High Level Representation of Kinesthetically Learned Motions for Human-Robot Collaborative Tasks

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I. INTRODUCTION

Robots that assist humans in collaborative tasks need to frequently transfer and manipulate objects in an intuitive manner. However, most assistive robots still lack human-like task fluency, mainly due to their inability to infer human intent and fully understand the objects in play. Such intuitive behavior can be encoded in a robot's motion by kinesthetically training it for a human partner's movements [1]. This method can be further extended for interacting with objects by training the robot's response for an object's affordance. Affordance is the propety of an object that determines its manipulability. For example, a hammer used to hit an object and a book used to hit the object, both fall into the same affordance class of "used for hitting". Therefore this property can be utilized for planning the low-level grasping motions.

Early approaches to grasp planning train a set of basic skills on a robot, and attempt to reason a set of causes and effects; while Nguyen et. al. [2] proposes an approach based on Convolutional Neural Networks (CNN) to classify objects by affordance. But this approach requires large datasets to achieve high accuracy. Other methods approach grasping as a reinforcement learning problem. We follow a hybrid approach to grasp planning based on Active Vision techniques [3], where a 2D model is optimized using Elliptical Fourier Descriptors (EFD) [4] along with a force closure test. This method helps to determine the optimum points for grasping, for which trajectory can be planned. But the primary challenge for robots in collaborative environments is implementing human-like high-level abstract decision making by controlling low-level motions. This requires construction of a symbolic representation for evaluating plans composed of sequences of actions in a continuous environment [5]. Such a representation is created by reasoning about potential propositional symbols that describe the preconditions and effects of each action. The resulting representation can be expressed in PDDL (Planning Domain Description Language) that enables fast planning using a graph search planner for determining the optimal sequence of the learned actions.

This paper describes our methods and preliminary results towards developing a system that combines object recognition, grasp planning through demonstration and high level task abstraction into a comprehensive package for application in human-robot collaborative tasks.

II. METHODOLOGY

A. Planning of low-level motions

The object recognition is done by correspondence grouping [6] and this initial guess of the object location is used to filter the point cloud. To simplify detection, pure colored objects are used. We use the pixel centroid of the object to find the corresponding 3D point on the point cloud and then calculate the 3D coordinates of the Kinect sensor frame. Grasp points were determined based on a representation of the object contour using EFD. EFD was chosen due to its invariance to noise, and ability to preserve desirable features of an object. A generalized model for the Fourier approximation of a contour can be shown as follows:

$$P_x(t) = A_0 + \sum_{n=1}^{k} \left(a_n \cos \frac{2n\pi t}{T} + b_n \sin \frac{2n\pi t}{T} \right)$$
(1)

$$P_y(t) = C_0 + \sum_{n=1}^{k} \left(c_n \cos \frac{2n\pi t}{T} + d_n \sin \frac{2n\pi t}{T} \right)$$
(2)

First derivatives compute the tangent vectors to the model. Normal vectors N can be found by normalizing the derivative of the tangent vector Z.

Curvature is the main feature used in selecting model grasp points, and can be determined as the sign of the dot product between normal and tangent vectors:

$$Curvature = sign(\|Z \cdot N\|) \tag{3}$$

An algorithm (Algorithm 1) was designed to find the grasp point pair residing in optimal curvature regions. We model the robot gripper as a pair of frictionless contact points. Grasp points must pass a force closure test determined by the geometry of the Fourier descriptor.

Algorithm 1 Compute Optimal Grasping Pair	
1:	Rank all possible pair sets by descending $x + y$ curvature
2:	for each set x,y with positive α do
3:	$\beta = PerformForceClosure()$
4:	if β above threshold return
5:	Rank sets by ascending and repeat for negative α
6:	
7:	procedure Perform Force $CLOSURE(x, y)$
8:	$A = \frac{N_m 1}{\ N_m 1\ } \cdot \frac{Pm_1 - Pm_2}{\ Pm_1 - Pm_2\ }$
9:	$B = \frac{\ Nm_2\ }{\ Nm_2\ } \cdot \frac{\ Pm_1 - Pm_2\ }{\ Pm_1 - Pm_2\ }$
10:	return $A^2 + (\pi - B)^2$
4: 5: 6: 7: 8: 9: 10:	if β above threshold return Rank sets by ascending and repeat for negative α procedure PERFORM FORCE CLOSURE (x, y) $A = \frac{N_{m1}}{\ N_m1\ } \cdot \frac{Pm_1 - Pm_2}{\ Pm_1 - Pm_2\ }$ $B = \frac{Nm_2}{\ Nm_2\ } \cdot \frac{Pm_1 - Pm_2}{\ Pm_1 - Pm_2\ }$ return $A^2 + (\pi - B)^2$

