural signals in the mechanoreceptors. The different types of mechanoreceptors have distinct rates of adaptation, separating them into Slowly Adapting (SA) and Rapidly Adapting (RA) types, which are specialized at sensing mechanical stimuli of low and high frequencies, respectively [13], [14], [15]. The combination of different frequency bands of the mechanoreceptors allows humans to sense and distinguish mechanical stimuli of different frequencies with ease, due to the separate encoding.

Object manipulation tasks, due to their complexity, are broken into a series of action phases [12], which are analogous to states in a finite state machine (FSM). The action phases are often separated by sets of predicted tactile events [12], depicted in Fig. 2. The tactile events are ensembles of tactile signals from the different mechanoreceptors, which gives information on specific subgoals that have been or must be reached during the manipulation task. The predicted tactile events are embedded in human memory through the repetitive experience of the manipulation task. If the actual tactile events match the predicted tactile events, the following action phase is initiated. On the other hand, if there is a mismatch, the sensorimotor system quickly reacts to amend for the error through corrective actions.

B. Tactile event based grasping algorithm

Our proposed method of implementing a tactile event based grasping algorithm is shown in Fig. 3. From an ideally simulated grasping task, the tactile signals are extracted and processed into sets of window functions. These sets of signals are stored in the main controller as the memorized predicted tactile events. Alongside the memorized predicted tactile events, a grasping algorithm similar to the human grasping method is implemented in the form of an FSM in the main controller. It comprised six main states-Reach, Load, Lift, Hold, Place, and Unload-and two additional states for performing corrective actions: Re-Reach and Avoid.

A state transition in the grasping algorithm is triggered by the result of the comparison between the corresponding memorized predicted tactile event and the actual tactile signals, which arise from the pressure and vibration transducers on the tactile sensor mounted on the gripper fingers. The

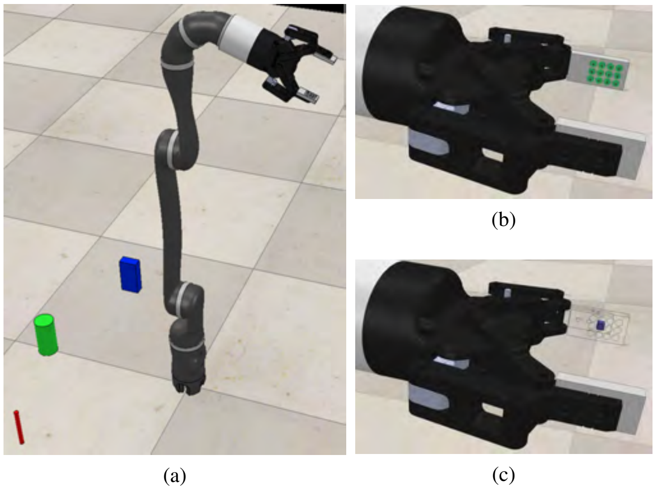


Fig. 4. (a) The simulated grasping scene with 2F-85 gripper, JACO^2 arm, and three rigid objects. (b) Twelve force sensors and (c) accelerometer embedded onto the gripper pad.

pressure and vibration transducers are analogous to the SA and RA mechanoreceptors, respectively.

Unlike the previous works that replicated the human grasping method [10], [11], using a simulation to store the predicted tactile events frees the operator from having to have a precise knowledge of the predicted tactile signal. The advantages of using simulators to memorize the predicted tactile events are that the ideal predicted tactile events could be easily found, which takes several years for a human being [16] or extensive number of trial-and-error for threshold setting in a heuristic tactile event based algorithm.

III. IMPLEMENTATION OF THE TACTILE EVENT BASED GRASPING ALGORITHM

We describe the procedure of extracting and processing the tactile signals used as the predicted tactile events, from the simulation. Then, the methodology for comparing the predicted tactile events to the actual tactile events is explained. Lastly, to complete our algorithm, the addition of states corresponding to corrective actions is described.

A. Extracting and processing the predicted tactile signals

For simulating the object grasping task, the CoppeliaSim (formerly V-REP) [17] simulator was used. As shown in Fig. 4a, the model of 2F-85 gripper (Robotiq, Canada) connected on to the JACO^2 6-DOF arm (Kinova, Canada) was created on the simulator, along with different rigid objects. Also, twelve force sensors and an accelerometer were attached to each finger pad of the simulated gripper, shown in Fig. 4b and 4c.

