Behavior Cloning for Varied Bite Acquisition Volume – Robot Assisted Feeding

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***Abstract*—Eating is an essential act of daily living for independent living and the loss the ability to feed oneself can have a drastic impact on one's quality of life. Robot assistive feeding systems have been developed that aim to relieve caregivers of the duty of feeding a patient but it is difficult to build a a manipulator that generalizes to a vast variety of food. This project involves developing a control primitive that learns to scoop a varied amount of food with a spoon using behavior cloning. A robotic arm learns to perform different scooping trajectories by mimicking the actions of expert demonstration through kinesthetic teaching. A Neural Network is trained to learn a control policy that maps the current state of the robot to the next state in trajectory. The model is trained to perform a light scoop and a heavy scoop and to execute the scooping motions. Through experimental trial, the robot successfully learns to scoop low and high amounts of food in the bowl.**

***Index Terms*—Robot-assisted feeding, Behavior cloning, Manipulation.**

I. Introduction

Eating is considered an activity of daily living (ADL) such as grooming, bathing, and brushing teeth. The inability to eat independently has a devastating impact on one's ability to live independently and a decline in self-worth. Approximately one million people in the United States depend on caregiver's assistance to eat. Assisted feeding is one of the most time-consuming tasks for caregiver's who operate in an extremely overloaded and stressful environment.

Robots can assist in feeding individuals who have impairment in upper limb mobility. Robot assisted feeding can be categorized as a two-step process. I) Bite Acquisition – such as stabbing food with a fork. II) Bite transfer: transferring acquired food to the user's mouth. Our concern in this project is reliable bite acquisition which involves manipulating food using a robotic arm. Food manipulation is one of the most intricate manipulation tasks humans perform daily because of the large variance in food shape, size, consistency, and texture. Developing a generalized bite acquisition control primitive that can manipulate all types of food is extremely difficult and has been attempted before. Scooping a desired amount of food into a spoon is a subset of bite acquisition that has not been explored into much detail.

Our project works on developing a control primitive that allows a robot arm to scoop a desired amount of food in a spoon by controlling the spoon trajectory and orientation. Humans can scoop food proficiently with little effort and mimicking human scooping motion is a possible solution to the problem at hand. Behavior cloning is a control strategy that teaches a robot to learn through kinesthetic teaching. That is by physically moving the robot to perform the scooping motion by a human expert.

In this project, we develop a policy that performs two scooping motions, light and heavy, by training a simple feed forward neural network that is trained on a dataset of sample trajectories of scooping motions through kinesthetic teaching.

II. Methodology

We briefly introduce the robot-assisted feeding system with operating procedures and its components

A. Setup

In this section we introduce the individual components of the food scooping system. To perform the scooping task, a standard tablespoon is attached to the gripper of the X-ARM 6 degree of freedom robot. The spoon can take any configuration in 3D space based on joint orientation of the X-ARM robot. A container filled with powdered sugar is placed on a horizontal surface in the operating vicinity of the XARM robot.

B. Assumptions

Since we are concerned with scooping varied volumes of food with the spoon, visual perception of food distribution in the bowl is out of scope of this project. To eliminate perceptive input requirement to the primitive, we define the following assumptions. The bowl is placed in a known position and the height of the food surface is kept constant and uniform. Allowing us to reduce the modelling problem to learning the spoon trajectory and orientation in 3D space. The spoon is placed at a starting position in the vicinity of the bowl because our principle concern is the scooping motion. proofreading, spelling and grammar.

C. Controller

The environment is modelled as a simple Markov Decision Process (MDP). The environment consists of states S, which is 1x12 vector consisting of end effector positions E and end effector velocities Edot. An action space A as 6-DoF robot actions. Given the expert's demonstration, we divide these into state-action pairs and apply supervised learning. The algorithm can be modelled as the following:

1) Collect trajectories T* from scooping demonstrations

2) The demonstrations are treated as straight action pairs:(s_t^*, a_t^*)

