BERTRAM: A Bartending Robot

Dept. of CIS - Senior Design 2011-2012

Seth Shannin
sshannin@seas.upenn.edu
Univ. of Pennsylvania
Philadelphia, PA

Kevin Xu
kevinxu@seas.upenn.edu
Univ. of Pennsylvania
Philadelphia, PA

Dr. Camillo Jose Taylor
cjtaylor@cis.upenn.edu
Univ. of Pennsylvania
Philadelphia, PA

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 physical manipulation of the robot and translating information from visual motion capture. Here we investigate teaching robotic motion through the development of an immersive teleoperation system for controlling the PR2. Unlike previous attempts to control the PR2 from a distance ('teleoperation'), we propose to also provide the operator with an 'immersive' experience by allowing the operator to experience the robot's environment from the robot's perspective.

We plan to evaluate the effectiveness of the system by attempting to mix and serve drinks with a Willow Garage PR2 humanoid robot controlled by a user of this immersive teleoperation system. Following the implementation of this system, we will then evaluate how the system can be used to allow the PR2 (or any robot for that matter) to rapidly acquire new behavior within a specific environment. If successful, we will have demonstrated a novel and easy way for a human operator to impart a specific movement sequence on to a robot. This paper details our progress in regards to implementing the immersive teleoperation system and our plans to use it to teach PR2.

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 (that is, free of direct control from a human operator) is an incredibly challenging process, for many different processes must be coordinated to make this possible. For instance, visual information 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 major type of approach that has been often explored involves the field of machine learning. The ability to learn can be a powerful intermediate step towards autonomy, since learning can allow a robot to adapt to new, unforeseen scenarios on its own. 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 individually planning the movement of each 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 paper we report on our progress towards teaching the WillowGarage PR2 Robot how to mix and serve drinks by first implementing an immersive teleoperation system for controlling the PR2. By 'teleoperation', we simply mean control from a distance. By 'immersive', we mean giving the human operator the illusion of being inside the PR2. The PR2 is a humanoid robot developed by Willow Garage [5] for the purpose of robotics research. It is omnidirectional and capable of telescoping height. What makes the PR2 especially attractive for robotics research is its pair of highly movable arms and grippers that allow grasping of many different kinds of objects. The PR2 also comes with a robust series of highly useful software development tools, including a versatile simulator that allows developers to perform trial runs on a virtual PR2 without risking damage to the actual robot. Institutions across the world have taught the PR2 a wide variety of human actions, such as baking cookies [1], scanning and bagging groceries [7], and fetching a sandwich from Subway [13]. However, unlike these examples, we propose to teach the PR2 a new behavior not through advanced task planning, but through human demonstration. Thanks to the University of Pennsylvania's GRASP laboratory, we have access to a real PR2 (as shown in Figure 1) that we can use to test the implementation of our system.

The chief component of our teleoperation system is the Microsoft XBox Kinect sensor. This sensor provides depth information at real-time speeds (30 frames per second), which essentially performs the computation that would have been required for stereo processing. Combined with various open source libraries [11], the Kinect also works with software that provides human motion sensing and tracking, which greatly simplifies the task of capturing human body movements. These Kinect libraries have already been used successfully in many projects involving real-time tracking of human motion, many examples of which can be found online [4].

We propose to use the Kinect as part of an immersive teleoperation system 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

Figure 1: PR2 robot at the University of Pennsylvania, nicknamed 'GRASPY'

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 moving all of the arm joints to a specific position within a specified time frame. By using ROS along with the PR2 and the Kinect, we will construct a system for operating the PR2 remoting while giving the operator the feeling of being within the robot itself. The effectiveness of this system in teaching the PR2 new tasks will then be evaluated.

What follows is an overview of work related to implementation of teleoperation systems and teaching robots human-like tasks. We then describe the components of our proposed immersive teleoperation system before delving into the technical implementation of each component. After this will be an evaluation of the current performance of the system and a summary of remaining work.

