

BERTRAM: A Bartending, Experimental, Reinforced-learning, Teleimmersive, Robotic, Autonomous Mixologist

Dept. of CIS - Senior Design 2010-2011

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ABSTRACT

Programming a robot to autonomously perform human tasks has been a long-time goal of robotics. Such endeavors have typically involved heavy computation due to the demands of visual processing, path planning, and motor coordination. Human demonstration has often been used to introduce a sequence of moves to a robot, both in the form of direct kinesthetic learning and visual motion capture. Here we investigate teaching motion and behavior via teleimmersive shadowing and reinforcement learning. We explore this method through the example of teaching a Willow Garage PR2 robot how to mix and serve drinks as a human bartender would.

If successful, the proposed method will demonstrate an easy way for the PR2 (or any robot for that matter) to rapidly acquire and refine different complex behaviors within a specific environment. This paper details our plan for achieving both shadowing and learning with the Kinect, PR2, and ROS.

1. INTRODUCTION

Constructing a fully autonomous and adaptive robot has been a long-time goal of robotics research. The possibility of a robotic butler is only one of many potential applications. However, real autonomous decision making is an incredibly challenging process, for many different processes must be coordinated - vision processing must be done quickly and accurately to respond to changes in the environment, accurate path planning is needed to navigate the environment, and precise motor coordination is needed to manipulate the environment. There have been many different attempts at overcoming these challenges involved in developing an autonomous robot. One approach that has been often explored is machine learning. The ability to learn is a powerful intermediate step towards autonomy, since learning can allow a robot to adapt to new, unforeseen scenarios. Teaching by human demonstration is a common approach to robot learning since it enables the transmission of complex behavior in a manner far easier than coding the movement of each individual motor and joint. However, choosing how exactly how the demonstrated behavior is delivered to the robot in such a way that it can record and reproduce that behavior is still a very challenging task.

In this proposal we outline a method to teach a Willow-

Garage PR2 Robot how to mix and serve drinks through shadowing of human motion captured by the Microsoft XBOX Kinect. The XBOX Kinect sensor from Microsoft provides depth information at real-time speeds (30 frames per second), which essentially performs the computation that would have been involved in stereo processing. Combined with various open source libraries[11], the Kinect also works with APIs that provide human motion sensing and tracking, which greatly simplifies the task of object recognition to detect body movement. These Kinect libraries have already been used successfully in many projects involving real-time tracking of human motion, examples of which can be found online[5].

The PR2 is a humanoid robot developed by Willow Garage[6] for the purpose of robotics research. It is omnidirectional, capable of telescoping height, and possesses a pair of highly movable arms and grippers that permits grasping of many different kinds of objects. The PR2 also comes with a robust series of software development tools, such as a visualizer, simulator, and logger. Willow Garage donated 11 PR2s to 11 different institutions for the purpose of conducting research on machine learning, dynamic object manipulation, and human-robot interaction[4]. Since then, these institutions have taught the PR2 a wide variety of human actions, such as baking cookies[1], scanning and bagging groceries[8], and fetching a sandwich from Subway[13].

We propose to use the Kinect to capture human movement in order to teach the PR2 how to mix and pour different kinds of drinks. The Kinect sensor provides a convenient way to capture a human demonstration of desired behavior. The captured data can be relayed to the PR2 via ROS, an open-source Robot Operating System[12]. ROS provides a convenient framework for inter-process communication and coordination. Processes that perform computation are visualized as nodes in a graph, with inter-process communication representing the edges of the graph. Nodes send information to each other in the form of messages. Nodes that wish to send messages to other nodes can 'publish' to a topic, and nodes wishing to receive these messages need only to 'subscribe' to these topics. ROS enables relatively short programs to issue surprisingly sophisticated commands to the PR2, such as continually tracking a moving point over time, as the following ROS python code snippet demonstrates[4]:

```

1 import rospy
2 from actionlib import SimpleActionClient
3 from pr2_controllers_msgs.msg import PointHeadAc-
tion, PointHeadGoal
4 from geometry_msgs.msg import Point
5
6 rospy.init_node('move_the_head')
7
8 client = SimpleActionClient(
9 '/head_traj_controller/point_head_action', Point-
HeadAction)
10 client.wait_for_server()
11
12 g = PointHeadGoal()
13 g.target.header.frame_id = 'base_link'
14 g.target.point = Point(1.0, 0.0, 1.0)
15 g.min_duration = rospy.Duration(1)
16
17 client.send_goal(g)
18 client.wait_for_result()

```

Lines 1-4 simply import the required modules. Line 6-10 create a new ROS node called 'move_the_head' and a controller that will move the head. Lines 12-15 order the head to stare at a pointer offset by (1, 0, 1) from the base of the PR2. By changing Line 14, the head of the PR2 can be commanded to look at another point. One can imagine enclosing that code in a loop and updating the target.point to have the head dynamically track a moving object. By using ROS along with the PR2 and the Kinect, we will demonstrate the effectiveness of teleimmersive demonstrative learning.