An ideally executed object grasping was simulated for grasping each object. The grasping task was pre-programmed into the simulator and was executed in an open-loop manner. The force sensor and accelerometer signals during the grasping task were exported using the Python remote API. Fig. 5a shows an example of the tactile signals that appeared during a simulated grasping task. Using ideal simulation signals does not raise problems, since it is the general trend of the signals within the trigger window that is important.

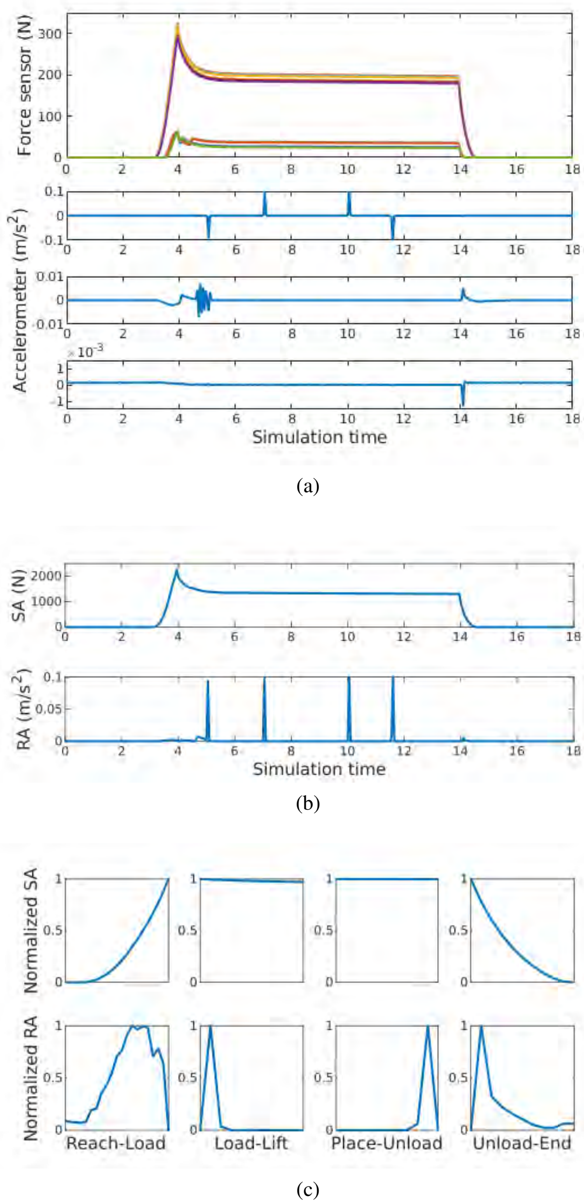


Fig. 5. (a) The raw force and accelerometer signals, (b) the processed tactile signals, and (c) the signals that are stored as the memorized predicted tactile events from the left finger of the simulated grasping task.

In the simulator, each force sensor provide 6 signals: F_x, F_y, F_z, T_x, T_y, and T_z. In this work, we neglected the effect of shear forces on the proposed algorithm, and thus, only the force signal corresponding to the normal force, F_z, was used. Next, the normal force values were summed up for each finger, which can be expressed as,

$$SA_i = \sum_{k=0}^{N} F_{z,k}, \tag{1}$$

where i refers to the finger number, k refers to the force sensors' indices on each finger, and N is the total number of force sensors on the finger. The reason for using the sum of the normal forces instead of individual values was to neglect the effect of the errors in the gripper position or orientation at the moment of grasping. By considering only the magnitude of the normal force, these errors are ignored, allowing the robot to grasp the object despite the uncertainty.

The simulated accelerometer provides a three-dimensional signal, $[a_x, a_y, a_z]$, at each time step. Since only a scalar quantity is required, the total magnitude of the accelerometer signals was used, which is expressed as,

$$RA_i = \sqrt{a_x^2 + a_y^2 + a_z^2}. \tag{2}$$

The graph in Fig. 5b is the processed version of the tactile signals in Fig. 5a, processed according to Equation (1) and (2).

Lastly, the processed signals were cut out from the transition points at a window length of 0.5 seconds. To generalize the use of the predicted tactile events to robots with different types of pressure and vibration sensors or grip force, the signals were normalized based on the maximum signal value in the window. The resulting memorized predicted tactile events are shown in Fig 5c.

