Haptically Guided Teleoperation for Learning Manipulation Tasks

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Abstract- **In this paper, we present a methodology that uses control signals provided through guided teleoperation to assist in the learning of new manipulation tasks. The approach incorporates haptic feedback that guides human behavior in performing a manipulation task using guidance forces derived from visual input data. The control signals provided by the user are then utilized by the robotic system to learn the control sequences necessary for task execution. A neural network learning method that incorporates historical information is utilized for the learning process. The primary focus of our approach is to develop a method to enable the robotic system to improve its ability to learn manipulation tasks, whether or not the instruction is provided by an expert or general user. The methodology is explained in detail, and results of a manipulation system learning an object-centering task is presented.**

I. INTRODUCTION

Recent trends in robotic applications have made possible the inclusion of mobile robotics in everyday life. Technological advances in locomotion have progressed such that mobility in a human-centric world is both feasible and realistic. As manipulation in the unstructured human environment can increase the robots ability to perform needed tasks, manipulation seems to be the natural extension for enabling the further integration of robotics in our society. The difficulty though is that manipulation of everyday objects not only depends on object features such as size, surface texture, and weight, but also on the characteristics of the desired manipulation task. Humans have learned to deal with these difficulties by improving their abilities through the accrual of experiences. As such, humans naturally become an excellent reference for robots to learn from concerning objects and how to interact with them. This learning process can be achieved through teleoperative-based instruction, in which humans demonstrate manipulation activities by directly interfacing with the robot controller, and the robot, in turn, learns to generalize the actions needed to accomplish the new task. For example, a caregiver can provide basic instruction to a robot in performing manipulation tasks necessary in preparing food for an invalid in the home. Through generalization, the robot can then learn to perform the related operations despite the varying characteristics of the task. To successfully realize this teleoperative-based instruction capability, two primary challenges must first be addressed: 1) developing a low-cost, robust interaction method in which non-expert users can quickly and easily gain access to the capabilities of the system and 2) extracting relevant input/output control signals from the human user which enable the manipulation system to learn the control sequences necessary for task execution. By combining a vision-based haptic feedback approach with a learning methodology based on temporal data sequences, we believe that we can address these two issues and enable the robotic system to improve its ability to learn manipulation tasks, whether or not the instruction is provided by an expert or general user.

Currently, few research efforts have focused on using haptic feedback extracted from environmental interaction to improve manipulation capability through learning. In [1], force feedback was introduced during the teleoperation sequence using potential-field methods, but slow computation times limited their effectiveness. In robot-assisted adaptive training [2], custom force fields were studied for human interaction with a robotic handle and in [3], vision-guided trajectory generation using a neural network was applied for grasping in a virtual environment. In medical applications, there have been a number of research efforts that incorporate haptics and manipulation. [4] involves utilizing a master controller and force sensors to detect a surgeon's hand movement during teleoperation, whereas [5] described research focused on vision-based haptic exploration. In fact, research such as found in [6-7] has shown the importance of haptic feedback in surgery tasks requiring manipulation. These studies document the performance increases that can be achieved when providing haptic feedback during teleoperation. In all these efforts though, utilizing haptic feedback to improve the learning of new manipulation tasks by the robotic system was not realized.

To improve current capability for learning of new robot manipulation tasks through teleoperation, we present a methodology that utilizes visual inputs directly in producing force guidance data to assist human operation of a teleoperated manipulation system. By combining visual data and force feedback, human decision is aided by haptic feedback to provide control signals to a manipulator device, which is then used for learning the control sequences necessary for task execution. The following sections describe this approach for using haptically guided teleoperation to assist in the learning of new manipulation tasks.

II. ALGORITHM: LEARNING NEW MANIPULATION TASKS

A. *Divided Force Guidance for Haptic Feedback*

A classical method found in path-planning applications is the potential field method in which forces are calculated that will repel a robot away from obstacles and attract a robot toward a designated goal location. Once these potential fields are calculated, the robot can theoretically navigate to a final goal position within an obstacle-strewn environment by transitioning along the force vectors. The goal of the haptic feedback system is to assist the user in implementing a new task through teleoperation such that the control signals provided by the user are not strongly dependant on operator expertise (since, as shown in [8], experience is closely linked with task performance when a user performs a teleoperated task). The potential field method can be adapted to provide haptic force feedback by producing potential-like forces that generate an *attractive* force as the user moves toward a given goal and generates a *repelling* force when the user moves away from the goal. The adaptation of the potential field method is required in order to first adjust for differences in object distances as well as object size. Of most importance though, is to account for the subtle differences that are typically found in the potential field method (such as small forces that might be generated when a robot is close to the goal). These forces must be emphasized since too small of a force generated in the haptic device will go unnoticed by the human user.