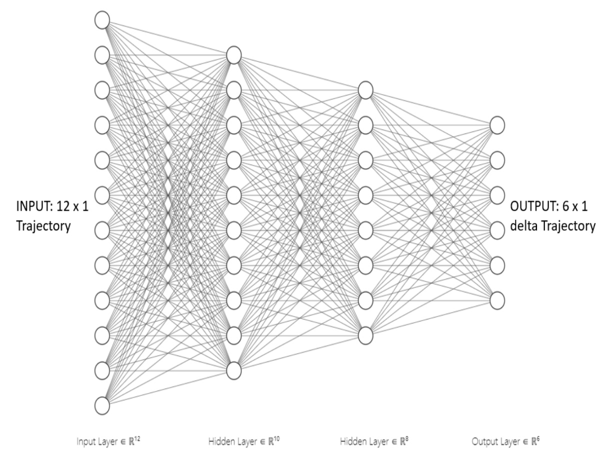

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Fig. 1. Feed Forward Neural Network

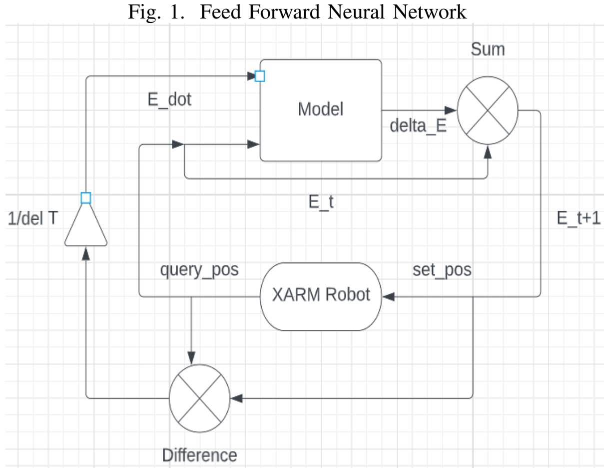

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Fig. 2. Control Primitive Block Diagram

3) Learn policy $\pi\theta$ policy using supervised learning by minimizing the loss function $L(a^*, \pi_\theta(s^*))$

To obtain the scooping demonstrations, we implement kinesthetic teaching by physically moving the robot arms to perform light and heavy scooping motions. The scooping trajectories T* are constructed by polling robot end effector positions E at intervals of $\Delta t = 0.01s$. End effector velocities Edot are calculated by forward difference method $(E(t+1) - Et)/\Delta t$. Policy $\pi\theta$ maps (E,Edot)⇒(Edelta). Where Edelta is the change in End effector position at time step t. The scooping demonstrations are a dataset of 50 scooping trajectories performed by the human expert for light and heavy scoops each. The individual trajectories consist of a 500×12 matrix of (E,Edot) corresponding to a 5s long collection time.

The supervised learning model is a simple feed forward neural network with an input layer of size 1×12 an output layer of size 1×6 along with two fully connected hidden layers as shown in figure 1. The input to the model is (E,Edot) and the corresponding output is (Edelta). Two different learning models are trained, one trained on the heavy scoop demonstrations MHeavy and the other on the light scoops MLight.

The control primitive works in the following manner. The initial position E is queried from the robot arm and is fed as the input to the predictive model MHeavy or MLight which outputs Edelta. The next position in time is computed by summing E+Edelta. The new position is the input for the next step in the computation. A block diagram of the control process is shown in figure 2.

III. Results

This section presents the execution of light and heavy scoops using the trained primitives.

The executed motion for the light and heavy scoops closely mimics the trajectory taught during kinesthetic teaching as shown in figure 3 and figure 4. MLight produces a trajectory that mimics the motion of a light scoop, thus acquiring a small quantity of food, applicable to foods that are consumed in small quantities at a time. While the model MHeavy produces a trajectory that involves a deep scoop into the food bowl, filling the spoon to its maximum quantity. The execution time for the scoops is 20s for the light scoop and 60s for the heavy scoop. The difference in times is due to MHeavy predicting smaller Edelta for each incremental step. Execution times for each trajectory can be improved by sending position set commands at a slower rate as the compute time is roadblocked by the robot arm movement.