2. RELATED WORK

There have been many previous teleoperation implementations for robotic systems. Kofman *et al.* [8] devised a system for controlling a robotic arm via teleoperation and sending visual feedback to the user. The setup used in their work involves multiple cameras aimed at the human operator to capture 3-D information about the operator's arm movements. This data is then sent to a remote site containing the robotic arm and mapped to its joints so it can mimic the motion of the human arm. The human operator is able to see the robotic arm via cameras positioned at the remote site that send visual feeds of both the entire arm and of vision from the point of view of the tip of the robotic arm. Fortunately for us, the Kinect, when paired with ROS, provides a much simpler and less complicated setup to capture arm motion and send them to the PR2's arm. We are far from the first to implement teleoperation of a robot via the Kinect and ROS. However, our ultimate goal includes not only developing an immersive teleoperation system for the PR2, but also seeing how this system can be used to teach the PR2 new behavior, such as mixing and serving drinks.

Other institutions have conducted research involving autonomous robots and handling drinks. Hillenbrand *et al.* [6] designed a semi-autonomous hand-arm robot for this purpose. 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. Processing of visual data from cameras 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 navigating 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. By combining different processes for object recognition, task based planning, and caged grasping, HERB was able to autonomously carry out commands issued from a graphical user interface to perform simple kitchen tasks, such as placing an object in a recycling bin or lifting a mug. The approach taken to teach by both of these works relies primarily on heavy amounts of computation to carefully plan each action that the robot will execute ahead of time. The chief difference in our system is that we intend to teach a robot to do these kinds of things more quickly and naturally by having a human operator of our teleoperatin system execute the actions first.

There has also been substantial work done in teaching the PR2 robot to perform various 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 for rapidly prototyping different 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.* [7] developed a grasping algorithm to enable the PR2 to pick up objects and attempt to locate and scan the barcode. Their technique allowed the PR2 to devise a plan to grasp the object from only a single 3D snapshot. Their algorithm emphasized the importance of positiong the PR2's gripper such that its shape most closely matched the shape of the object it attempts to grasp. Saito *et al.* [13] devised a way 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. If it fails to find one there, it then determines the next most likely place a sandwich could be found. These approaches to teaching the PR2 emphasize complex algorithms used to enable the PR2 to devise a plan from scrach to act autonomously in a given environment. Our approach is simpler in that we plan to use recorded input data from our immersive teleoperation system to give the PR2 a general sequence of actions to follow that can later be refined through more complex learning techniques.

There have also been other approaches involving data from human demonstration to allow a robot to perform specific tasks. In a relatively early attempt, Chalodhorn *et al.* [3] used motion capture to teach a bipedal humanoid robot how to walk by imitation. Joint angles obtained from motion capture data recorded from a human demonstrator wearing a motion capture suit were mapped to joint angles on the robot. This data was combined with predictions based on sensory information to reproduce a human-like gait in the robot. Kormushev *et al.* [10] taught a robot new motor skills through kinesthetic teaching, which is teaching by physical contact. The robot had two distinct modes of operation: a learning phase and a reproduction phase. First, the robot was shown how to clean a whiteboard by direct human manipulation of the robot's joints, recording both position and force information. Subsequently, the robot would translate the learned information to its own frame of reference and attempt to duplicate the teacher's movement pattern on the whiteboard. Kormushev *et al.* [9] 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.

Our method has several advantages over these 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. The Kinect also provides motion capture without the need of complicated setups involving motion capture suits or multiple cameras. Secondly, an immersive scheme for controlling the robot enables a human operator to more naturally move the robot in a given situation compared to manipulating the robot directly by physical contact or through a joystick-based control scheme. Immersive teleoperation also enables direct control of robots that cannot be easily subject to demonstration through physical contact, 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 and enhancement. This technique could be generalized to other humanoid robots besides the PR2 to teach them different kinds of behavior.

3. SYSTEM MODEL

Specifically because a teleimmersive system is meant to be used by human operators to control a robot, the external/visible part of this design must be simple. The number of devices used to get input from the user and to deliver feedback should be small, and these devices should require minimal effort to use. To that end, a good portion of the control data captured from the user is captured passively. After the initial setup phase, the user should be able to control the system with minimal effort; the system should just watch the user and translate the user's movements into control instructions for the PR2.