With regards to haptic feedback, we would like to create a potential field that modulates the haptic feedback forces in order to assistively guide the user toward the target location. This is achieved by using a methodology we call divided force guidance [9], such that calculated forces are correlated based on size and distance from object determined by vision-based methods (Figure 1). Our basic assumption is that the feedback system consists of an eye-in-hand setup in which the camera is mounted to the end-effector of the manipulator arm (Figure 2). Using this configuration, visual data is first used to calculate the dimensions of the target object. As the user commands the manipulator device, the distance from the target (calculated based on the distance offset from the end-effector pointing direction) is determined and used to output a haptic feedback force.

The object in the robot's coordinate frame $\mathbf{P_O} = (x_o, y_o, z_o) \in R^3$ is observed by a camera and translated by T_{Obj}^{Cam} into the camera coordinate frame $\mathbf{P_O^C} = (x_o^c, y_o^c) \in R^2$. The positional difference between $\mathbf{P_O^C}$ and the center of the image plane $\mathbf{P}_{Center}^{C} = (x_{center}^{c}, y_{center}^{c}) \in R^2$ is directly used to generate a guidance force $\mathbf{F_{Joy}} = (F_x, F_y) \in R^2$ in the joystick, after being translated by a function T_{Cam}^{Joy}. After acquiring the target object position, x- and y-directional forces are generated based on the following equations:

$$F_x = \begin{cases} k_{pc}\, \mathrm{T}_{\mathrm{Cam}}^{\mathrm{Joy}}\left((1-\sigma)\cdot x_o^c - \sigma \cdot x_{center}^c\right), & if\; x_{joy} \geq x_{offset} \\ k_{nc}\, \mathrm{T}_{\mathrm{Cam}}^{\mathrm{Joy}}\left(\sigma \cdot x_{center}^c - (1-\sigma)\cdot x_o^c\right), & if\; x_{joy} < x_{offset} \end{cases}$$

$$F_y = \begin{cases} k_{pc}\, \mathrm{T}_{\mathrm{Cam}}^{\mathrm{Joy}}\left((1-\sigma)\cdot y_o^c - \sigma \cdot y_{center}^c\right), & if\; y_{joy} \geq y_{offset} \\ k_{nc}\, \mathrm{T}_{\mathrm{Cam}}^{\mathrm{Joy}}\left(\sigma \cdot y_{center}^c - (1-\sigma)\cdot y_o^c\right), & if\; y_{joy} < y_{offset} \end{cases}$$

where σ is the approach ratio ($0<\sigma<1$) that is set based on manipulator speed and teleoperation time delays (e.g. the faster the manipulator movements, the smaller the approach ratio), k_{pc} and k_{nc} are positive and negative coefficients which changes values between {low, high} for situations in which the object is identified as far, near, or too close, x_{joy} and y_{joy} represents the x- and y-coordinates of the current joystick position, and (x_{offset}, y_{offset}) is a changing offset position that iteratively determines waypoints that approach the target object around which the haptic forces are generated. The guidance forces computed allow the haptic feedback system to influence the user to move the manipulator arm toward the object. Once a position is attained that is centered directly on the target location, this force is effectively set to zero.

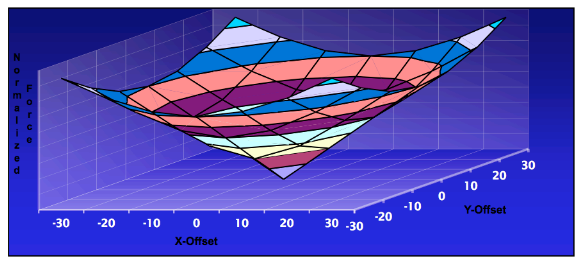

Figure 1. Depiction of guidance force values associated with an object that is offset from the camera center (in camera units). Normalized z-value correlates with the magnitude of the force felt by user using the haptic device.