IV. Future Work

There exists room for improvement in the size and quality of the dataset used to train the model. More sample trajectories with varying start locations will produce a more robust scooping trajectory. The complexity of the model can be increased which may improve the trajectory speed and robustness of the control output. An LSTM based model that accounts for previous trajectory can be tested for feasibility. Implementation of the control primitive on the Obi feeding robot will contribute to the real-world viability of the behavior cloning based scooping strategy.

V. Acknowledgment

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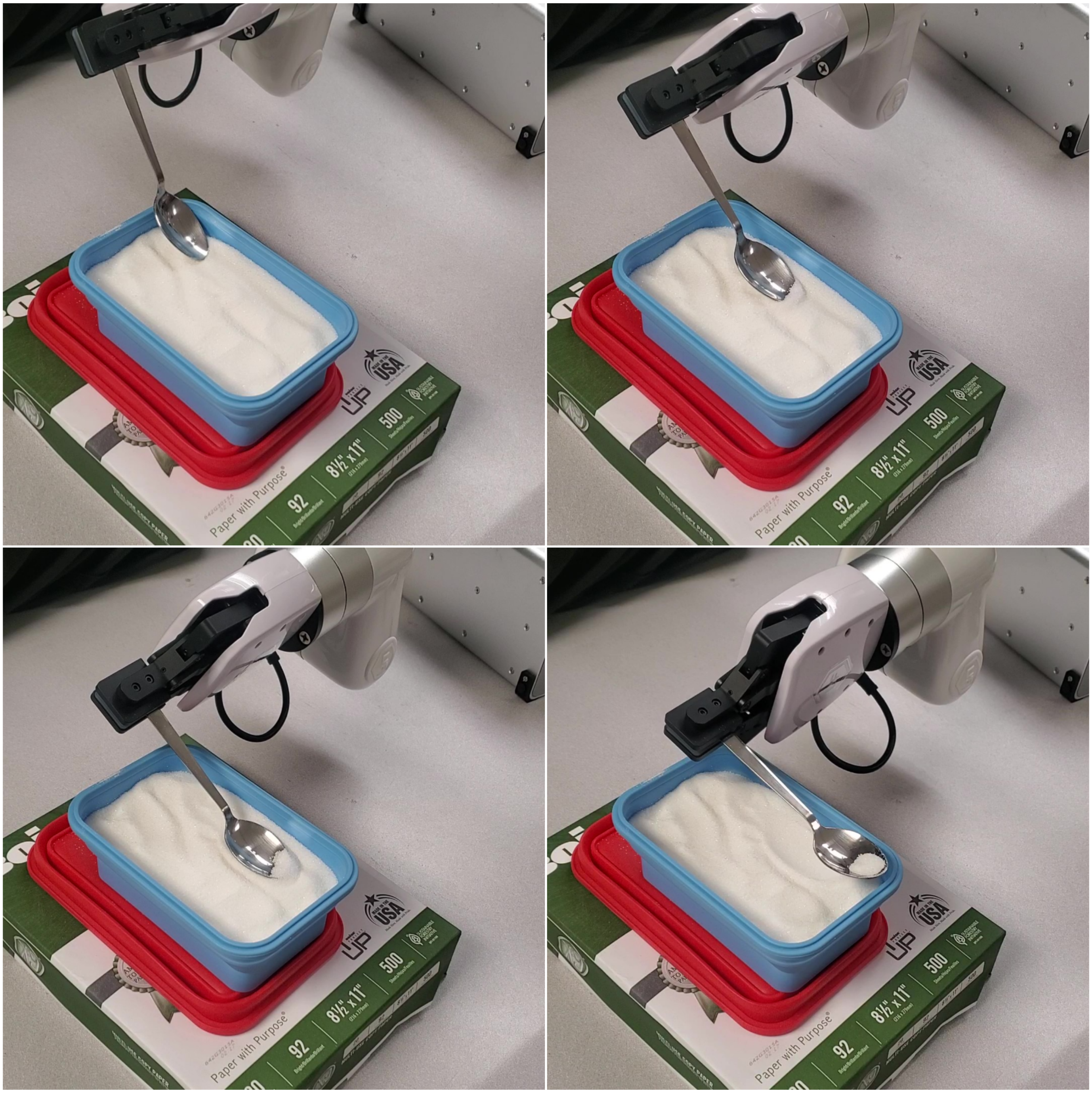

Fig. 3. Light Scoop Execution.