Our method has several advantages over existing approaches. First of all, the Kinect sensor provides accurate real-time human motion tracking that can be mapped to specific movement in the PR2 thanks to ROS. Secondly, teleimmersion enables a human teacher to more precisely show a robot how to move in a given situation compared to kinesthetic learning, which involves manipulating the robot directly by physical contact. Teleimmersion also enables demonstrations for robots that cannot be easily subject to kinesthetic techniques, such as very large or very small robots. Our method, if successful, would allow for rapid demonstration of different sequences of behavior to the PR2, which could be stored and queued up for later reproduction. This technique could even be generalized to other humanoid robots besides the PR2 to teach them different behavior.

2. RELATED WORK

Other institutions have conducted research involving autonomous robots and handling drinks. Hillenbrand *et al.* [7] designed a semi-autonomous hand-arm robot for serving drinks. The hand-arm was capable of responding to user input by choosing a drink from a variety of different containers, opening the drink if necessary, pouring the liquid into a glass, and then offering the drink to the user. It was capable of not only picking up bottles and cups, but also of unscrewing bottle caps. Stereo processing was combined with object recognition to identify the drinks, after which grasp planning was used to actually pick up and manipulate the drink. Srinivasa *et al.* [14] designed an autonomous robot capable of navigat-

ing a household-like environment and manipulating a wide variety of everyday objects. Consisting of an arm mounted on a segway, HERB used a powerful array of six multi-core processors to successfully traverse its environment and interact with objects around it, such as cups and drawers.

There has also been significant work done in teaching the PR2 robot to perform human tasks. Bohren *et al.* [2] used the PR2 and ROS to build a robotic system for retrieving a beer from a refrigerator. In their work, they developed a task-level execution system known as SMACH for rapidly prototyping robotic applications. The PR2 had to navigate an obstacle map to reach the refrigerator, use object recognition and grasp planning to identify the door handle and the drinks, and ultimately use facial recognition to deliver the beer to a human recipient. Each step of the process contained detail planning and image processing in order to carry out the expected behavior. Klingbeil *et al.* [8] developed a grasping algorithm to enable the PR2 to pick up objects and attempt to locate and scan the barcode. Their technique bypassed the training phase by allowing the PR2 to devise a plan to grasp the object from only a single 3D snapshot. Saito *et al.* [13] devised a method for the PR2 to intelligently navigate large environments via semantic search. The PR2 attempts to find a specific object by first searching areas that would logically contain that item. When asked to retrieve a sandwich, the PR2 first inspected a nearby refrigerator in its environment.

All of these robots relied on some combination of vision processing and path planning to carry out their tasks. However, there have been other approaches involving demonstration learning to allow a robot to perform a specific job. In a relatively early attempt, Chalodhorn *et al.* [3] used motion capturing to teach a bipedal humanoid robot how to walk by imitation. Joint angles from motion capture data from a human demonstrator wearing a motion capture suit were mapped to joint angles in the robot. This data was combined with predictions of future state based on sensory information to reproduce a human-like gait in the robot. Kormushev *et al.* [9] taught a robot new motor skills through kinesthetic teaching. The robot had two distinct modes of operation: a learning phase and a reproduction phase. During the learning phase, the robot was shown how to clean a whiteboard by direct human manipulation of the robot's joints, recording both position and force information. During the reproduction phase, the robot would translate the learned information to its own reference frame and attempt to duplicate the teacher's movement pattern on the whiteboard. Kormushev *et al.* [10] also used kinesthetic learning to teach a robotic arm how to flip a pancake. A human teacher first moved the arm to demonstrate the movement required to flip a pancake 180 degrees in the air and catch it again. In subsequent trials, reinforcement learning techniques were applied such that the robot could evaluate the performance of its flips and attempt to adjust the motion of the arm for better future flips.

3. PROJECT PROPOSAL

We propose to teach a PR2 robot how to mix drinks via teleimmersive demonstration learning methods. One of our goals is to have the PR2 be able to recall different drink mixing recipes acquired from watching a human demonstra-

tor perform them in the past. Ideally, if presented with a setting consisting of bottles and glasses, the PR2 should be able to distinguish and select the desired bottles and then pour them into glasses by combining its stored library of known mixes with reinforcement learning techniques./

The most visible metric of success will be how well the PR2 can perform as a bartender. We can determine how often the PR2 successfully serves a requested drink. It is important to note, however, that the real measure of success is how well teleimmersive learning via Kinect can be used for robots to acquire new motions and behaviors.