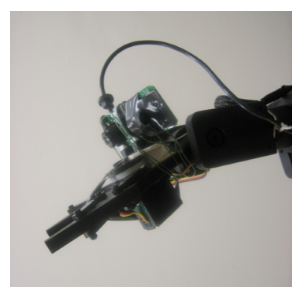

Figure 2. Eye-in-hand configuration for extracting visual data used in divided force guidance approach.

B. *Learning through Haptically Guided Manipulation*

Given implementation of a new task by the user, the goal of the system is to learn the relevant control signals that enable execution of the new task without requiring interaction from the human. Although the task we present for learning in Section III is focused on object centering, the methodology proposed is designed to allow learning of manipulation tasks in which both the position and orientation of the end-effector is significant (such as pouring a cup of coffee or grooming with a hair brush). Thus, the learning algorithm is defined in the joint, versus Cartesian space. We note from the kinematics that define a manipulator system that the joint angles needed to command positioning of the end-effector are inherently coupled. To maintain end-effector position, changing the joint angle of any one joint requires an associated change in the kinematic chain of joint angles that lead to the last joint connected to the end-effector. As such, any learning methodology that is utilized should account for this dependency in its implementation. We accomplish this by utilizing a hierarchically structured framework of feedforward neural networks whose structure correlates to the manipulator's kinematic chain of joint angles. In addition, since we desire to learn the sequence of control signals that enable execution of a task, we must incorporate the temporal dependencies inherent to the task. This feature is integrated into the learning algorithm by adding in previous joint angle values to the input pattern fed into the neural network. The final learning framework is thus represented as follows (Figure 3):

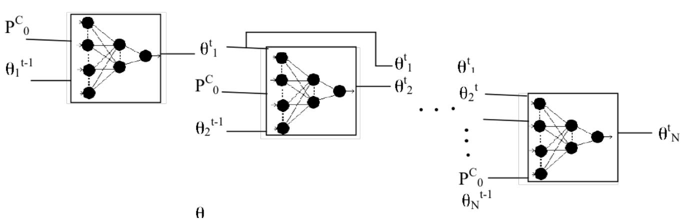

Figure 3. Hierarchical Neural Network Structure where the output from each level feeds as an input into the next level

where $\mathbf{P}_\mathbf{O}^\mathbf{C} = (x_o^c, y_o^c)$ represents the position of the object in the camera frame of reference, $(1,...,N)$ is the respective position of the joint within the kinematic chain, θ is the joint angle commanded during one step in the teleoperated task sequence, and $t \in \{0,T\}$ is the respective step in the teleoperated task sequence, which terminates at step T. In this hierarchy, there is one level associated with each joint (resulting in a 5-level structure for a 5-DOF manipulator arm). The input into each level consists of the position of the object, the learned joint angles extracted from the lower-level neural networks, and the current joint angle associated with that level (e.g. the angle output from the neural networks associated with joint *1* through *N-1* and the angle of joint *N* would feed into the neural network at level *N*). The output of each level consists of the next angle to command the respective joint. In this algorithmic implementation, the neural network at each level has one hidden layer and is trained in sequence using the standard backpropagation algorithm.

By coupling haptically guided teleoperation with learning from temporal data sequences, we provide a methodology to learn new manipulation tasks from human interaction. Since visual servoing is a well-understood manipulation task, the following section discusses results of applying our method to this related object-centering task. Our objective is to show the feasibility of using haptically guided teleoperation such that an untrained user can instruct a robot to learn.

III. EXPERIMENTAL RESULTS

A. Test Setup

Our manipulation system (Figure 4) consists of a 5-DOF manipulator arm (attached to a stationary Pioneer3AT mobility platform), a USB camera, and a laptop for hosting of the robot controller. The Pioneer Arm is a relatively low-cost robot arm that is driven by six open-loop servo motors, providing 5 degrees-of-freedom with an end-effector capable of grasping objects up to 150 grams in weight. For acquisition of the visual data, we mount a small USB webcam on the gripper so our system can transmit the workspace view observed by the end-effector to the user. The maximum frame rate of the camera is approximately 30 fps/sec with pixel resolution of 320x240. It also has a diagonal 54 degrees of field-of-view angle with focus range of 5cm to infinity.

The haptic device (Figure 5) used by the human operator is a force-feedback joystick (Microsoft SideWinder2 force feedback joystick), which has a 16bit 25MHz on-board processor capable of delivering 100 different forces and 16 programmable function buttons. The haptic device is also coupled with a user interface that receives the streaming images retrieved from the camera attached directly to the robot end-effector.

