NAIST-IS-MT1651045

Master's Thesis

Tactile-based Pouring Motion inspired by Human Skill

Takuya Kiyokawa

March 14, 2018

Graduate School of Information Science
Nara Institute of Science and Technology

A Master's Thesis
submitted to Graduate School of Information Science,
Nara Institute of Science and Technology
in partial fulfillment of the requirements for the degree of
Master of ENGINEERING

Takuya Kiyokawa

Thesis Committee:

Professor Tsukasa Ogasawara	(Supervisor)
Professor Kenji Sugimoto	(Co-supervisor)
Associate Professor Jun Takamatsu	(Co-supervisor)
Assistant Professor Ming Ding	(Co-supervisor)

Tactile-based Pouring Motion inspired by Human Skill*

Takuya Kiyokawa

Abstract

In this thesis, we propose a tactile-based pouring motion for robots inspired by the pouring skills of humans. Conventional vision-based pouring motions are subject to restrictions such as pouring material shape, pouring material color, illumination, background clutter and occlusions. In the proposed tactile-based pouring motion, the weight of a grasped container is estimated from the robot fingertip force, and the weight is continuously observed during the pouring motion. The pouring amount is calculated from the estimated weight. Since the grasped objects deform while being poured due to the movement of the gravity center, we implement a tactile-based grasping strategy for pouring such objects. The proposed method considers the deformation and the gravity center shift using tactile sensors on fingertips, and adjusts the grip force. Therefore, if the mass can be estimated while performing this grasping strategy, a tactile-based pouring motion can be realized. In this thesis, we aim to verify whether both the tactile-based grasping strategy and the tactile-based pouring motion generation are compatible. Pouring experiments using our robotic system showed that it was possible to estimate the pouring amount within 50 g. The results suggest that there is a possibility that it can be poured with the precision equal to or higher than the best value of pouring amount by vision-based pouring motion.

Keywords:

Tactile-based manipulation, pouring motion, pouring skill, mass estimation

*Master's Thesis, Graduate School of Information Science,
Nara Institute of Science and Technology, NAIST-IS-MT1651045, March 14, 2018.

Contents

List of Figures

List of Tables

1 Introduction

Recent studies in robot manipulation are shifting to more complicated tasks such as humans daily activities rather than the manipulation of rigid objects. Robot manipulation of deformable objects involving the movement of the gravity center is still difficult, such as pouring a glass of water. Vision sensing enables robots to pour a specific amount of the liquid by observing the liquid to be poured. However, vison sensing is subject to many restrictions such as illumination, background clutter, and occlusion. On the other hand, tactile sensing can effectively perceive many internal states of grasped objects such as a gravity center shift and the material amount change in the grasped container.

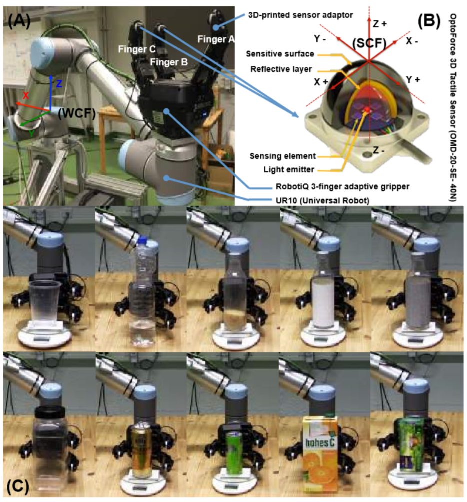
In this thesis, we enable robots to pour a specific amount of material into containers without depending on the external information of objects and the surrounding environment. We construct a basic framework of tactile-based pouring motion inspired by a human skill.

1.1 Related Work

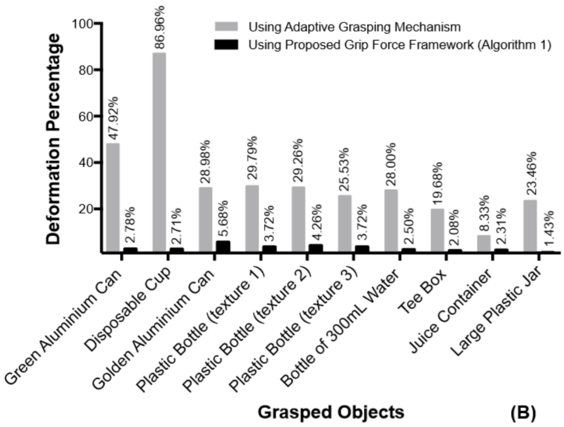
In this section, we explain related researches divided into four sections: tactile-based manipulation, pouring motions in industrial fields, vision-based pouring motions, and pouring motions by skill transfer from humans.

1.1.1 Tactile-based Manipulation

Tactile perception for robots is a key approach to obtain both some physical properties of objects and the physical phenomenon during grasping. Many studies of tactile object recognition are focusing on the perception of interaction by active approaches to objects [1, 2]. Drigalski *et al.* [3] conducted a textile identification of thin, deformable objects using 3D force sensors. Matsubara *et al.* [4] proposed a criterion in active touch point selection for fast object shape estimation. Kaboli *et al.* [5] constructed a methodology for discrimination based on a object's center of mass using 3D force sensors. Teshigawara *et al.* [6] developed a slip-detecting sensor using tactile information. Wang *et al.* used wavelet analysis for slip prediction [7, 8]. Kaboli *et al.* [9] constructed a tactile-based grasping strategy for deformable objects and heavy objects. As a result, it was possible to suppress the deformation rate to 6% or less from the original size for all experimental objects by using the proposed robotic system. Fig. 1.1 shows the robotic grasping system and a result of deformation percentage. Currently, the elemental technologies based on tactile manipulation have been developd. However, tactile-based, dexterous, routinely-performed skills like pouring motion has not been realized. This thesis focuses on the realization of pouring motion based on tactile information.



(a) Grasping system

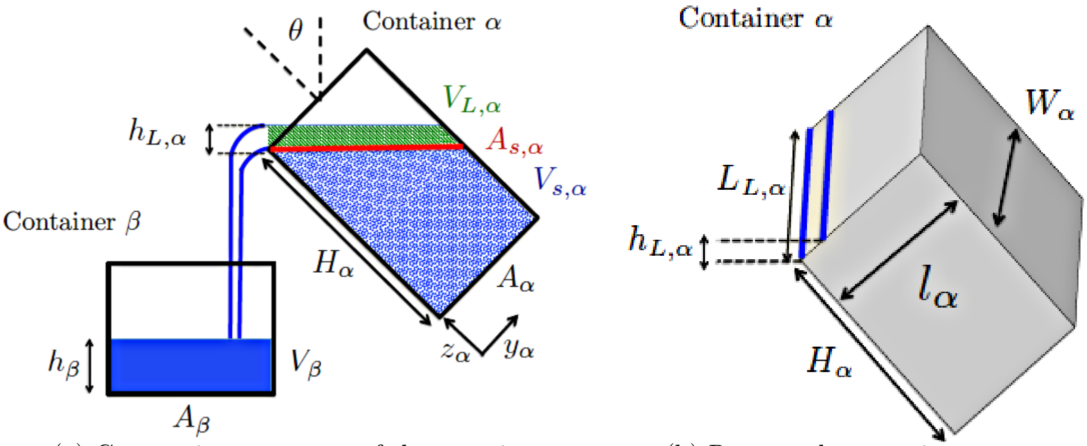


(b) Deformation percentages of grasped objects

Figure 1.1: **Grasping system for deformable objects and a result in [9]**

1.1.2 Pouring Motions in Industrial Fields

The pouring motion by a robotic system has been put to practical use in industry fields rather than in home environments. Noda *et al.* [10–13] proposed a casting robot which can pour liquids by estimating the pouring amount. The motion trajectory is generated based on an outflow rate model with a ladle model and the feedback of loadcell values for pouring a specific amount of liquid. Kennedy *et al.* [14] realize a motion for pouring precise amount of liquids using the outflow rate model with a rectangular-parallellepiped-shaped container using visual feedback. These methods need an accurate shape model of the specific container for the pouring motion. For home robots, it is difficult to obtain all the precise models of containers.

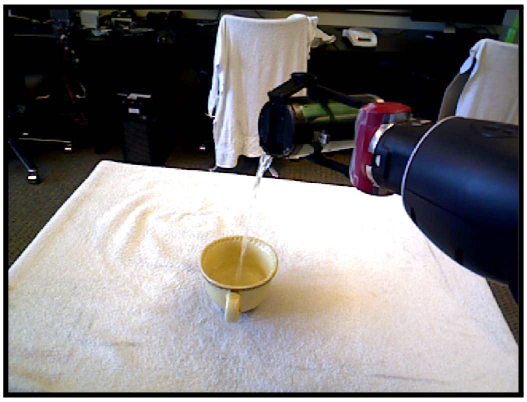


(a) Geometric parameters of the containers (b) Rectangular container geometry

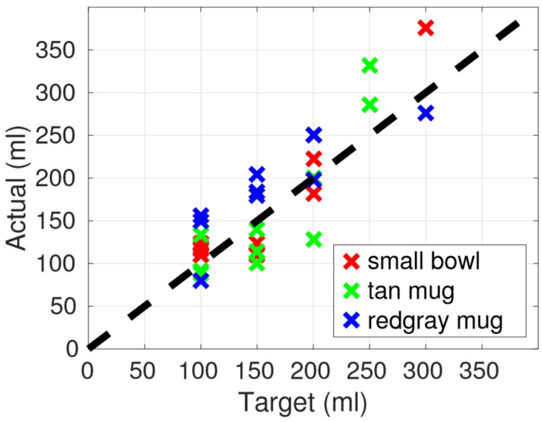
Figure 1.2: **Container geometry for a pouring model [14]**

1.1.3 Vision-based Pouring Motions

To enable home robots to pour, a pouring method imitating humans has been tried out. Sugita *et al.* [15,16] proposed an outflow rate model based on a cylindrical approximated container and visual feedback to pour into an accurate position in a container. Yamaguchi *et al.* [17] explored a stereo vision system for recognizing liquid outflow as 3D points (a point cloud). Schenck *et al.* [18] proposed a model-free method based on visual feedback using a recurrent neural network, which is currently the state of the art method in visual feedback pouring. In the vision-based algorithms, the vision system needs to extract the region of liquid during pouring or estimate the volume by measuring the height of liquid in the container from vision data. The issue with vision-based algorithms is that they are to be influenced by not only external information of materials and containers (e.g. the color and the shape) but also the illumination and occlusions in home environments.