3.1 Anticipated Approach

Our method consists of two phases. First the robot will shadow a human teacher, remembering the actions so that it can subsequently try to reproduce them. It will then attempt to improve its execution of the learned motion through reinforcement learning.

For the first part, we propose using teleimmersive operation to demonstrate behavior to the PR2 so that it can imitate and reproduce these motions at a later time. At the base level, the hardware layer of the PR2 will be managed by ROS. This will be combined with the Microsoft XBOX Kinect to capture human motion and to provide the teleimmersive framework. Using the mounted Kinect, the PR2 will observe a human trainer go through the process of selecting bottles and pouring them into glasses. Specialized software will then attempt to map the motions of the human trainer onto the motor system of the PR2.

The second phase utilizes software that lets the PR2 attempt to reproduce the observed motions under a reinforcement learning environment. In addition to simply trying to replicate the motion in identical situations, the PR2 will evaluate its own performance in scenarios where objects are not placed in the exact same location as they were for the human demonstrator. The end goal is that the PR2 can refine its acquired motions and adapt to new situations via reinforcement learning techniques.

ROS is a fairly mature and ubiquitous piece of software that can take care of many of the more sophisticated computational tasks (such as path planning, image segmentation, etc.) that we would otherwise have to devote significant amounts of time to developing. Likewise, we intend to make heavy use of the Kinect API, which comes with very strong support for human joint detection. While we expect both ROS and Kinect to have relatively steep learning curves, we do not anticipate these being the limiting factor in how much progress we are able to achieve. Rather, we expect the area of novel difficulty to be the combining of these two distinct systems into one coherent system which can be used for teleimmersive learning.

3.2 Evaluation Criteria

We will evaluate the performance of our proposed system to teach the PR2 by experimentally determining how quickly and easily the PR2 can acquire new behavior. We will start with very simple motions, such as simply lifting and pouring a single cup or bottle. Once the PR2 is capable of completing those actions after shadowing a human demonstrator,

we can attempt to teach it increasingly complex sequences of mixing and pouring. We can measure the PR2's success rate in repeating a recorded movement over multiple trials. The goal here is to show that many different movement sequences can be taught to the PR2 using the same motion capturing setup from the Kinect.

If time permits, we also plan to evaluate the PR2's ability to adapt to variable conditions. For instance, we can measure how far a bottle can be moved from its expected position before the PR2 becomes unable to pick it up. The weight of the bottle can also be changed to see how well the PR2 can adapt to grasping nearly-full versus nearly-empty drink containers. We can measure how the success rate of the PR2's drink mixing is affected as a function of these variables (distance moved, weight of drinks, etc).

3.3 Block Diagram

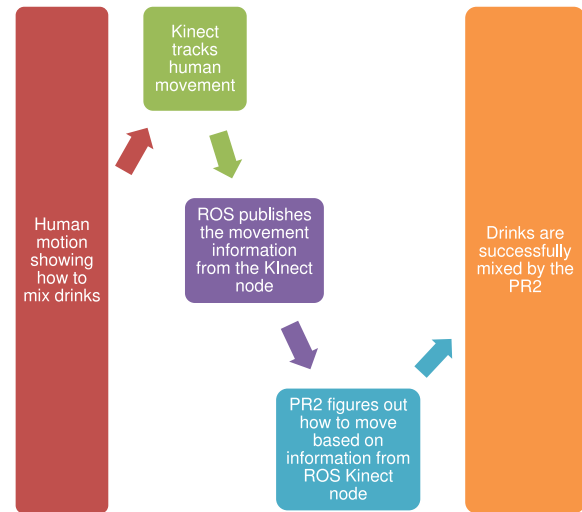


Figure 1: Block Diagram Summarizing Anticipated Approach

4. RESEARCH TIMELINE

The following is a list of milestones we hope to reach as the fall and spring semesters progress.

- **ALREADY COMPLETED:** Preliminary reading and project selection. Project proposal completed.
- **PRIOR-TO NOV.1:** Complete ROS tutorials and practice using ROS.
- **PRIOR-TO DEC.1:** Capture human movement with Kinect. Experiment with PR2 simulator.
- **PRIOR-TO WINTER BREAK:** Issue commands to PR2 simulator by human gestures captured by Kinect. Progress report completed.
- **PRIOR-TO FEB.1:** Attempt real trials on the actual PR2.
- **PRIOR-TO MAR.1:** Achieve a simple, successful drink mixing with the PR2.

- PRIOR-TO APR.1: Develop a more complex sequence of drink mixing with the PR2.
- COMPLETION TASKS: Verify that the PR2 can successfully mix a drink. Conduct accuracy testing. Complete write-up.
- IF THERE'S TIME : Investigate ways to improve the PR2's ability to adapt and learn from different drink configurations.

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