Robotic Coaching of Complex Physical Skills

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ABSTRACT

The research area of using robots to coach complex physical skills is underserved. Whereas robots have been used extensively in the form of robotic orthoses to rehabilitate early trauma patients, there is more that can be done to develop robots that help children, the elderly and late-stage rehabilitation patients to excel at physical skills. In order to do this, we must develop robots that do not actuate on the students, but coach them through hands-off modalities such as verbal advice and demonstrations. This approach requires sophisticated perception, and modeling of the student's movement in order to deliver effective advice. Preliminary results suggest that these goals can be achieved with consumer-grade sensing hardware. We present planned future work towards achieving this vision.

Keywords

Robotic Coaching of Physical Skills, Socially Assistive Robots

1. INTRODUCTION

Much research has been conducted in rehabilitation robotics to develop robotic orthoses for early rehabilitation following traumatic injury. These orthoses, such as the Hacoma Lokomat, attach to the human body in order to help it actuate.

Immediately after lower extremity trauma, many treatment centers make use of Hocoma's Body Weight Supported Treadmill Training (BWSTT) orthosis, the Lokomat[3]. Patients using BWSTT orthoses are strapped into a bodyweight-support harness on top of a treadmill, and their legs are actuated by the BWSTT to walk atop the treadmill. The Lokomat has been shown to work as well as traditional physiotherapy for stroke patients, while requiring a much lightened physiotherapist load[2].

However, there is an opportunity to develop robots that not only help early trauma patients to recover typical motor function, but that also help people with typical motor function to excel at physical skills. For example, there is an opportunity to develop more effective late-stage rehabilitation tools for patients that are at the point of walking around freely. As children who are proficient at a physical skill are more likely to stay active well into their teenage years and beyond[6], robots should coach children to become excellent at physical skills, such as shooting a basketball or hitting a tennis serve.

Outside of early rehabilitation, we do not want our human or robot coaches to touch us, so in these domains we no longer require an orthosis that attaches onto the patient, but rather a coach that teaches the student from a distance. We call this contact-free approach to training physical skills, "Robotic Coaching of Physical Skills."

Early work in this area often takes a minimalist route in terms of perception and understanding, following the paradigm of robots performing physical demonstrations, and asking humans to replicate the movement without the robot having a deep understanding of the human's motion. This work is generally applied to elderly fitness coaching, pediatric fitness coaching, and rehabilitation. [1] have used the Nao robot to demonstrate gestures to elderly patients, helping them to remain fit, and [5] have shown that children were attentive to the robot coach that demonstrated a physical dancing task.

However, little work has been done in developing robotic systems that can perceive and understand human movements to the point of giving effective advice on how best to improve. There are a number of required functions that a robot must perform in order to achieve this goal, which must be investigated by the following research questions:

Q1. What modalities best balance accuracy and unobtrusiveness in a perception suite aiming to observe complex physical skills that are performed by a human?

Q2. What algorithms effectively quantify problems and also mine the inter-dependencies between these problems in a motion?

Q3. Given these interdependencies, what algorithms effectively prioritize the order in which the problems should be addressed by the human for most rapid improvement?

Q4. What techniques should be employed to effectively communicate prioritized advice to the human through verbal advice and demonstration?

In the following sections, we discuss present and future work towards this end.

HRI'15 Extended Abstracts, March 2–5, 2015, Portland, OR, USA.
ACM 978-1-4503-3318-4/15/03.
http://dx.doi.org/10.1145/2701973.2702726.

2. PRESENT WORK

Our present work focuses on physical skills possessing complex and interwoven sub-movements involving the entire body, and that have a clear supervisory signal indicating whether the skill was a success. Basketball possesses the aforementioned characteristics, and is popular with children across all socioeconomic demographics. As such, we chose the basketball application domain, where we use a Nao robot to teach children how to shoot a basketball from a fixed position, according to the setup shown in Figure 1. We track the skeleton of the student using a Kinect sensor, and track whether the ball successfully entered the hoop using a ShotTracker net sensor. The robot then provides physical and verbal demonstrations to coach the student.