(a) An input image for vision-based pouring



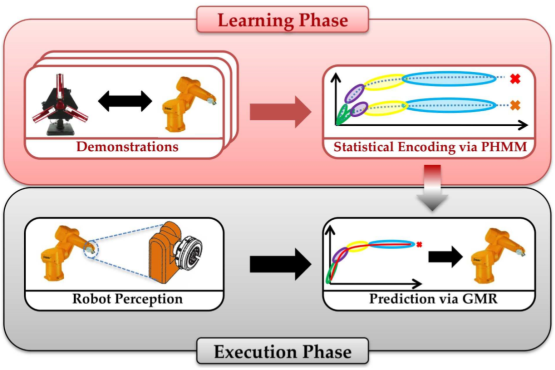
(b) Results of each pouring containers

Figure 1.3: **Input and results in a vision-based pouring motion [18]**

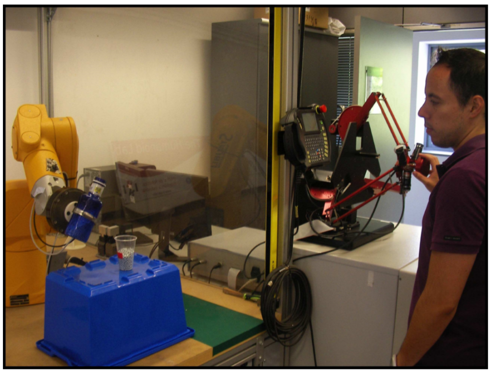
1.1.4 Pouring Motions by Skill Transfer from Humans

Yamaguchi *et al.* [19–21] modeled pouring skills observed from human demonstrations. The pouring model has several variations of the pouring motion such as tipping over, shaking and tapping. The pouring robot (PR2) was trained to select the appropriate pouring behavior using the pouring model with variations. Tamosiunaite *et al.* [22] proposed a learning method to obtain the parameters of dynamic movement primitives (DMP) from human demonstrations. Rozo *et al.* [23] use parametric hidden Markov models for training the robot. Human teleoperates a robot using a haptic device, and use the data from the demonstrations to allow to learn the motion. These pouring motions by skill transfer from humans enable robots to effectively learn a dextrous motion by passing the human skills to the robot.

Robots have more accurate sensing abilities than humans. There should be an optimum pouring motion with a robot using its sensing abilities. One of the sensing abilities is to be able to sense the weight with fingertip sensors. In this thesis, we consider the motion generation for pouring a specific amount of a material using the weight sensing.



(a) Teleoperation experiment of pouring task



(b) Previous proposed learning framework

Figure 1.4: **Force-based learning framework and the experiment [23]**

1.2 Motivation

This thesis focuses on constructing a basic tactile-based pouring motion inspired by a human pouring skill. To pour a specific amount of a material, the robot observes the mass of the grasped objects until a specific amount is reached. The mass of a grasped object is estimated from the robot fingertip force, and the weight is continuously observed during the pouring motion. The pouring amount is calculated from the estimated weight. Since the grasped objects handled during pouring motion are deformable objects involving the movement of the gravity center, we implement a tactile-based grasping strategy for such objects. The proposed method considers the deformation and the gravity center shift using tactile sensors on fingertips, and adjusts the grip force. Therefore, if the mass can be estimated while performing this grasping strategy, a tactile-based pouring motion can be realized.

The purpose of this thesis is to verify whether both a conventional tactile-based grasping strategy and the proposed tactile-based pouring motion generation are compatible. In experiments of pouring motions using the proposed robotic system, we evaluate the ability of the mass estimation method in terms of three material types.

1.3 Contributions

The main contributions of this thesis are:

1. The proposed tactile-based pouring motion is based on a human skill. Our robotic system uses only 3D force sensors on the fingers and estimate the mass of a grasped object.

2. The proposed mass estimation method uses the sensing data of the fingertip force in the direction of gravity. The estimation error was less than 50 g in all phases of the pouring motion, which are the initial state, outflow state, and end state.

1.4 Thesis Overview

The rest of this thesis is organized as follows:

Chapter 2 details the methods proposed in this thesis.

Chapter 3 describes the design and implementation of the proposed methods.

Chapter 4 describes the pouring experiments and results.

Chapter 5 discusses the tactile-based method by comparing with other research in order to consider future directions.

Chapter 6 concludes this thesis and discusses future works.

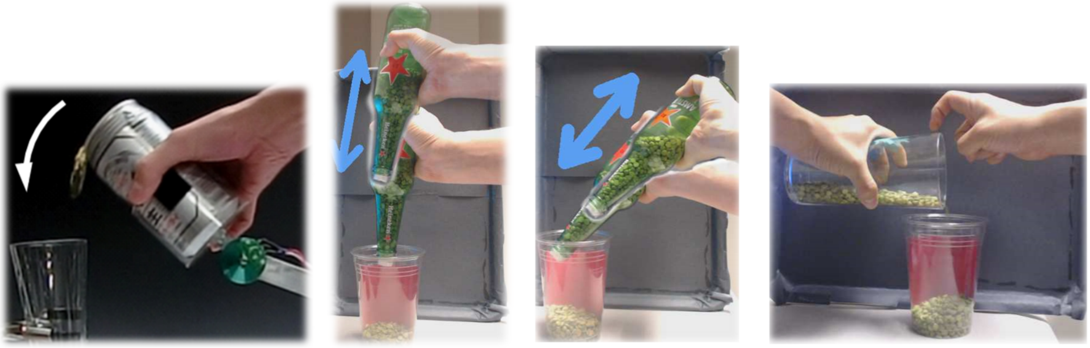
2 Methodology

Based on a pouring model by Yamaguchi *et al.* , we construct a basic tactile-based pouring motion. This chapter introduces the previous proposed pouring model based on human skills and explains some assumptions and the overview of the methodology of proposed pouring motion.

2.1 Human Skills of Pouring Motions

Yamaguchi *et al.* created a behavior model for a general pouring task with several variations: targets, material types, container shapes, initial poses of containers, and target amounts. The model is constructed based on skills from human demonstrations [21]. The human skills are divided into four types of pouring motions which are Tipping over, Shaking A, Shaking B, and Tapping. Combining these types of pouring motions, humans complete the motion for pouring a specific amount of material. Yamaguchi *et al.* modeled the compound pouring motion as finite state machines, as shown in Fig. 2.2. This thesis focuses the pouring motion by tipping over.

During pouring motion by tipping over, the edge point of the source container takes a constant position and only the tilting angle θ changes, as shown in Fig. 2.3. Also there are two types of the pouring motions by tipping over, depending on the forearm motions. Fig. 2.4 shows the two types which are the pouring motion by forearm pronation and by compound motion of ulnar flexion and forearm pronation.



(a) Tipping over [24] (b) Shaking A (c) Shaking B (d) Tapping

Figure 2.1: **Four types of pouring motions [21]**

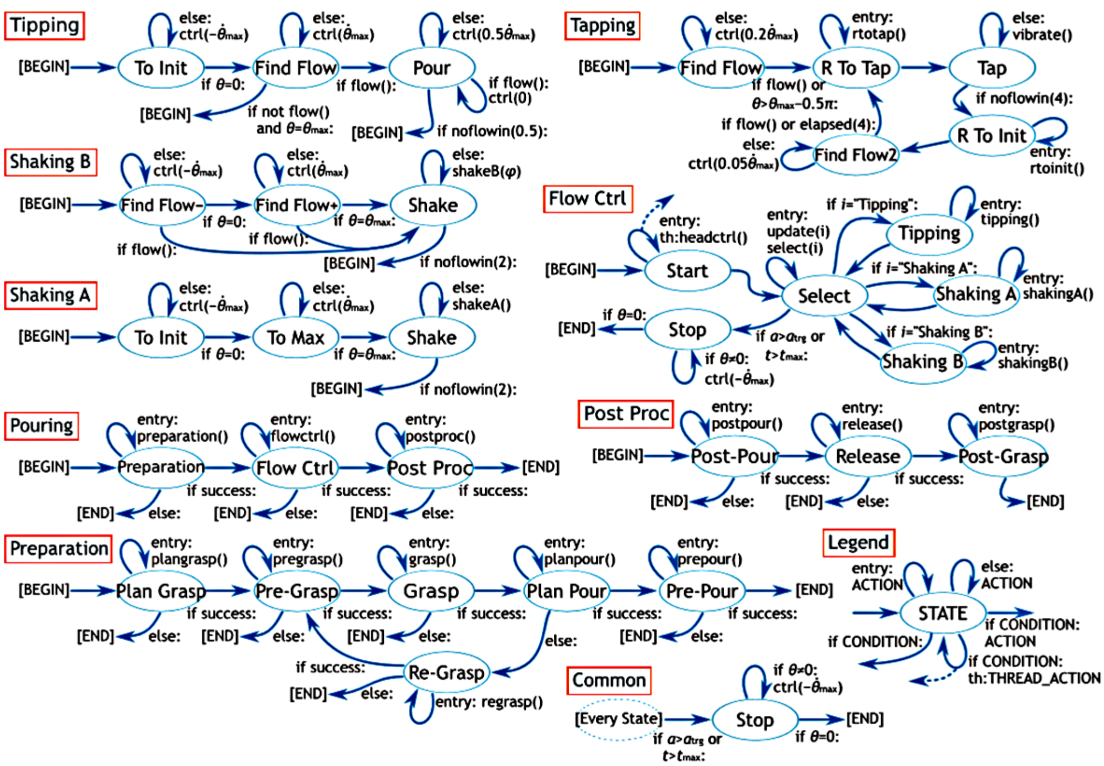


Figure 2.2: **Finite state machines for pouring tasks [21]**

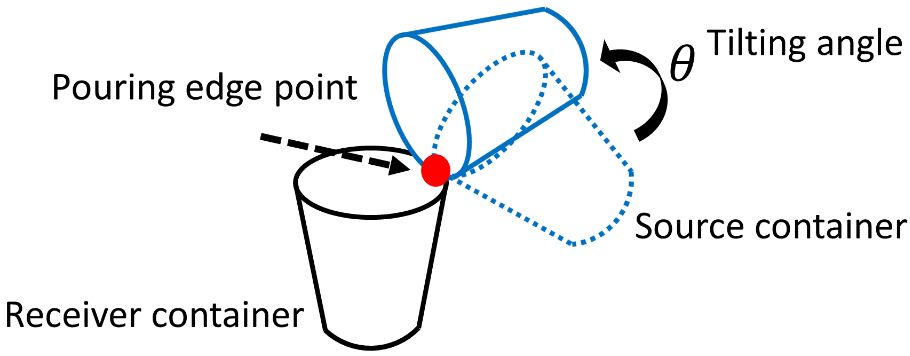


Figure 2.3: **Pouring motion by tipping over**

(a) Tipping over by pronation

(b) Tipping over by pronation and ulnar flexion

Figure 2.4: **Two types of pouring motions by tipping over**

The proposed pouring motion refers the finite state machine of pouring flow by tipping over derived from human demonstrations, as shown in Fig. 2.5. The To Init is a state when θ is not zero. $\theta = 0$ is defined as the initial pose, and θ should be less than θ_{max} where the source container is upside down. ctrl($\dot{\theta}$) means to control θ with its velocity $\dot{\theta}$. The Find Flow shows the state while robot detects the outflow. flow() becomes true if flow observed, noflowin(Δt) becomes true if no flow observed in Δt, and $\dot{\theta}_{max}$ is the maximum velocity of θ. The Pour means the state during pouring. The robots control the orientation of the source container.