For reaching to the object that needs to be grasped we train Multi-dimensional Interaction Probabilistic Movement

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Primitives (Pro-MP) [1] with multiple reach to grasp demonstrations. During the learning phase the sensing module observes the centroid of the object and its two grasping points, along with the joint angles of the robot's arm. At each time step t, the 7 observed degrees-of-freedom (DOF) of the robot arm and the 9 observed dimensions of the object are concatenated into the following object-robot state vector:

$$\mathbf{y}_{t} = [y_{1,t}^{O}, \cdots, y_{9,t}^{O}, y_{1,t}^{R}, \cdots, y_{7,t}^{R}]^{T}$$
(4)

The trajectory of each DOF is further parameterized by weights such that:

$$p(\mathbf{y}_t | \bar{\mathbf{w}}) = \mathcal{N}(\mathbf{y}_t | \mathbf{H}_t^{T} \bar{\mathbf{w}}, \boldsymbol{\Sigma}_{\dagger})$$
(5)

$$\bar{\mathbf{w}}_i = [(\mathbf{w}_1^O)^T, \cdots, (\mathbf{w}_9^O)^T, (\mathbf{w}_1^R)^T, \cdots, (\mathbf{w}_7^R)^T]^T \quad (6)$$

In the reproduction phase, the robot end-effector trajectory is inferred by computing the posterior probability distribution of the weights w conditioned on the observed object configuration. This method helps to predict the required trajectory for grasping and moving objects in any configuration that it wasn't trained for.

B. High level symbolic representation

In order to generate a plan to perform the task, the robot must learn a high level representation of the task space. To start, the robot must be provided with a list of state variables (s_i) describing the environment and a set of options (o_i) , temporally abstract actions that change the state of the environment. Task data is collected in the form of (s, o, r, s); where s is all state variables before performing the option, o is the option name, r is the reward of performing the option, and s is all state variables after performing the option. For every sample, its mask is calculated by comparing the changed state variables between s and s and each unique mask is assigned its own partition. Along with the mask, each option also relates to an initiation set I_{oi} that enumerates the set of all world states from which option o_i can be initiated and an effect set which returns the set of all world states after performing option o_i . The mask, initiation set, and effect set of each option are then used to create symbols which describe the high level symbolic space which describes the domain. Each option has symbolic precondition and effect sets associated with it. The preconditions element contains the list of symbols that must evaluate to true in order for the option to be executable and the positive effects is a set of symbols that are set to true by executing the option, while negative effects consists of the symbols to be set to false when the option is executed. These symbolic descriptions of options allow the robot to generate an informed option plan relating each option with its relationships to the environment, generating an option "path" to a desired world state.

III. RESULTS AND FUTURE WORK

The proposed system is being implemented on the Telerobotic Intelligent Nursing Assistant (TRINA) system [7]. This robotic platform consists of a dual-armed humanoid torso (Rethink Robotics Baxter), an omnidirectional mobile base (HStar AMP-I), and two three-fingered grippers (Righthand Robotics ReFlex grippers). A Microsoft Kinect 2 was attached



(a) Grasp Detection (b) Monkey & Treasure Game Fig. 1: Implementation of proposed methods



Fig. 2: Grasp planning for object in different positions and orientations

to the robot's chest for detecting objects and human motions in the interaction space.

The right arm of TRINA was kinesthetically trained for reaching motions towards an object in different positions and a human, with 18 demonstrations each. The robot was able to reproduce the trained human-like trajectories for new positions and orientations (vertical and horizontal) of the object (Fig. 2). This demonstrated the generalization of robot's arm motions for different states of the environment. The method for symbolic representation of such low-level motions was tested using a monkey playroom and a treasure game (Fig. 1b). Through simulation, 32000 option samples were collected for which 56 partitions were created. Completing the grounding generation [5], a graph search in the Probabilistic PDDL domain would lend us the desired sequence of actions.

The future work will extend the symbolic representation for single robot task to human-robot collaboration tasks (e.g., handing-over, collaborative moving, collaborative object organization). The high-level collaborative task plan will be composed using option symbols learned from human partner and teleoperated robots, and implemented using the Pro-MP for reaching and grasping, and human-robot motion coordination.

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