B. Comparison between the predicted and actual tactile events

The memorized predicted tactile events are compared to the actual tactile signals to decide whether a state transition in the grasping algorithm should occur. In this work, the cross-correlation between the predicted and actual tactile event signals is used to compare the similarity of the events.

Similar to how the memorized predicted tactile signals were normalized, the actual tactile signals were also normalized in batches of 0.5 seconds in real-time. The normalized actual signals were cross-correlated with the signals of the predicted tactile events. The normalized cross-correlation is found by using,

$$R_{XY,normalized}(n) = \frac{R_{XY}(n)}{\sqrt{R_{XX}(0)R_{YY}(0)}}, \tag{3}$$

where $R_{XX}(0)$ and $R_{YY}(0)$ refer to the autocorrelation of the predicted and expected signals.

The lag in the cross-correlation output was not considered to give flexibility to the tactile signals' timing, as the relative timing between the actual SA and RA signals might not always be the same. The two events were considered to be similar when all the actual tactile signals, which are SA_{right}, SA_{left}, RA_{right}, and RA_{left}, showed a maximum normalized cross-correlation value greater than 0.9 and 0.7 for SA and RA, respectively.

C. Corrective actions for tactile event based grasping algorithm

When the predicted and the actual tactile events fail to match, the manipulator must take corrective action to adjust itself for a stabler grasp. In our algorithm, three corrective actions were added: Re-Reach, Lift-Load, and Avoid. Fig. 6a shows the detailed actions taken in each of the corrective actions. The triggers for the execution of the corrective actions were not collected from simulation but added heuristically through hard-coding.

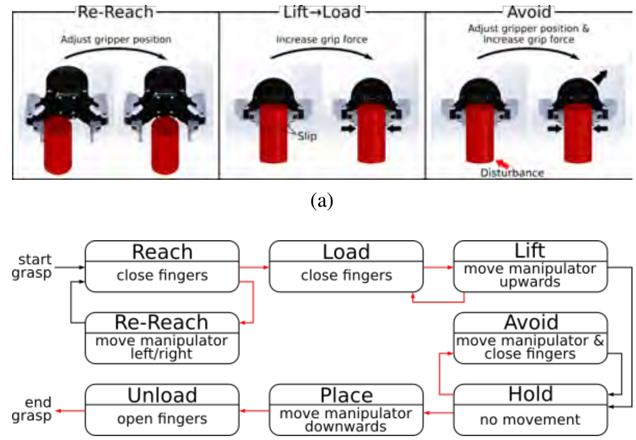


Fig. 6. (a) The programmed corrective actions. b) The complete state diagram for our grasping algorithm. The red transitions denote transitions that are triggered through tactile events.

By combining these corrective actions with the main six states of the algorithm, we obtained a complete tactile event based grasping algorithm with eight states. The resulting algorithm is depicted in Fig. 6b in the form of a state machine diagram. The state transitions that are triggered through the tactile events are depicted as red arrows.

IV. EXPERIMENTAL RESULT

We introduce the robot system that used the proposed tactile event based grasping algorithm to perform grasping tasks, describing the assembly of each robot components. Then, the grasping experiment setup and the results are demonstrated.

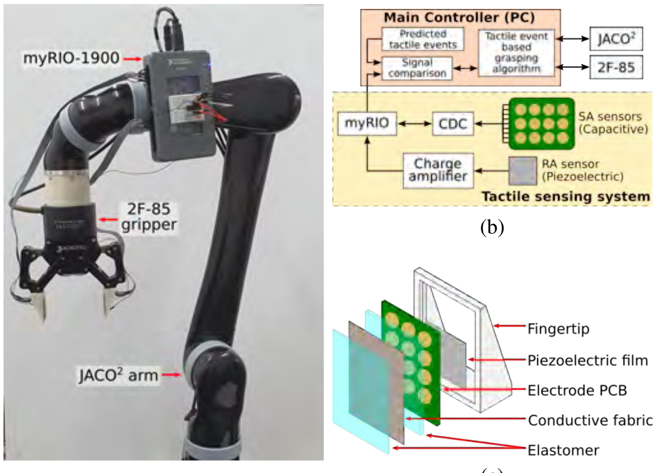
A. Manipulator with mechanoreceptive tactile sensors

For the robot system, shown in Fig. 7a, a 2F-85 gripper attached to the JACO^2 6-DOF arm was used, identical to the manipulator model used in the simulation. The original gripper fingers were replaced with customized fingers with tactile sensor pads, composed of capacitive and piezoelectric transducers for pressure and vibration sensing, respectively.