We consider the robot pouring motion by tipping over from pronation which is not a compound motion.

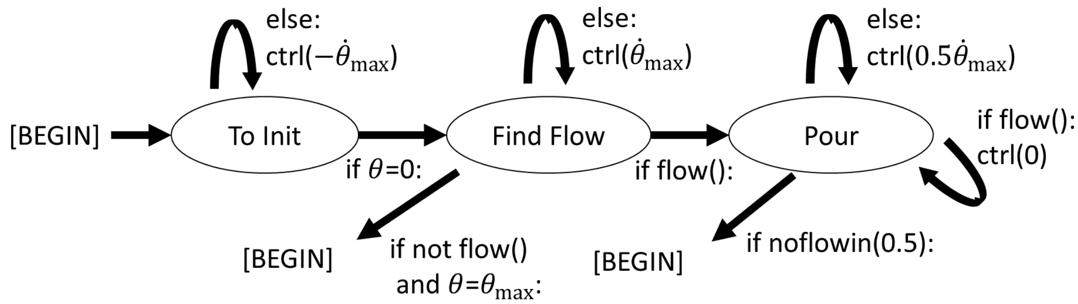


Figure 2.5: **Finite state machine pouring motion by tipping over**

2.2 Assumptions

The initial assumptions for the experiments are:

- One hand is used.
- Each container is already opened (if it has a lid or top).
- A container model is given, where each model consists of a cylinder for a graspable part and a circle for the mouth. Currently, labels of container types and material types are given. Future work will obtain these from tactile information.
- The initial poses of the containers (target and source) are given.
- The robot can acquire the weight of each source container and the density of each material.

In this thesis, we confirm the feasibility of compatibility between tactile-based grasping strategy and tactile-based mass estimation. The cooperative operation of the dual arms and the opening and closing manipulation of the container lid are not considered in this thesis. Since we also do not explore the estimation problem of unknown parameters such as object shape and pose, we assume the above items.

2.3 Overview of the Proposed Pouring Motion

In this section, we first explain the overview of our approach to let the robot pour a specific amount of material. The pouring robot needs to equip with the grasping strategy and the pouring motion, for pouring any materials and for grasping any containers. Fig. 2.6 shows the processing flowchart for proposed pouring robot, which is divided into two components, the pouring motion (Fig. 2.6 blue part) and the grasping strategy (Fig. 2.6 red part) based on tactile information. The flowchart is constructed based on the finite state machine of tipping over by Yamaguchi *et al.* as shown in Fig. 2.5.

We use a grasping strategy by Kaboli *et al.* [9], as shown in Chap. 3. To allow the robot to pour the specific amount of a material, the robot estimates the mass of the material in the container and detects material outflow. If the outflow is detected or the target amount is reached, the robot regulates the wrist angle of the arm. In this thesis, we do not discuss the outflow detection and the angle regulation method. The mass estimation verified in this thesis is described in the next section.

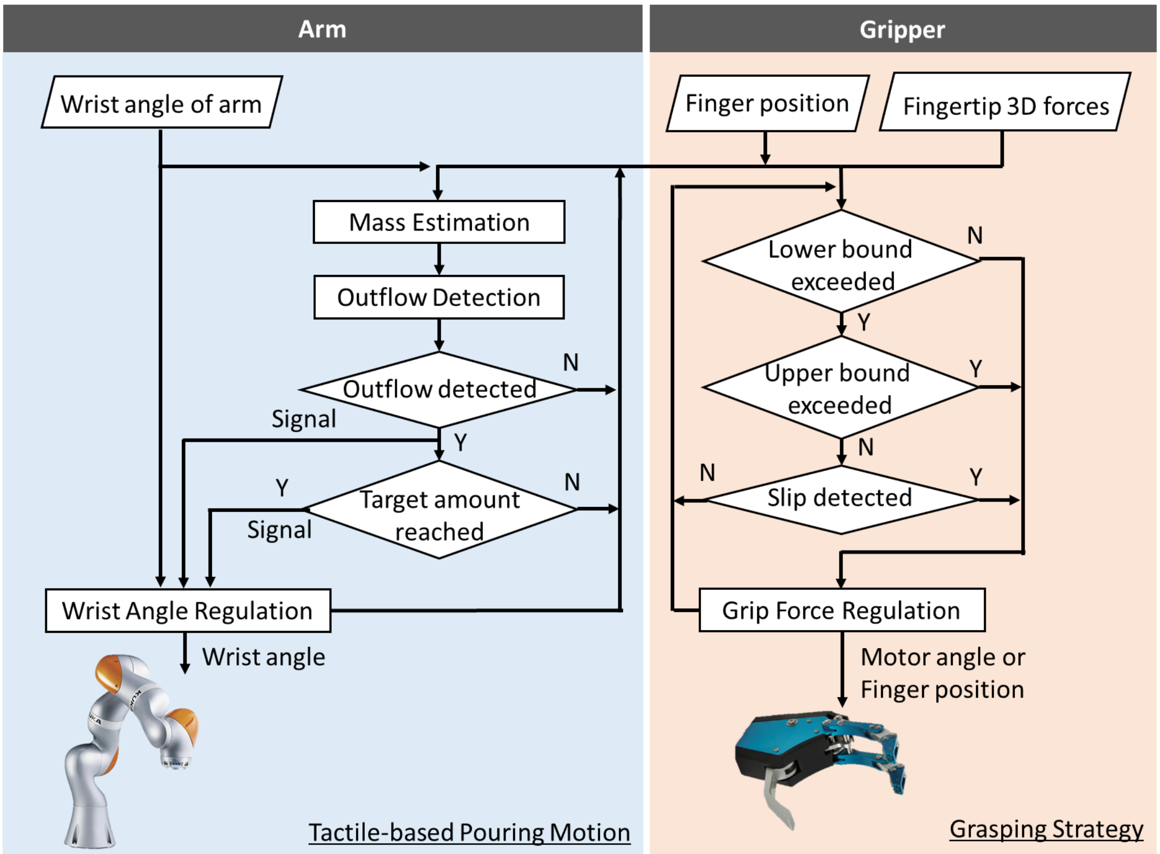


Figure 2.6: **Flowchart of proposed tactile-based pouring motion**

2.4 Tactile-based Mass Estimation

The proposed method estimates the mass of the material using the mass of the container. Based on static state of contact point without slip, we calculate the sum of the fingertip forces in the vertical direction. By balance of forces in the vertical axis direction, the sum value shows the weight of the grasped object as shown in Fig. 2.7 (when the robotic hand has three fingers). The A, B, C denote the finger index and g is the acceleration of gravity.

The m^{obj} is calculated as

$$m^{obj} = \frac{w^{obj}}{g}, \quad w^{obj} = |\sum_{i}^{n} \boldsymbol{f}_{z_i}|, \tag{2.1}$$

where i represents an index of fingers and g is gravitational acceleration. The estimated mass $\tilde{m}^{obj}$ can be described as

$$\tilde{m}^{obj} = am^{obj} + b, \tag{2.2}$$

where a and b are the regression coefficient and intercept.

These parameters are identified in a preliminary experiment. Finally, using the mass of the source container m^{sc} as a known parameter, the estimated material mass $\tilde{m}^{mat}$ can be expressed as

$$\tilde{m}^{mat} = \tilde{m}^{obj} - m^{sc}. \tag{2.3}$$

We estimate the mass of material to confirm whether or not the target amount has been reached.

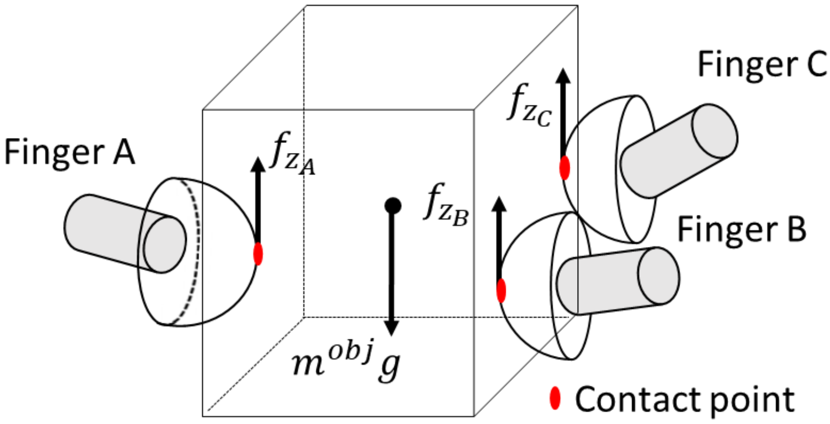
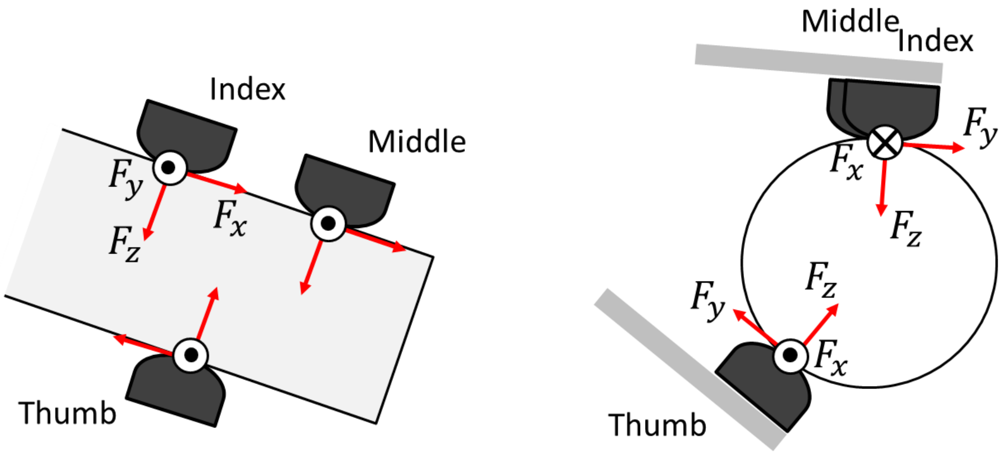