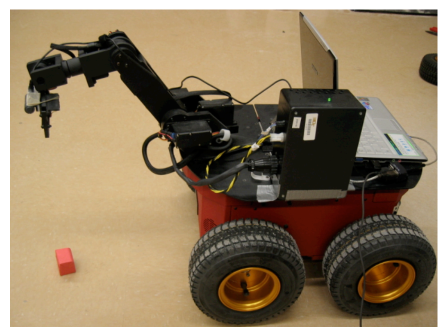

Figure 4. Manipulation System using Pioneer Arm

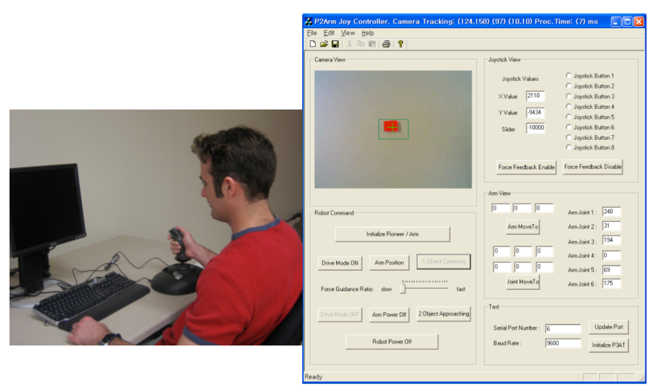

Figure 5. Master Interface (Haptic + Vision) for Teleoperation

B. Results

In many manipulation tasks, the first step in the control sequence is to position the arm such that the target object is located within reach of the end-effector. We denote this pre-grasping process as object-centering when movement in one of the planes is constrained (Figure 6). As the primary focus in this paper is to provide an evaluation of the learning methodology, we simplify the vision-processing requirements by placing a brightly colored object against a uniform background. This allows the use of thresholding techniques to extract size and distance parameters for calculation of the values needed by the divided force guidance and learning methods. We first validate our divided force guidance technique using our master interface by conducting 20 trials for five selected places for *object centering*. The visual data from the camera system mounted on the robot is analyzed every 33ms and a target object is acquired and tracked. The guidance force is then generated directly from the visual data to guide the human operator using the haptic control device to move the arm toward the top of the object. In these trials, the approach ratio is chosen as 0.5 and the dimensions of the object is (25mm, 30mm) as measured in the x-y plane.

(a) Before (b) After

Figure 6. Camera view of before and after *Object Centering* task. The arm is manipulated by a human operator who 'sees' through this view and 'feels' the guidance force directly generated from this visual data. The '+' mark indicates the size of the object, and the '□' indicates the center area.

Figure 7 shows typical graphs of distance change in *object centering* when the force guidance is enabled and disabled. With the guidance force, we can see the arm is moving toward the object making a clean path, whereas without the force guidance the arm hesitates at the beginning (since the operator has to decide where to move the arm) and takes more time in centering (see Figure 8). The average time for object centering (for a certain target position) was 2.1 sec for the first 10 trials and 1.8 sec for the latter 10 when the guidance force was enabled, while it took 3.2 sec and 2.4 sec respectively when the force was off. We can see that the average time with the force guidance is 29% less in total, and 33% smaller in the first 10 trials. The common decrease in the latter 10 trials in both cases shows that the human operator "learned" to operate better, and we can also see that the average time in the latter part with force guidance was still 25% faster than that without force guidance (see Table I).

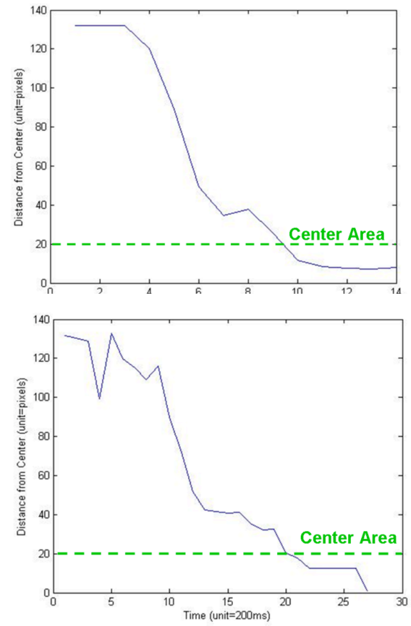

Figure 7. Distances from object center in time domain: (top) Force Guided (bottom) Force Guide Disabled