The twelve electrodes shown in Fig. 7c are capacitive electrodes, which work as transducers corresponding to the SA mechanoreceptors. The electrodes construct a parallel plate capacitor with the conductive fabric that covers the finger. When there is a pressure applied onto the fingertip, the elastomer and the conductive fabric is deformed so that the distance between the conductive fabric and the capacitive electrodes decreases. This creates a change in capacitance, which can be expressed as,

$$\Delta C = \varepsilon_r \varepsilon_0 A (\frac{1}{d_1} - \frac{1}{d_0}), \tag{3}$$

where ε_r is the relative permittivity, ε_0 is the permittivity of free space, A is the area of the electrode, d_1 and d_0 are the final and initial distance between the conductive fabric and the



(a) (b) (c)

Fig. 7. (a) The robot system with fingertips with tactile sensors. (b) The schematic diagram of the robot system. (c) The exploded view of the tactile sensor structure.

electrode. The capacitance is measured using a capacitance-to-digital converter (CDC) chip, AD7147 (Analog Devices, USA), placed at the base of the fingertips. The pressure applied on the finger is inferred from ΔC.

The sensor for acquiring stimuli of high frequencies, which is equivalent to RA mechanoreceptors, was made from a silver ink metalized PVDF film sheet (TE Connectivity, Switzerland). The piezoelectric film sheet was cut into a small piece and pasted onto the large electrode on the backside of the PCB, shown in Fig. 7c, which is a grounded electrode, using silver paste. The opposite side of the piezoelectric film was wired to a charge amplifier to convert the charge output of the piezoelectric film to voltage. The relationship between the charge produced on the piezoelectric film and the voltage output from the charge amplifier is

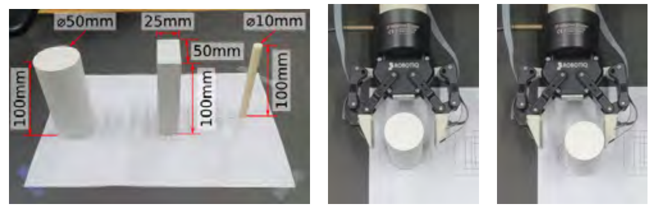
$$V_{piezoelectric} = -\frac{Q}{C_f}, \tag{4}$$

where Q is the charge produce on the film and C_f is the feedback capacitance in the charge amplifier.

The CDC chip and the charge amplifier were both connected to myRIO-1900 (National Instruments, USA). The tactile signals are sent from myRIO to the main controller, where the memorized predicted tactile events are stored and the tactile event based grasping algorithm is run. The electronic schematic of the robot system is shown in Fig. 7b.

B. Experiment setup for grasping under positional uncertainties

To evaluate the performance of our tactile event based grasping algorithm, we conducted grasping experiments on three different objects, shown in Fig. 8a. The objects are placed on their corresponding markers, of which the markers in the center are the expected ideal position of the objects. The manipulator's initial position and orientation are set so that it performs an ideal grasping with respect to objects



(a) (b) (c)

Fig. 8. (a) Objects placed on the marked positions and their dimensions. (b) Object placed on its expected position. (c) Object that is intentionally misplaced.

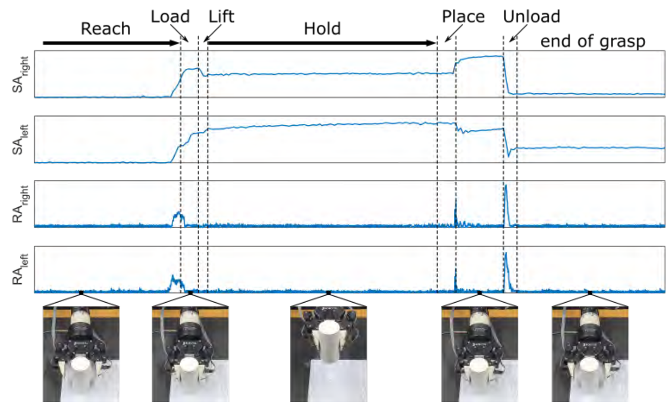


Fig. 9. The full tactile signal during a grasping task.

placed at the central marker. Fig. 8b shows an example of when the object is placed at the center marker, which is its expected position.