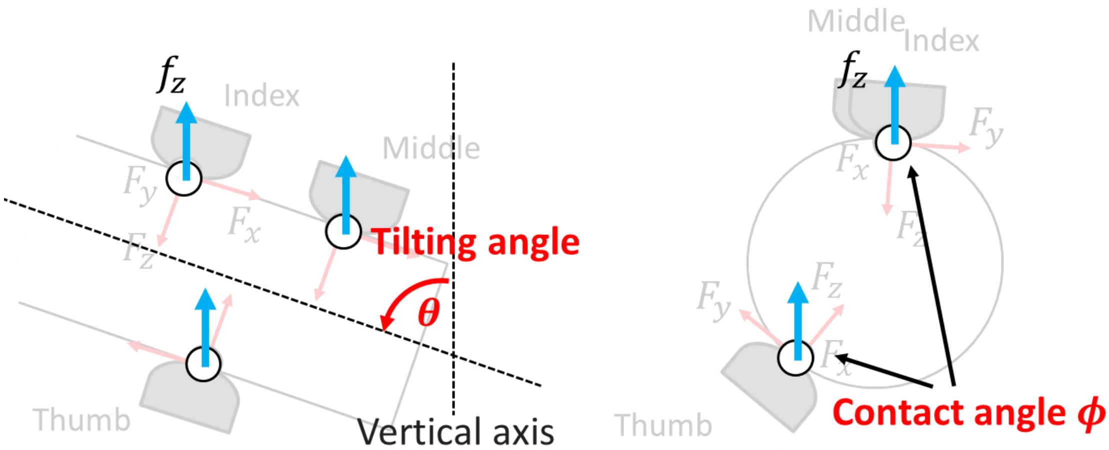
Figure 2.7: **Fingertip forces in the vertical direction at contact points**

To obtain the weight of the grasped object by weight, f_{z_i} are calculated. The f_{z_i} are geometrically calculated by using the fingertip force measurement value in consideration of the pose of the coordinate system existing on the fingertip contact point. Fig. 2.8 shows the positional relation between each fingertip coordinate system when the robot hand has three fingers. F_x, F_y, and F_z mean the axes on the fingertip coordinate system. Fig. 2.9 shows the parameters for calculating f_z on each fingertip coordinate system.



(a) Illustration seen from fingertip side (b) Illustration seen from container spout side

Figure 2.8: **Positional relation between each fingertip coordinate system**



(a) Illustration seen from fingertip side (b) Illustration seen from container spout side

Figure 2.9: **Geometric parameters for calculating f_z on each fingertip**

3 Design and Implementation

This chapter provides a brief explanation of our design and implementation of tactile manipulation system needed to evaluate the proposed method. Sec. 3.1 describes our hardware system. Sec. 3.2 and Sec. 3.3 detail the pouring motion by our robotic arm and a grasping strategy used for our robotic hand, respectively.

3.1 System Overview and Specifications

Fig. 3.1 and Fig. 3.2 show the overview of our robotic system and the structure components for the robotic system. (a) shows an LBR iiwa 14 R820, a 7-DoF manipulator by KUKA. (b) is a TRX-S, a 3-finger 1-DoF robotic hand by THK CO., LTD. (c) shows the 3D optical force sensor configured as shown in Fig. 3.1.

Inside the force sensor, photodiodes are measuring the amount of reflected light, originally emitted by the LED. By comparing the measured values on the photodiodes, the acting forces can be precisely reconstructed and not just the magnitude, but also the direction [25]. Tab. 3.1, Tab. 3.2 and Tab. 3.3 show the mechanical specifications of (a), (b) and (c) respectively. To realize the pouring motion incorporating human skills, we use the LBR iiwa which has the same degrees of freedom as a human arm. We adopted a compact, lightweight TRX-S with a three finger structure widely used in the research field. Further, since the robotic hand has a mechanism with one degree of freedom using a stepping motor, it is easy to control with a high positioning accuracy. We adopted the OptoForce sensor that can acquire data at high speed (up to 1 kHz). The tactile force sensor has a compact size, it can be easily mounted on the fingertip, and it is dustproof and waterproof (the sensor conforms to IP65 of IEC-standards).

The overview of the software system configuration is shown in Fig. 3.3. The details of the software system are described in following sections.

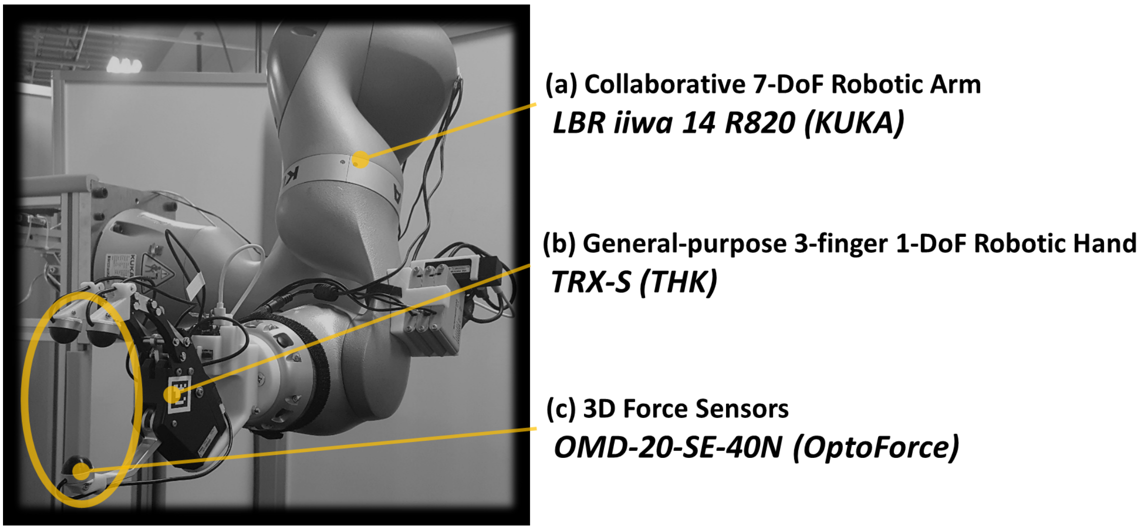
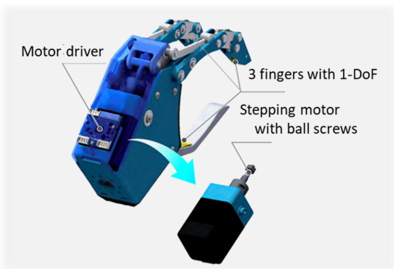
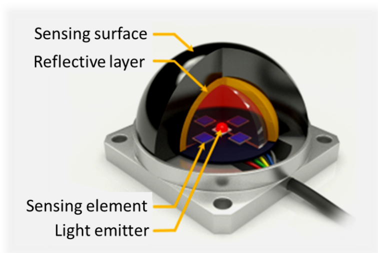


Figure 3.1: **Proposed robotic system.** The system has three components, which are a robotic arm, a robotic hand and three fingertip force sensors. The robotic arm and the robotic hand are phisically connected by a 3D-printed jig on the flange of the robotic arm. The force sensors are attached to the fingertip of the robotic hand by a 3D-printed jig.

(a) LBR iiwa 14 R820 (KUKA)



(b) TRX-S (THK)



(c) OMD-20-SE-40N (OptoForce)

Figure 3.2: **Structure components of our robotic system**

Table 3.1: **Specifications of the robotic arm**

Specification	Value / Type
Model	LBR iiwa 14 R820
Number of controlled axes	7
Volume of working envelope	1.8 m^3
Pose repeatability	0.1 mm
Weight	approx. 29.9 kg
Related payload	14 kg
Maximum reach	820 mm

Table 3.2: **Specifications of the robotic hand**

Specification	Value / Type
Model	TRX-S
Fingertip force	10 N
Grasping force	30 N
Load capacity	3 kg
Weight	320 g
Grasping diameter	10 - 100 mm
Actuator	Stepping motor with ball screw

Table 3.3: **Specifications of the force sensor**

Specification	Value / Type
Model	OMD-20-SE-40N
Nominal capacity	(f_z): 40 N (f_x, f_y): $\pm$ 20 N
Typical deformation	(f_z): 2 mm (f_x, f_y): 1.5 mm
Dimensions (h× w× l)	17×25×25 mm^3
Weight (with 1 m cable)	23 g
Maximum sampling frequency	1000 Hz

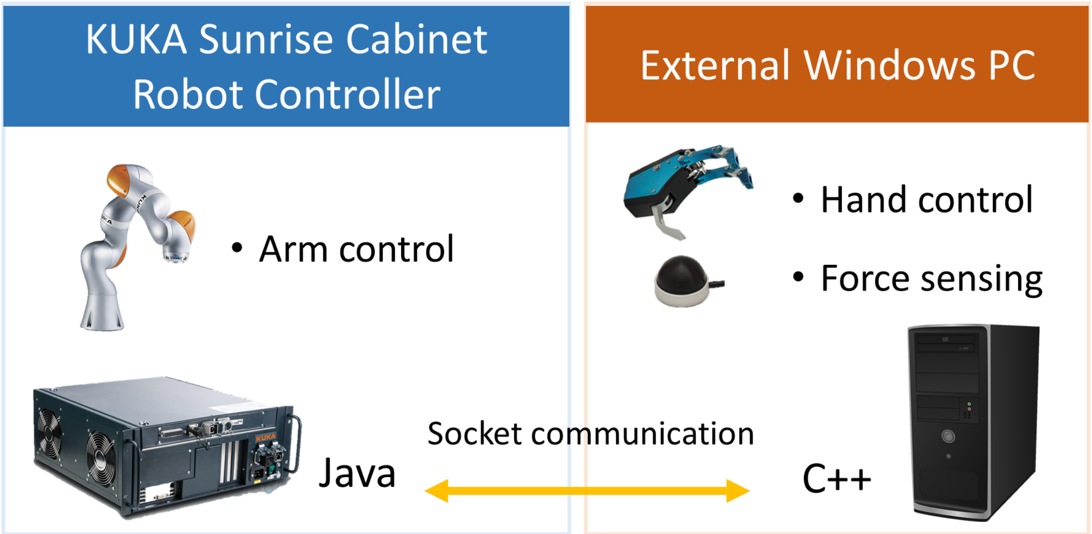


Figure 3.3: **Overview of the software system configuration**

3.2 Tactile-based Pouring Motion

We implemented the tactile-based pouring motion following the pouring model by tipping over by Yamaguchi *et al.* . We developed all the programs of robot arm motions using KUKA Sunrise Workbench and Sunrise Serving. The software enables us to easily create the applications using motion classes. Using the motion classes, we can generate axis-specific motions and can set Cartesian end points. The robot moves to the points with set velocity, acceleration or jerk.