Thus far, we have developed an operational perception suite (Q1), developed a problem quantification algorithm (Q2), and explored preliminary data modeling techniques for identification of problem salience, and prioritization (Q3). More information about this work can be found in [4].

In order to test the accuracy of the Kinect sensing suite (Q1), we performed a pilot study in which we recorded 521 free throws from 11 participants. Each recording entailed a 40 dimensional vector time-series of joint-angles throughout the duration of the motion, as well as a supervisory success flag of whether the shot entered the basket. For example, one of the 40 dimensions would be a time-series of the joint angle of the right knee throughout the shot.

We used a simple, heuristic approach in order to test whether the current sensing suite was sufficiently accurate to inform an understanding of the student's motion that could lead to useful advice. After pre-processing (smoothing and discretization), we used a supervised machine learning approach to train a classifier to predict whether a shot would enter the basket based on the student's shooting movement. If a classifier is able to accurately predict whether a motion would be successful, then the data is sufficiently nuanced to be separable into good and bad examples, and it would most likely be possible to devise an algorithm to prioritize problems (Q3) and effectively advise on how to improve (Q4).

Using a Support Vector Machine with a Radial Basis Kernel, we were able to classify shooting motions better than always predicting the most likely outcome that the ball would not go into the basket: 82.6% versus 71.8%, respectively on the testing set. This leads us to believe that the data collection method is promising. However, we have noticed that the wrist joint angle, which is crucial to this particular motion, is noisy, and occasionally occluded by the basketball. As such, we plan to add an additional wrist sensor to the perceptual setup, and expect that this will improve results.

We have also begun work on a physical demonstration system for the Nao robot. Thus far, the Nao robot is able to maintain static stability while imitating a student's gesture, as recorded by the Kinect. We have found that the Nao robot is a plausible candidate for teaching the motion, as it has sufficiently fine motor control to demonstrate motion differences between both participants with very large differences in skill level, and competitively trained participants with very similar motions. There are some issues regarding the differing dynamics of the Nao compared with a human. We have come up with a number of heuristics to account for these thus far, for example using the Nao hand open/close behavior to approximate the human wrist.

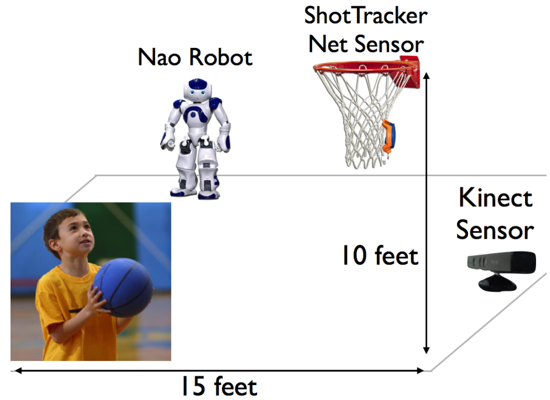

Figure 1: Setup for the basketball shooting application domain.

3. FUTURE WORK

Our goal is to conduct research on all of the questions listed in Q1-Q4. We first plan to supplement the sensory suite with a wrist angle sensor in the hopes of achieving a near-perfect classification rate of shooting motion success (Q1). Once this step is completed, we will investigate the suitability of varying complexities of machine learning approaches to model the inter-relationships between problems in a motion (Q2), and prioritize the order in which they should be fixed (Q3), including regressions and more complex probabilistic graphical models such as Bayesian networks. We plan to expand on our current demonstration system by adding the capability for the robot to exaggerate a problem, as well as to give verbal advice (Q4).

We are planning a study to test the effectiveness of the robot in giving prioritized advice based on the output of our prioritization model, versus un-prioritized advice. The principal outcome measure will be the shooting percentage increase of the student after the advice has been delivered, with secondary measures being self-reported desire to practice again, engagement, and attributions toward the robot.

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