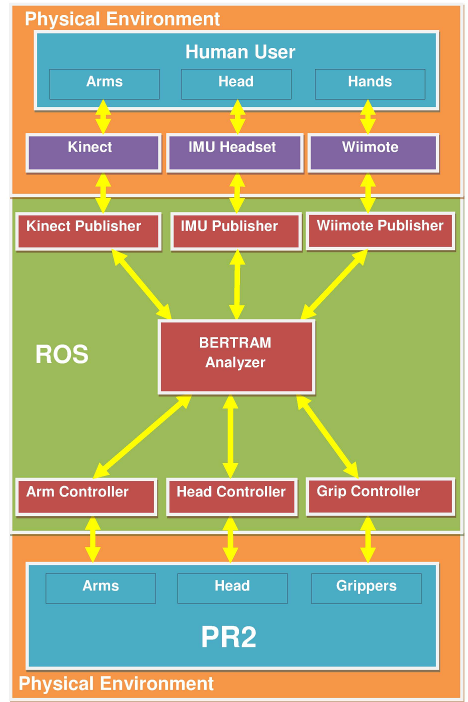

Figure 2: Block Diagram Summarizing System Model

To facilitate this process, we use a couple separate devices and some fairly sophisticated software stacks. While the devices mostly consist of cameras and accelerometers to track the users motion, there are a couple handheld button devices to allow the user to perform non-humanoid operations on the robot (such as freezing a joint or triggering certain routines).

The true nexus of the system is ROS (Robot Operating System). Although the user will never interact directly with ROS, all communication between the user and the PR2 (in the form of commands or feedback) must pass through ROS. ROS abstracts over devices and I/O, providing a common interface for accessing any data stream or controlling any device. Using ROS, we can easily take data from the many tracking devices, process all the data to come up with movement plans for the PR2, and then actually command the PR2 to move in the desired manner. This system architecture is shown Figure 2.

Other than the PR2 robot itself, the Microsoft Kinect is perhaps the most prominent and obvious device in the teleimmersive operation system. The hardware uses an infrared projector and stereo RGB cameras to create a 3D scene image complete with depth information. It sends these raw video frames to ROS, which then forwards the feed to a processing node. This processing node analyzes the video stream, identifies humanoid figures in the frames, and tracks these figures' joints. The Kinect does have some shortcomings though in that it does not reliably track wrist, finger, or head movements. We use separate accelerometers to track these motions.

We capture wrist motion by having the user hold one Nintendo Wiimote with Wii MotionPlus in each hand. The Wiimote is a video game controller with multiple buttons, a direction pad, and built-in accelerometers. In this sense, it is quite convenient. The user holds one Wiimote in each hand (this is what they were designed for). The user now has convenient access to a number of control buttons and also has an accelerometer to track the wrist joints.

In order to track the user's head movements, we have the user wear a hat with a three-axis accelerometer. This can track the yaw, pitch, and roll of the user's neck joint and can therefore capture all head motions. The device is approximately the size of a quarter and can be attached to any surface via velcro.

The final hardware device is a pair of Vuzix augmented reality glasses. Essentially, this is a pair of glasses with a mini LCD screen in each lens. We take the video feed from the PR2's onboard stereo cameras and pipe it directly into each eye. This is the immersive step which closes the loop.

There is one other significant component to this system. This is what we have termed in Figure 2 the `BERTRAM Analyzer`. This is a software node residing in ROS. Its primary function is to stitch together the motion and position data from all the input devices (Kinect, Wiimotes, head IMU). It collates all the information and then maps the user's motions into equivalent motions for the PR2.

4. SYSTEM IMPLEMENTATION

Most of the interesting work in this project takes place inside the `BERTRAM Analyzer`, which collates all the captured motion data from the user and processes this data to generate commands for the robot. ROS provides bindings for both `C++` and `Python`. We chose to use Python due to our familiarity with the language and due to the relative verbosity of `C++`. The analyzer registers for interrupt events from the Wiimotes and head-mounted IMU and actively polls the Kinect sensor.

5. PROJECT PROPOSAL

We propose to teach a PR2 robot how to mix drinks via teleimmersive demonstration learning methods. One of our major goals is to have the PR2 be able to reproduce different drink mixing recipes acquired from watching a human demonstrator perform them in the past. Our other major goal involves having the PR2 adapt its behavior by learning from failed attempts. Given a setting consisting of many different bottles and glasses, the PR2 should be able to distinguish and select the desired bottles and them 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.