We control the robotic arm motion and obtain the wrist angle of the robotic arm by Java code on the KUKA Sunrise Cabinet robot controller We control the robotic hand and obtain the force sensing data by C++ code on Windows PC with Intel Core i5. The force sensing data is processed on the Windows PC, then the derived command values for the robotic arm are sent to the KUKA Sunrise Cabinet robot controller.

3.3 Grasping Strategy

During pouring motions, the center of mass of the grasped object is moving and the object has possibility to deform the shape. We implement the grasping strategy robust to the deformation and CoM changes of the object [9]. We rearrange the strategy by 3-finger with 3-DoF for implementing in our 1-DoF robotic hand system. Fig. 2.6 (right) shows the basic flow of the reconstructed algorithm from the conventional strategy. We identify the parameters based on [9]. The entire algorithm of grasping strategy including the identification part is described in Algorithm 1. $\boldsymbol{f}_{N_i}$ and $\boldsymbol{f}_{T_i}$ mean the normal and tangential force vectors at the contact points of the 3 fingers. The subscript i denotes the index of finger ($i = A, B, C$). P_i is the corresponding position. f_{N_ϵ} is lower bound for the normal forces and is set in the range of 0.2 N $\leq f_{N_\epsilon} \leq$ 0.5 N, according to grasping object' s stiffness. $\bar{f}_N$ is upper bound for the normal forces set to 2 N $\leq \bar{f}_N \leq$ 5 N in order to reduce local deformation, according to each target object's stiffness. δ is the detection threshold for change ratio of the tangential force within short time period Δt. The friction coefficient μ_i is estimated when the first slip is detected. The ratio of the tangential force norm $|\boldsymbol{f}_T|$ to the normal force norm $|\boldsymbol{f}_N|$ are calculated as an estimated friction coefficient μ_i on the corresponding contact point.

The motion of TRX-S hand can be controlled pulse signal to stepping motor or the command value of finger position with set speed. Then, the hand motion is controlled by C++ code on the Windows PC and send the command values outputted from the grip force regulation by serial communication via USB.

Algorithm 1 Identification and Grip Force Regulation

1: **procedure** IDENTIFICATION
2:     initialize the robotic system
3:     **while** $\exists i : |\boldsymbol{f}_{N_i}| \leq f_{N_\epsilon}$ **do**
4:         $P \leftarrow P + 1$
5:     *slip_happens* $\leftarrow$ **False**
6:     starts lifting up objects
7:     **repeat** $|\Delta \boldsymbol{f}_{T_i}| \leftarrow |\boldsymbol{f}_{T_i}(t)| - |\boldsymbol{f}_{T_i}(t - \Delta t)|, \ \forall i$
8:         **if** $\exists i : |\Delta \boldsymbol{f}_{T_i}| \geq \delta$ **then**
9:             *slip_happens* $\leftarrow$ **True**
10:             **goto** 16
11:     **until** object is lifted up
12:     **if** not *slip_happens* **then**
13:         **repeat** $P \leftarrow P - 1, \ \forall i$
14:             $|\Delta \boldsymbol{f}_{T_i}| \leftarrow |\boldsymbol{f}_{T_i}(t)| - |\boldsymbol{f}_{T_i}(t - \Delta t)|, \ \forall i$
15:         **until** $\exists i : |\Delta \boldsymbol{f}_{T_i}| \geq \delta$
16:     $\mu_i \leftarrow |\boldsymbol{f}_{T_i}| / |\boldsymbol{f}_{N_i}|, \ \forall i$
17:     $|W| \leftarrow |\Sigma_i \boldsymbol{f}_{z_i}|$
18:     $P \leftarrow P + 1, \ \forall i$
19: **procedure** GRIPPER CONTROLER
20:     **while** True **do**
21:         **if** $\exists i : |\boldsymbol{f}_{N_i}| \leq f_{N_\epsilon}$ **then**
22:             $P \leftarrow P + 1$
23:         **else**
24:             **if** $\exists i : |\boldsymbol{f}_{N_i}| \geq \bar{f}_N$ **then**
25:                 $P \leftarrow P - 1$
26:             **else**
27:                 **if** $|\boldsymbol{f}_{T_i}| / |\boldsymbol{f}_{N_i}| \geq \mu_i$ **then**
28:                     $P \leftarrow P + 1$

4 Experiments

This chapter details experiments for confirming the mass estimation is possible while performing tactile-based grasping. We implement a certain pouring motion by our robotic system and estimate mass in each state of the initial state before pouring, the state of pouring (outflow state) and the pouring end state (pored state). We obtaine the true value obtained by a mass meter and a force plate and calculate the estimation error to verify whether mass estimation during grasping is possible.

4.1 Identification for TRX-S hand motion

Before mass estimation experiment, we conduct an identification experiment by TRX-S opening / closing motion. This is to identify the relation between the contact angle in Fig. 2.9 and the hand position pulse. By using the identified model, the contact angle can be determined from the hand position pulse during pouring motion, and the f_z can be calculated at that time.

Identification Experiment

Fig. 4.1 shows the experimental setup for the identification of TRX-S hand motion. We use an RGB camera and three visual markers to obtain the pose of the fingertips on both the thumb side and the index side. Attaching different visual markers near the thumb and index finger and mount so that one side of the square visual marker is parallel to the bottom surface of the OptoFotce sensor. The hand position pulse increases with every 100 pulses from 0 to 4400 pulses and detects the visual markers at each hand position. The zero pulse means the fully open state of the hand and the 4400 pulses is defined as the fully close state. From the detected orientation of the visual marker, we calculate the inclination angle from the horizontal axis of the F_z axis on the fingertip coordinate system of the OptoForce sensor.

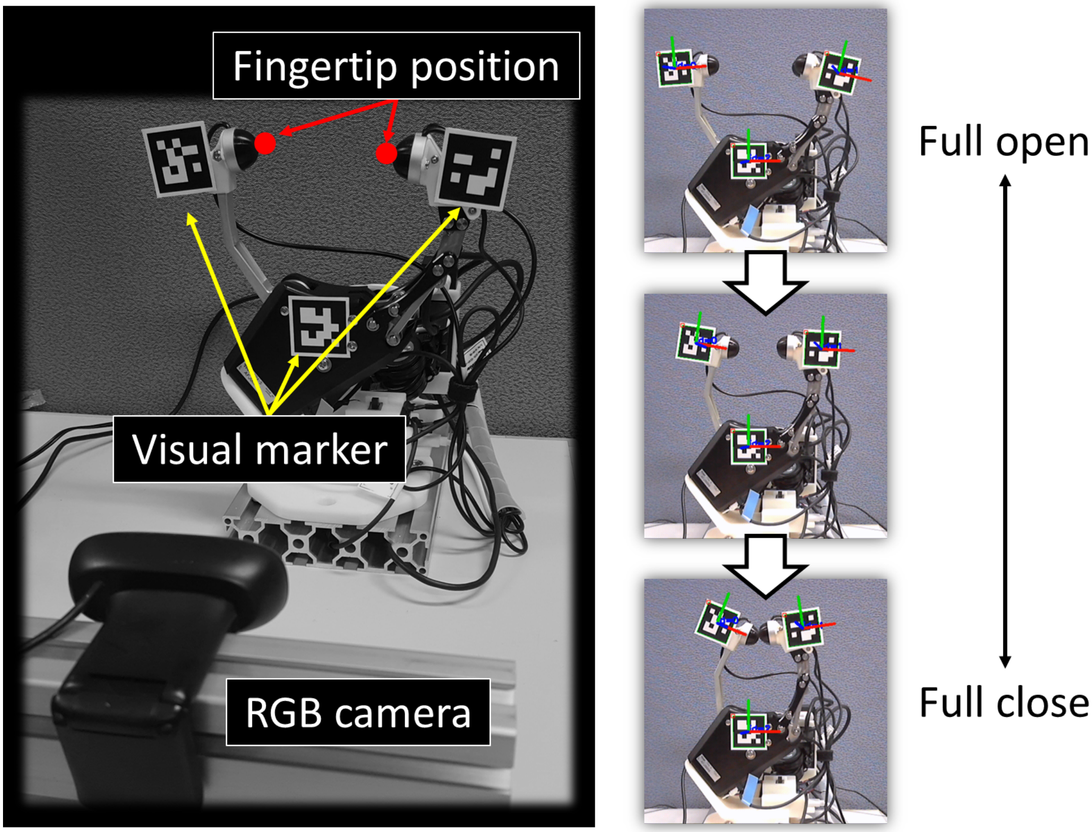


Figure 4.1: **Experimental setup for TRX-S hand motion identification.** In the experiment, the relation between the hand position pulse and the fingertip pose (red circle) are identified.

Identification Result

Fig. 4.2 shows the measured values that relate the contact angle ([deg]) in Fig. 2.9 and the hand position pulses ([pulse]) in the identification experiment. The identified single regression models for the three fingers are shown as follows:

$$\tilde{\phi}^{thumb} = -0.0064 \times P^{thumb} + 5.73, \tag{4.1}$$

$$\tilde{\phi}^{index,middle} = 0.00527 \times P^{index,middle} - 14.44. \tag{4.2}$$

We use the identification parameters on the index finger side also for the model of middle finger. The single regression of the thumb motion yielded a determination coefficient of 0.998. The single regression of the index and middle motion yielded a determination coefficient of 0.997.

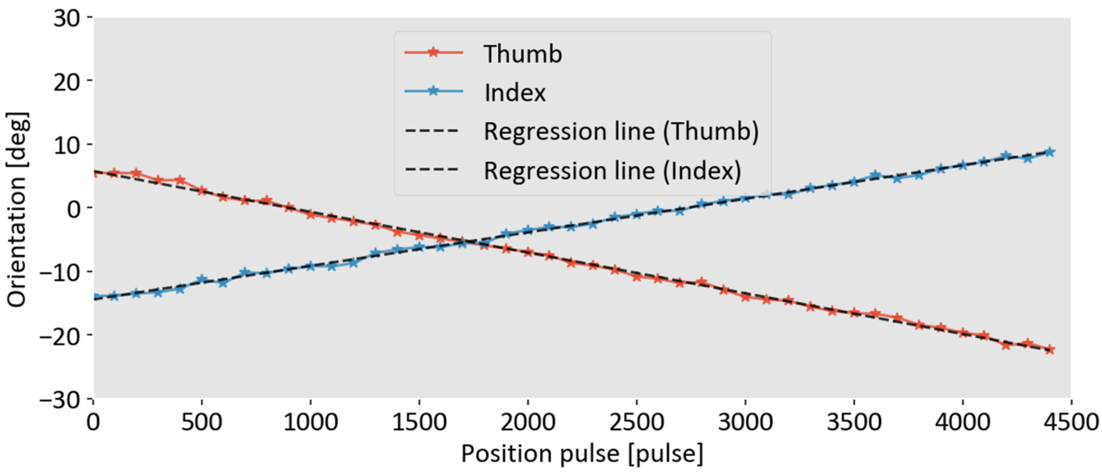


Figure 4.2: **Result of the identification experiment.** This graph shows the relation between the orientation of fingertips and hand position pulse. The two lines show two relations on both the thumb side and index side.