For deliberately misplacing objects, eight markers for the misplaced positions were marked around the central marker. The misplaced positions were set to $\pm$1.5cm within the direction of the finger stroke and $\pm$1cm in the direction normal to the palm of the gripper, which were set by considering the gripper's maximum stroke and dimensions of the tactile sensor. Fig. 8c shows an example of a misplaced object. Three grasping attempts were made at each position, resulting in 27 grasping trials per object and a total of 81 grasping trials.

C. Results

Fig. 9 shows the tactile signals collected when the robot grasped the cylindrical object placed at its expected position. The Reach-Load, Load-Lift, and Place-Unload transitions were triggered through a cross-correlation comparison to the predicted tactile events stored in the controller's memory.

To evaluate our method's grasping performance, the grasp success rate was computed from the results. A grasp was noted as successful when the gripper was able to both hold the object for at least 3 seconds and also place the object down without the object falling over. Table I shows the grasp success rate of our method for each object. The larger objects showed perfect performance when they were at their expected positions. The gripper often failed to stably grasp the thick cylinder when the object was misplaced outwards

TABLE I

GRASPING SUCCESS RATE FOR EACH OBJECT.

Object	Well-placed		Misplaced	
	∼Hold	∼Unload	∼Hold	∼Unload
Box	100%	100%	100%	100%
Thick cylinder	100%	100%	83%	83%
Thin cylinder	100%	67%	75%	25%
Average	100%	89%	86%	69%

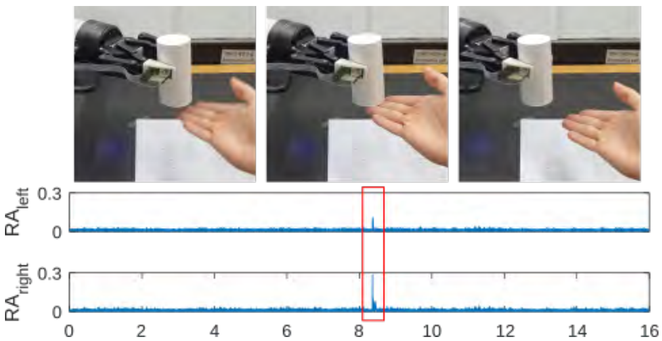


Fig. 10. Detecting object collision from RA signals and reacting to the collision in the Avoid state.

from the gripper. In the case of grasping the thin cylindrical object, most of the failure occurred from failing to place the object in an upright orientation correctly. Disregarding the placing task, if only the picking phase is considered, the algorithm showed perfect performance when picking up objects at their expected positions and an average of 86% success rate when picking up misplaced objects.

Since the effect of the Avoid state is not shown in the object grasping experiment, a separate demonstration was performed. The manipulator was held at the Hold state and the operator hit the object. Unlike in other state transitions, the predicted tactile events for the transition between Hold and Avoid were not memorized. Therefore, a threshold trigger was used to make the transition. Fig. 10 shows the manipulator in the Avoid state.

V. DISCUSSION AND CONCLUSION

In this paper, we propose a method to implement a tactile event based grasping algorithm using memorized predicted tactile events. The tactile events extracted from the simulation are stored in memory and referred to when they perform a grasping task based on the human-like grasping algorithm. The performance of the proposed method was evaluated through real-life experiments. We found that our proposed method was able to pick up objects with 86% success rate. This implies that our proposed method allows for the grasping of objects even if there are uncertainties in the object localization or robot control.

Improvements in the tactile sensor are desirable for a better grasping performance. There were several cases where the piezoelectric film failed to identify very weak dynamic stimuli, leading to grasp failures. Using more realistic noise-included simulation signals could also increase the robustness of the method when implemented on a real robot. Deleting heuristic parts in the method can be made possible using learning techniques, which we will deeply investigate.

ACKNOWLEDGMENT

This work was supported by the Korea Institute of Machinery and Materials (KIMM) in 2020 [NK224G, Development of core machinery technologies for autonomous operation and manufacturing]

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