5.1 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. For example, the sequence of moves involved for mixing a martini will be different than the ones involved in mixing a gin and tonic. In the next part, the PR2 will then attempt to improve its execution of the learned motion through reinforcement learning. For instance, if we move a cup two centimeters away from its expected position, and the PR2 fails to pick it up, it can try again by adjusting its recorded sequence of moves.

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. The Kinect will provide nodes that can publish motion capture data, which in turn can be subscribed to by nodes controlling parts of the PR2. In this way,the PR2 can 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 augmented by reinforcement learning techniques. In addition to simply trying to replicate the motion in identical situations, the PR2 will evaluate its own performance in changing environments. For instance, objects may placed in the exact same location as they were placed for the human demonstrator. The end goal is for the PR2 to 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. The Kinect has already been integrated with ROS with great success. 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.

5.2 Evaluation Criteria

6. SYSTEM PERFORMANCE

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. This success rate can be then be correlated with the complexity of the demonstrated command. The goal here is to show that many different movement sequences of varying difficulty 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. The success rate of the PR2's drink mixing can be analyzed as a function of these variables (distance moved, weight of drinks, etc).

7. REMAINING WORK

The following is a list of milestones we hope to reach as the spring semester progresses.

- 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.

8. REFERENCES

[1] Abby Abazorius. Cookies, anyone? `http://web.mit.edu/newsoffice/2011/cookies-anyone.html`.

[2] Jonathan Bohren, Radu Bogdan Rusu, E. Gil Jones, Eitan Marder-Eppstein, Caroline Pantofaru, Melonee Wise, Lorenz Mosenlechner, Wim Meeussen, and Stefan Holzer. Towards autonomous robotic butlers: Lessons learned with the PR2. In *ICRA 2011*. Willow Garage, 2011.

[3] Rawichote Chalodhorn, David B. Grimes, Keith Grochow, and Rajesh P. N. Rao. Learning to walk through imitation. Technical report, University of Washington, 2007.

[4] Freenect. Freenect - kinect projects. `http://www.freenect.com`.

[5] Willow Garage. Pr2 overview. `http://www.willowgarage.com/pages/pr2/overview`.

[6] Ulrich Hillenbrand, Bernhard Brunner ad Christoph Borst, and Gerd Hirzinger. The robutler: a vision-controlled hand-arm system for manipulating bottles and glasses. Technical report, Institute of Robotics and Mechatronics, 2004.

[7] Ellen Klingbeil, Deepak Rao, Blake Carpenter, Varun Ganapathi, Andrew Y. Ng, and Oussama Khatib. Grasping with application to an autonomous checkout robot. In *ICRA 2011*. Stanford University, 2011.

[8] Jonathan Kofman, Xianghai Wu, Timothy J. Luu, and Siddharth Verma. Teleoperation of a robot manipulator using a vision-based human-robot interface. In *IEEE Transactions on Industrial Electronics*, volume 51. IEEE Industrial Electronics Society, Oct 2005.

[9] Petar Kormushev, Sylvain Calinon, and Darwin G. Caldwell. Robot motor skill coordination with em-based reinforcement learning. In *IROS 2010*. Italian Institute of Technology, 2010.

[10] Petar Kormushev, Dragomir N. Nenchev, Sylvain Calinon, and Darwin G. Caldwell. Upper-body kinesthetic teaching of a free-standing humanoid robot. In *ICRA 2011*. Italian Institute of Technology, 2011.

[11] OpenKinect. Welcome to the openkinect project. `http://openkinect.org`.

[12] Morgan Quigley, Brian Gerkey, Ken Conley, Josh Faust, Tully Foote, Jeremy Leibs, Eric Berger, Rob Wheeler, and Andrew Ng. ROS: An open-source robot operating system. Technical report, Stanford University, 2009.

[13] Manabu Saito, Haseru Chen, Kei Okada, Masayuki Inaba, Lars Kunze, and Michael Beetz. Semantic object search in large-scale indoor environments. In *IROS 2011*. University of Tokyo and Technische Universität München, 2011.

[14] Siddhartha S. Srinivasa, Dave Ferguson, Casey J. Helfrich, Dmitry Berenson, Alvaro Collet, Rosen Diankov, Garratt Gallagher, Geoffrey Hollinger, James Kuffner, and Michael VandeWeghe. HERB: a home exploring robotic butler. Technical report, Carnegie Mellon University, 2009.