4.2 Tactile-based Mass Estimation

This section describes mass estimation experiment during pouring motions and the calibration of fingertip force sensors. Calibration is required to estimate the mass using OptoForce sensors on the fingertips, beforehand.

Calibration of The Fingertip Force Sensors

The proposed pouring motion needs to estimate the material mass in the container during pouring. We first identify a regression model to estimate the mass of the grasped object from the fingertip force sensors. In this experiment, the robot grasps and lifts up objects with known mass. The experimental scenario of lifting up motion for the calibration is shown in Fig. 4.3. We conduct three trials for three different weights of a material, 100 g, 200 g, 250 g, and 300 g. The actual mass of the grasped object includes 76 g of the container mass.

Calibration Results

Fig. 4.4 shows the calculated weight using this equation, $w^{obj} = |\sum_i^n \boldsymbol{f}_{z_i}|$. Fig. 4.5 shows the results of the mass estimation. As a result of this experiment, a regression model for the mass estimation was identified as below

$$\tilde{m}^{obj} = 1.22 \times \frac{w^{obj}}{g} + 9.25. \tag{4.3}$$

The coefficient of determination of this regression model is 0.998. The number on the bar graph is the mass estimation error. The estimation error of all the weights is less than 3 g.

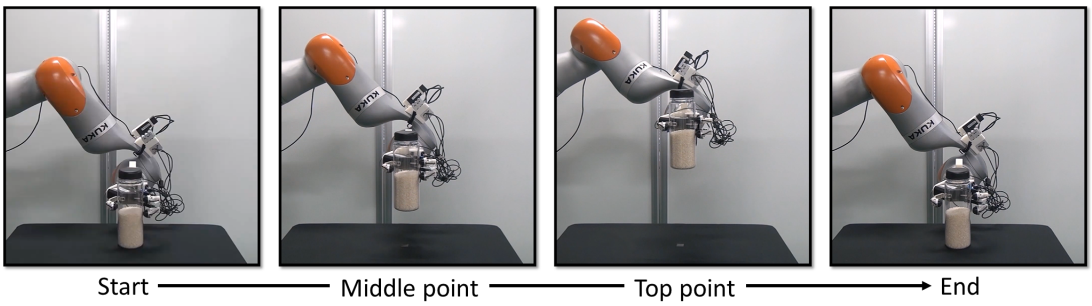


Figure 4.3: **lifting up motion for calibration of fingertip force sensors**

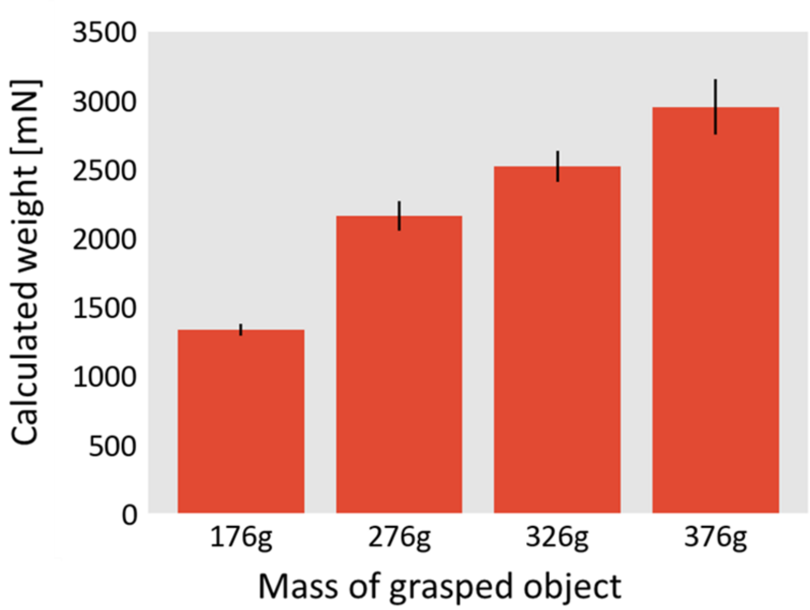


Figure 4.4: Calculated weight from fingertip forces

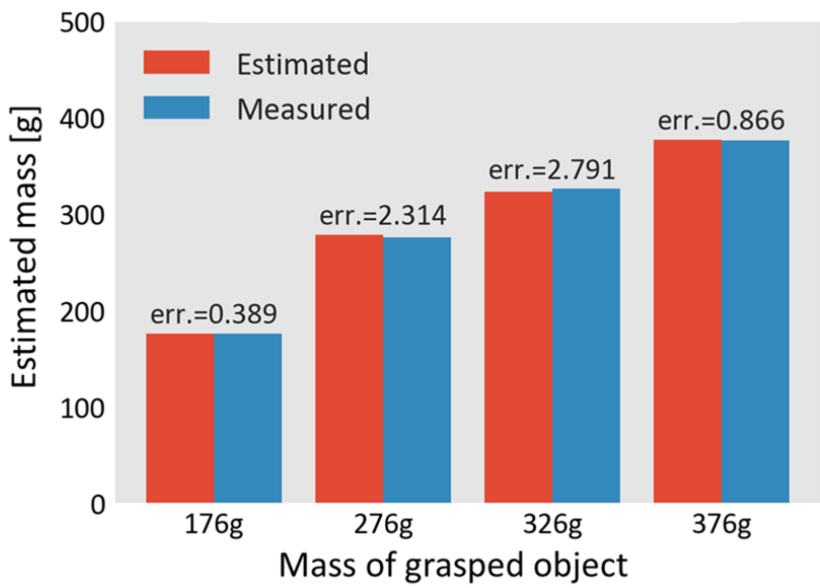


Figure 4.5: Mass estimation result

Pouring Experiments

We use the monochrome camera (Fig. 4.7 lower left) to capture the pouring motions, and use the force plate (Fig. 4.7 upper left) to measure the mass of the material during pouring motions. The specifications of the camera and the force plate are summarized in Tab. 4.2 and Tab. 4.3, respectively. We let the robot pour three materials with diffenrent grain size (Fig. 4.6) into the receiver contianer from the source container of a rigid bottle. The rigid bottle is 60 grams without the cap. The initials amounts for each material are set as shown in Tab. 4.1. In the experiment, the robot pours the material in the source container by a certain motion. Fig. 4.8 shows the snapshot images of the pouring motion obtained from the monochrome camera. The visual markers are used for validation of joint angles and the hand position obtained from robotic internal sensors.

The robot first grasps the container with the material and lifts up the object. Then, the robotic hand moves to starting position to pour. The robot pours the material with a constant rotating velocity v =8 deg/s, as shown in Fig. 2.3. To synchronize the force plate, the camera, and the robotic motion, we use a hammer with a visual marker and hit the force plate while capturing the motions, as shown in Fig. 4.9. All the data are synchronized at the time when the hammer hits the force plate. We analyze the synchronized measurement data to evaluate the mass estimation.

(a) Red beans (b) Rice grains (c) Coffee powder

Figure 4.6: **Materials for pouring**

Table 4.1: Materials for pouring

Symbol	Material	Grain size	Initial amount
(a)	Red beans	Large	200 g
(b)	Rice grains	Middle	200 g
(d)	Coffee powder	Small	100 g

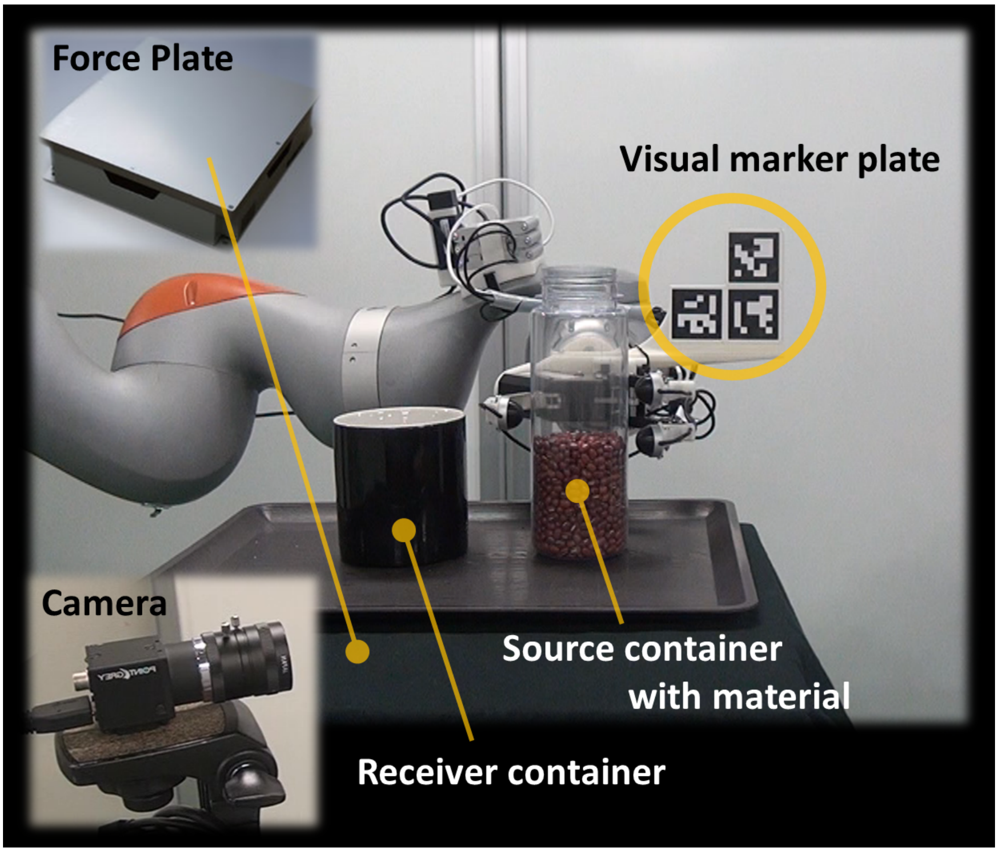


Figure 4.7: **Experimental setup for pouring materials.** In the pouring experiment, the robot pour the materials by tipping over and grasp the container using the Algorithm 1

Table 4.2: Specifications of the monochrome camera

Specification	Value / Type
Model	FL3-U3-13Y3M-C
Resolution	1.3 Mega pixels
Electronic shutter	0.006 ms - 1 s
Pixels (H x V)	1280 x 1024
Frame Rate	150 fps