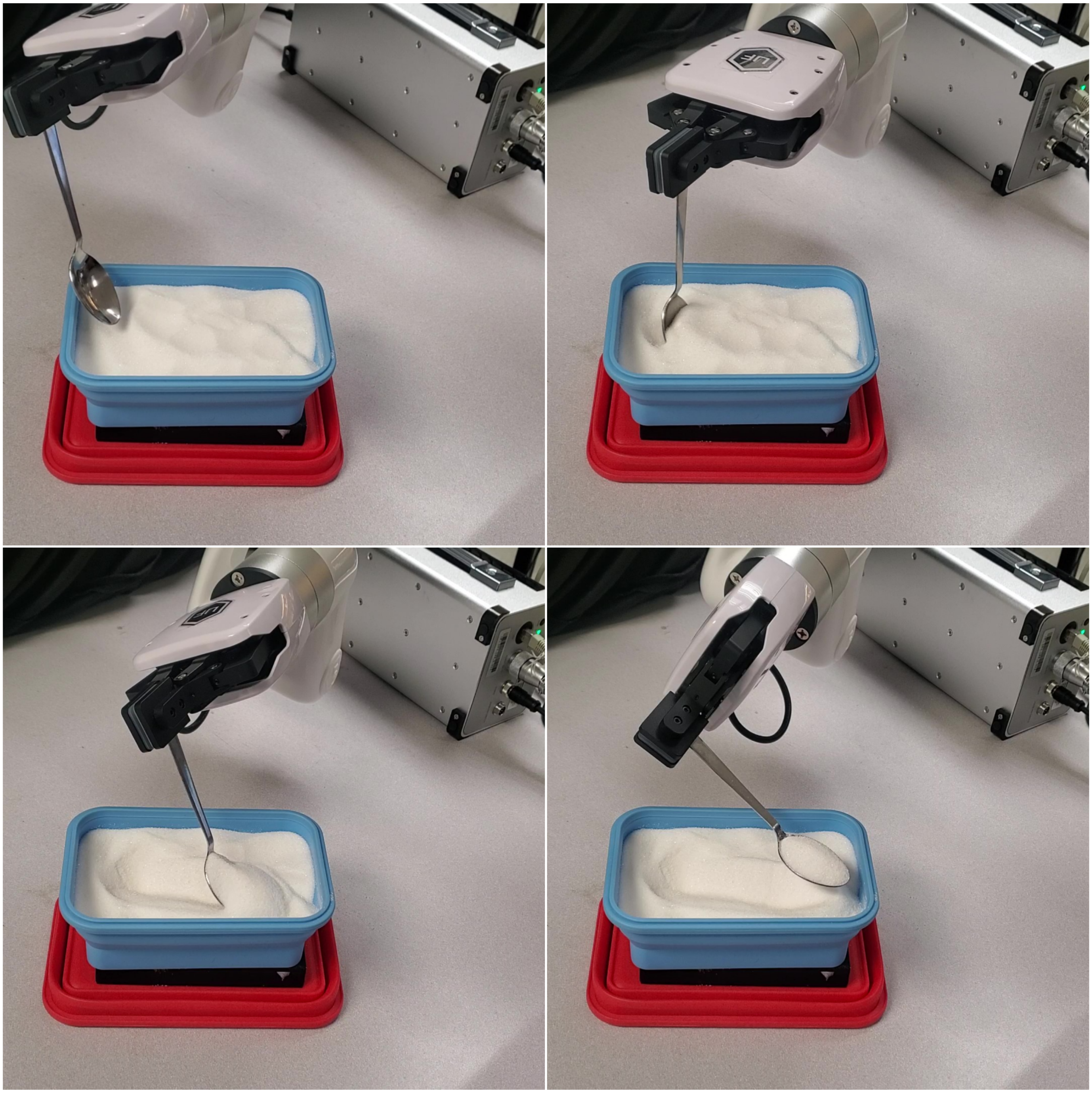

Fig. 4. Heavy Scoop Execution.