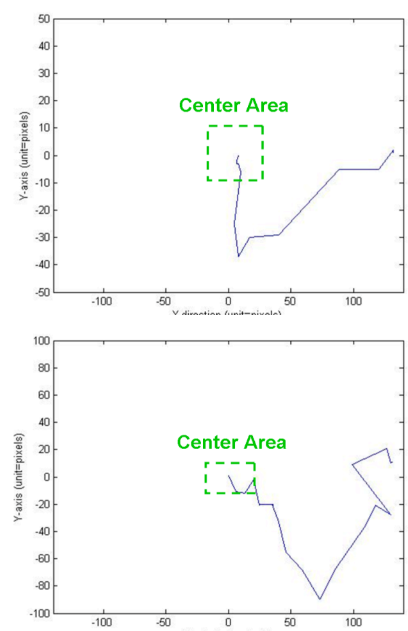

Figure 8. Arm movement trajectories towards the center: (top) Force Guided (bottom) Force Guide Disabled

TABLE I. AVERAGE TIME FOR *OBJECT CENTERING*

Trials	Time Comparison in Object Centering		
	With Force Guidance	Without Force Guidance	Effectiveness
First 10 trials	2124 ms	3165 ms	33% Faster
Last 10 trials	1793 ms	2383 ms	25% Faster
Total Average	1956 ms	2774 ms	29% Faster

We then tested our learning approach and show the results derived from applying our learning methodology to one of the object-centering task sequences. Figure 9 depicts the end-effector locations during the teleoperated task sequence. Figure 10 depicts the resulting task sequence learned by the manipulator (i.e. extracted from the trained neural network). By defining the error based on the difference between the end-effector position at the conclusion of the final step in the teleoperated versus learned sequence, the error is calculated at 4.4% for this case of the object-centering task.

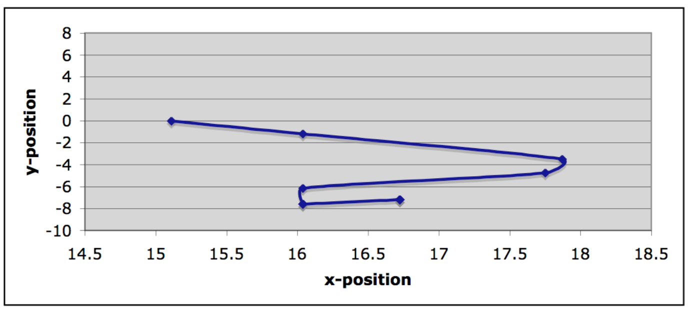

Figure 9. End-effector position associated with task sequence as commanded through teleoperation

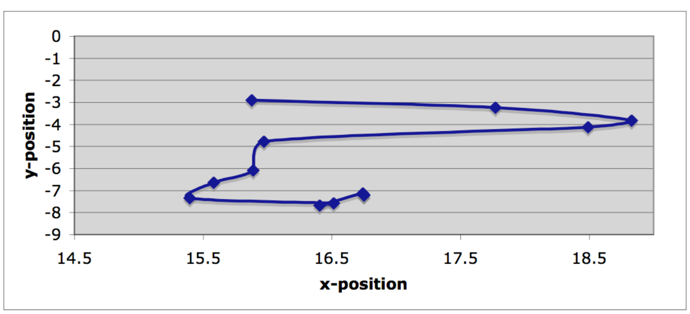

Figure 10. End-effector position associated with task sequence as commanded with trained neural network

V. CONCLUSIONS

In this paper, we present a methodology that enables learning of new manipulation tasks using teleoperation guided by haptic feedback forces. The approach uses vision as a means of providing feedback data to the user during task execution. The corresponding temporal data sequence of joint angles is then utilized by the robotic system for learning using a hierarchical neural network structure. Although the task we present for showing the feasibility of the approach is focused on object centering, the methodology proposed is designed to allow learning of manipulation tasks in which both the position and orientation of the end-effector is significant (such as pouring a cup of coffee or grooming with a hair brush). Future work will involve expanding the set of new manipulation tasks and fully assessing the capability of the system to extrapolate its knowledge to execute tasks with common characteristics.

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