Table 4.3: Specifications of the force plate

Specification	Value / Type
Model	SS-FP40AO-SY
Dimensions (h× w× l)	$110 \times 400 \times 400$ mm^3
Rated payload	(f_x, f_y): ± 2500 N (f_z): + 5000 N (M_x, M_y, M_z): ± 500 Nm
Resolution	(f_x, f_y, f_z): 0.305 N (M_x, M_y, M_z): 0.0305 Nm
Data update frequency with USB	1000 Hz (Maximum)

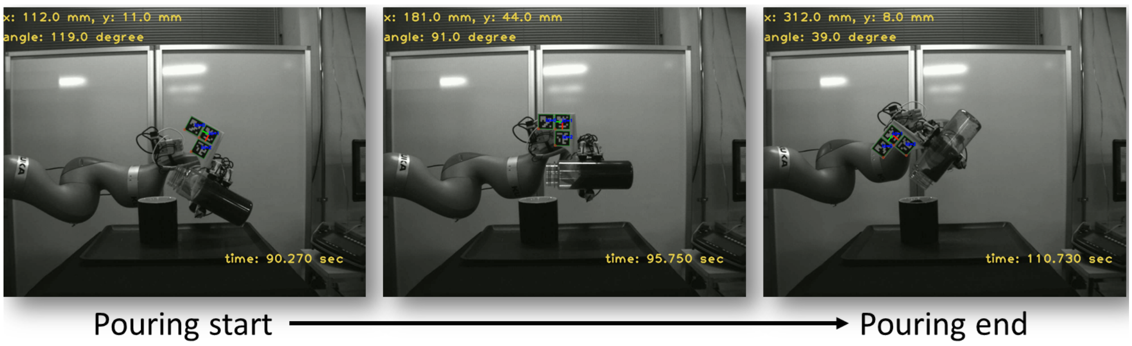


Figure 4.8: **Snapshots of the pouring experiment**

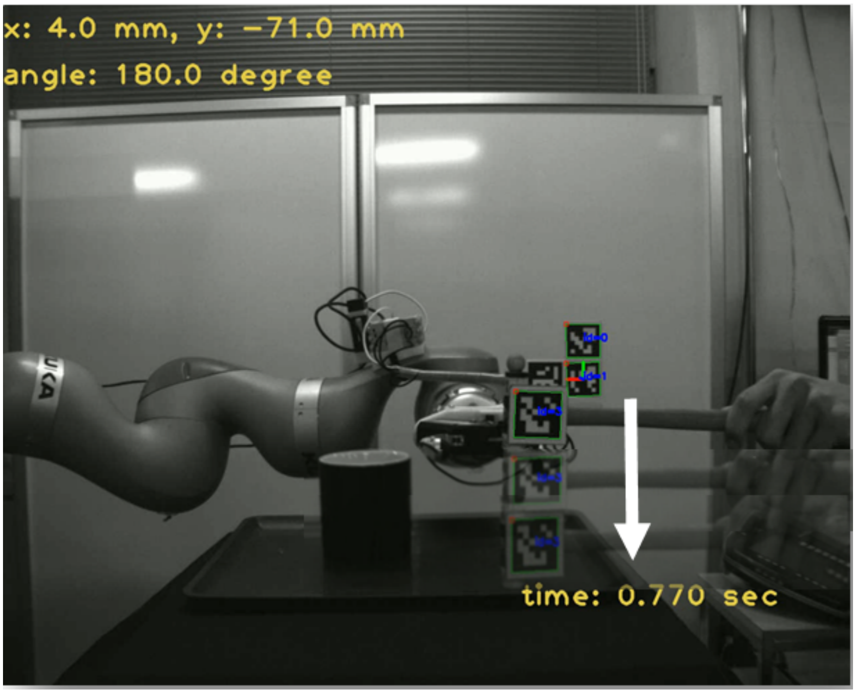


Figure 4.9: Action for synchronization

5 Results

5.1 Tactile-based Mass Estimation

We evaluate the estimation accuracy of tactile-based mass estimation method during the proposed pouring motion. Fig. 5.1, Fig. 5.2, and Fig. 5.3 show data measured from fingertip force sensors and the force plate, and the moving average of the fingertip force sensing data of each material. The Force sensors on the graph shows the mass calculated from fingertip force sensors using the Eq. (2.1). The Moving average is obtained by smoothening the data of Force sensors which is the raw signal acquired at 1000 Hz. As the smoothening method, 1000 points moving average is used. The Force plate is the mass measured by the force plate and is calculated by dividing the data of z-axis in the Force plate coordinate system by the gravitational acceleration. For the Force plate, 3000 points moving average was applied to raw signal of the force plate acquired at 1000 Hz. The measurement data is synchronized data from pouring start to pouring end of Fig. 4.8. In the graphs, three phases are drawn by gray, red, and blue. The phases are used for analysis of the mass estimation. The gray part means initial state before outflow starts. The red part means outflow state that the material is flowing out. The blue part means poured state after pouring end. The three phases are determined by using data measured from the force plate.

As a result, all the fingertip force sensing data shows the signal waveform like a sawtooth wave. The sawtooth wave is due to opening and closing motion of the robotic hand implementing the grasping strategy. However, the Moving average successfully represents the mass of the material during pouring motions.

As a final result, the mass estimation error in each phase is shown in Fig. 5.4. The graph shows an estimation error of less than 50 g in all phases for all materials.

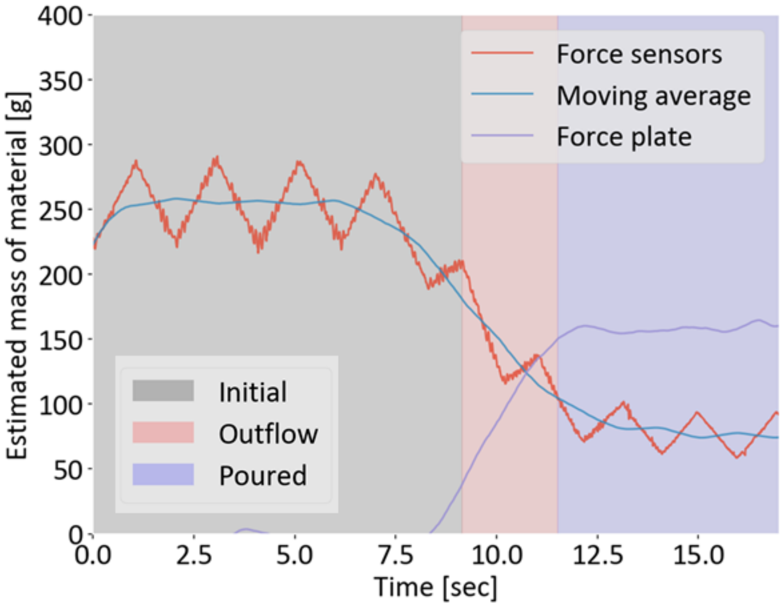


Figure 5.1: **Mass estimation result of red beans**

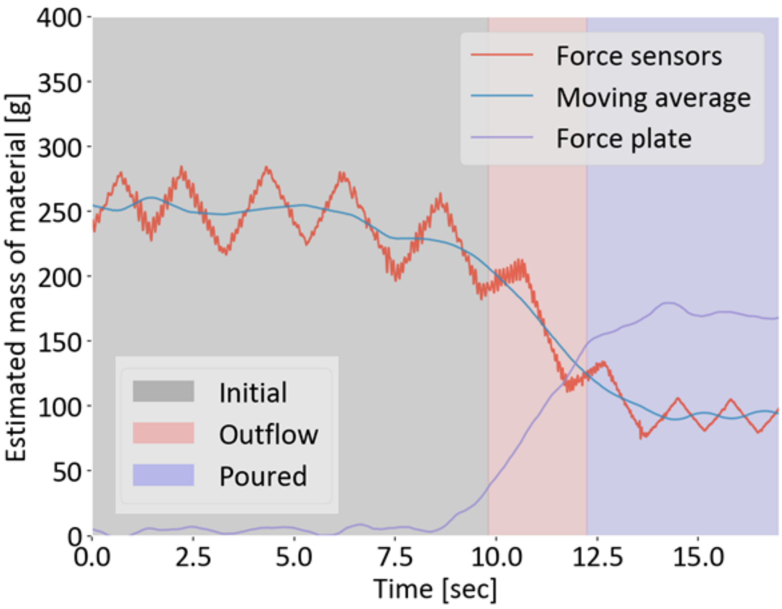


Figure 5.2: **Mass estimation result of rice grains**

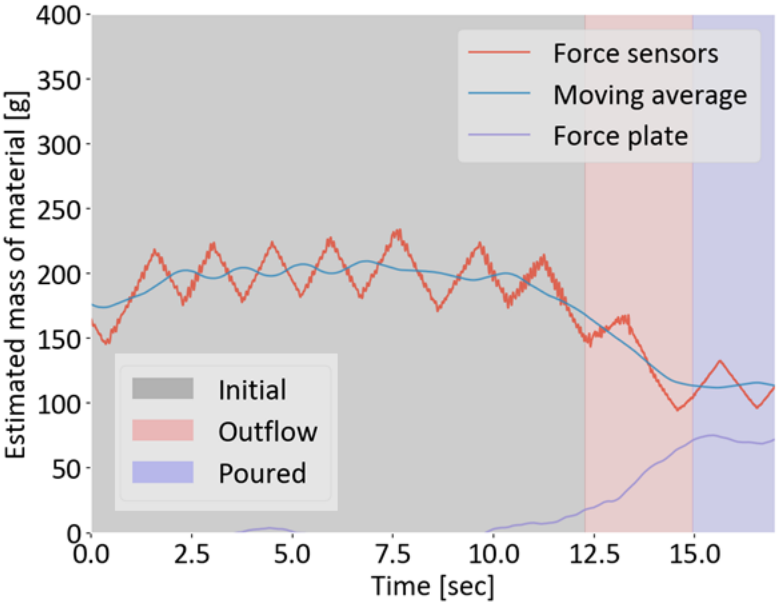


Figure 5.3: **Mass estimation result of coffee powder**

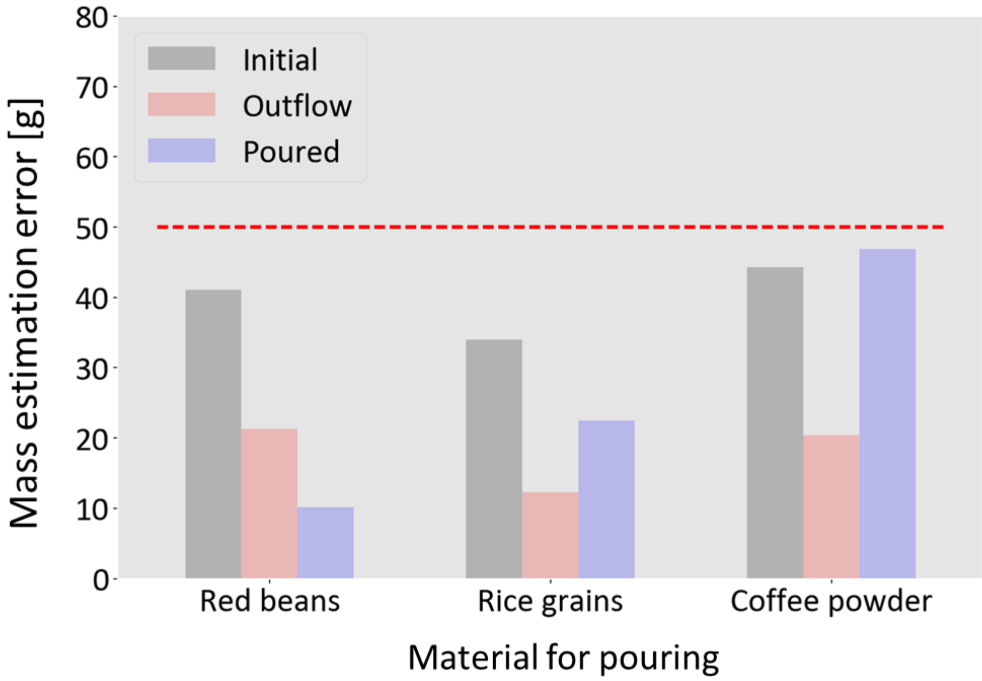


Figure 5.4: **Mass estimation error of all the materials**

6 Conclusions

6.1 Summary

We proposed a tactile-based pouring motion using 3D force sensors. The proposed pouring motion is without depending on the surrounding environments such as illumination and occlusions. To pour a specific amount of a material based on the tactile feedback, we proposed a mass estimation method using 3D forces of three fingertips. The estimation error is less than 50 g. The results suggest that there is a possibility that it can be poured with the precision equal to or higher than the best value of pouring amount by vision-based pouring motion.

6.2 Future Work

We will verify the proposed tactile-based mass estimation to pour a specific amount of materials and conduct pouring experiment giving the target amount of the material to the robot. We will also try to construct the tactile-based pouring strategy by implementing other pouring skills such as shaking and tapping to apply to other variations of containers, materials.

For the pouring motion of deformable objects such as materials in pouch containers, the robot lets two arms coorperative actions and realizes a grasping and a pouring motion that do not fall it down even if the shape deformation occured.

Regarding the pouring to the target position of the receiver container, the visual feedback is realistic at present.

Acknowledgements

First, I am deeply grateful to Professor Tsukasa Ogasawara, Professor Kenji Sugimoto, Associate Professor Jun Takamatsu, Assistant Professor Gustavo Alfonso Garcia Ricardez, and Assistant Professor Ming Ding as well as the readers of this thesis, and I am gratefully indebted for their very valuable comments on this thesis. I would also like to acknowledge my colleagues and all members in the Robotics laboratory, who have encouraged me.

Finally, I must express my very profound gratitude to my parents for their understanding and support during my years of study.

References

[1] Ravinder S. Dahiya, Giorgio Metta, Maurizio Valle and Giulio Sandini: "Tactile Sensing From Humans to Humanoids," *IEEE Transactions on Robotics*, vol. 26, no. 1, pp. 1-20, 2010.

[2] Huaping Liu, Yupei Wu, Fuchun Sun and Di Guo: "Recent progress on tactile object recognition," *International Journal of Advanced Robotic Systems*, vol. 14, no. 4, p. 1729881417717056, 2017.

[3] Felix von Drigalski, Marcus Gall, Sung-Gwi Cho, Ming Ding, Jun Takamatsu, Tsukasa Ogasawara and Tamim Asfour: "Textile Identification Using Fingertip Motion and 3D Force Sensors in an Open-Source Gripper," in *Proceedings of the 2017 IEEE International Conference on Robotics and Biomimetics (ROBIO 2017)*, pp. 424-429, 2017.

[4] Takamitsu Matsubara and Kotaro Shibata: "Active tactile exploration with uncertainty and travel cost for fast shape estimation of unknown objects," *Robotics and Autonomous Systems*, vol. 91, pp. 314-326, 2017.

[5] Kunpeng Yao, Mohsen Kaboli and Gordon Cheng: "Tactile-based Object Center of Mass Exploration and Discrimination," in *Proceedings of the 2017 IEEE-RAS International Conference on Humanoid Robots (Humanoids2017)*, pp. 876-881, 2017.

[6] Seiichi Teshigawara, Takahiro Tsutsumi, Yosuke Suzuki and Makoto Shimojo: "High Speed and High Sensitivity Slip Sensor for Dexterous Grasping," *Journal of Robotics and Mechatronics*, vol. 24, no. 2, pp. 298-299, 2012.

[7] Nawid Jamali and Claude Sammut: "Slip Prediction using Hidden Markov Models: Multidimensional Sensor Data to Symbolic Temporal Pattern

Learning," in *Proceedings of the 2012 IEEE International Conference on Robotics and Automation (ICRA2012)*, pp. 462-468, 2012.

[8] Yancheng Wang, Kailun Xi and Deqing Mei: "Slip Detection in Prosthetic Hand Grasping by using the Discrete Wavelet Transform Analysis," in *Proceedings of the 2016 IEEE International Conference on Advanced Intelligent Mechatronics (AIM2016)*, pp. 1485-1490. 2016.

[9] Mohsen Kaboli, Kunpeng Yao and Gordon Cheng: "Tactile-based Manipulation of Deformable Objects with Dynamic Center of Mass," in *Proceedings of the 2016 IEEE-RAS International Conference on Humanoid Robots (Humanoids2017)*, pp. 752-757, 2016.

[10] Yoshiyuki Noda and Kazuhiko Terashima: "Flow Rate Model for Tilting-Type Automatic Pouring System and Flow Rate Feedforward Control by using Inverse Model," *Transactions of the Japan Society of Mechanical Engineers Series C*, vol. 72, no. 722, pp. 3147-3154, 2006. (in Japanese).

[11] Yoshiyuki Noda, Kazuhiko Terashima, Makio Suzuki and Kunihiro Hashimoto: "Outflow Weight Sequence Control Realizing Automatic Pouring Robot with High-precision," *SICE Transactions on Industrial Application*, vol. 9, no. 14, pp. 98-107, 2010. (in Japanese).

[12] Atsushi Ito, Yoshiyuki Noda and Kazuhiko Terashima: "Outflow Liquid Falling Position Control by Considering Lower Ladle Position and Clash Avoidance with Mold," in *Proceedings of the 2012 IFAC Workshop on Automation in the Mining, Mineral and Metal Industries*, pp. 240-245, 2012.

[13] Yoshiyuki Noda, Ryusuke Fukushima and Kazuhiko Terashima: "Falling Position Control of Outflow Liquid from Ladle in Tilting-Ladle Type Automatic Pouring Machine," *Transactions of the Japan Society of Mechanical Engineers Series C*, vol. 78, no. 794, pp. 3446-3458, 2012. (in Japanese).

[14] Monroe Kennedy III, Kendall Queen, Dinesh Thakur, Kostas Daniilidis and Vijay Kumar: "Precise Dispensing of Liquids Using Visual Feedback," in *Proceedings of the 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS2017)*, pp. 1260-1266, 2017.

[15] Yusuke Sugita, Sakyo Matsushita, Takahiro Ozeki and Akio Namiki: "Pouring Motion of Liquid with Visual Feedback," in *Proceedings of the 2012 JSME Conference on Robotics and Mechatronics (ROBOMECH2012)*, 2A1-F02, 2012. (in Japanese).

[16] Yusuke Sugita, Humiyasu Takahashi and Akio Namiki: "Behavior Pouring Liquid considering Drop Position by Robot Arm using Vision Feedback," in *Proceedings of the 2014 JSME Conference on Robotics and Mechatronics (ROBOMECH2014)*, 1A1-N01, 2014. (in Japanese).

[17] Akihiko Yamaguchi and Christopher G. Atkeson: "Stereo vision of liquid and particle flow for robot pouring," in *Proceedings of the 2016 IEEE-RAS 16th International Conference on Humanoid Robots (Humanoids2016)*, pp. 1173-1180, 2016.

[18] Connor Schenck and Dieter Fox: "Visual closed-loop control for pouring liquids," in *Proceeding of the 2017 IEEE International Conference on Robotics and Automation (ICRA2017)*, pp. 2629-2636, 2017.

[19] Akihiko Yamaguchi, Christopher G. Atkeson, Scott Niekum and Tsukasa Ogasawara: "Learning Skills from Human Demonstrations: Initial Attempt on a Pouring Task," in *Proceedings of the 32nd Annual Conference of the Robotics Society of Japan (RSJ2014)*, 1I3-04, 2014.

[20] Akihiko Yamaguchi, Christopher G. Atkeson, Scott Niekum and Tsukasa Ogasawara: "Learning Pouring Skills from Demonstration and Practice," in *Proceedings of the 2014 IEEE-RAS International Conference on Humanoid Robots (Humanoids2014)*, pp. 908-915, 2014.

[21] Akihiko Yamaguchi, Christopher G. Atkeson and Tsukasa Ogasawara: "Pouring Skills with Planning and Learning Modeled from Human Demonstrations," *International Journal of Humanoid Robotics*, vol. 12, no. 3, p. 1550030, 2015.

[22] Minija Tamosiunaite, Bojan Nemec, Ale Ude and Florentin Wrgtter: "Learning to Pour with a Robot Arm combining Goal and Shape Learning for Dy-

namic Movement Primitives," *Robotics and Autonomous Systems*, vol. 59, no. 11, pp. 910-922, 2011.

[23] Leonel Rozo, Pablo Jimenez and Carme Torras: "Force-based Robot Learning of Pouring Skills using Parametric Hidden Markov Models," in *Proceedings of the 9th International Workshop on Robot Motion and Control (RoMoCo2009)*, pp. 227-232, 2013.

[24] Makoto Wada, Takanobu Ogawa, Hiroaki Tamura, Kimiaki Yamashita and Akiyoshi Obinata: "Experimental and Numerical Study of the Motion of a Liquid Pouring from a Beverage Can," *Transactions of the Japan Society of Mechanical Engineers Series B*, vol. 79, no. 806, pp. 1963-1972, 2013.

[25] OptoForce: Optical Force Sensors - Introduction To The Technology (White Paper). pp. 1-7, OptoForce, 2015.

[26] Beatriz Len, Antonio Morales and Joaquin Sancho-Bru: From Robot to Human Grasping Simulation. pp. 15-30, in *Springer International Publishing*, 2014.