Human Physical Movements for Kinematic Learning for Robots

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Abstract

We describe an ongoing effort to capture and transfer human physical movements to inform robotic kinematic modeling and learning. This concept is inspired by human neuro-plasticity and the observed phenomenon of "Homuncular Flexibility", a seemingly innate ability of humans to inhabit and adapt to control forms that do not directly map to existing physical embodiments. We describe its application for industrial robots such as thermal spray robotic arms, which features a different set of degrees of freedom and other physical constraints than a human arm. The goal of the effort is to digitize human "muscle memory" and expert knowledge in order to provide training data for robotic learning.

Background

The current practice for programming industrial robots such as thermal spray robotic arms to process novel shapes involves a human expert creating an initial model of the path based on an initial best guess and adjusting the model based on the output. This can be extremely time consuming. The key challenge can be viewed as two separate learning processes; the mapping of human motions under human physiological constraints to robotic motions under robotic constraints, and the identification of rules and strategies that shape expert movements. One state of the art method to overcome this challenge is kinesthetic programming by demonstration, where individuals physically move the robot, with the exerted forces measured. The robot can then imitate the trajectory and force recorded during the demonstration. This method contains several limitations: 1) the machine can be large and difficult to manipulate physically, 2) the machine may have capabilities that the human physically does not (e.g. extremely high speed), thus the machine is limited to the human's demonstration, and 3) the adaptability of the robot is limited to what was recorded during the demonstration, so it may not readily scale or adapt to modifications or perturbations in the environment.

Expert humans can manually use thermal spray equipment to repair a part with ease, even for completely different shapes or parts, and within different environments. Their strategies may be considered tacit knowledge, much like the skill of catching a fastball or sinking a golf putt. Often, the human expert may not be consciously aware and therefore may not be able to articulate his/her own strategies. The exact cues that lead to the human experts' behaviors may not be consciously known. Therefore it often cannot be articulated or modelled. Because this type of human intelligence cannot be formally characterized easily, it has been passed on in the same way for millennia, a combination of trial and error and using the master-apprentice model. To enable machines to become an apprentice, we must address the limitation of digitizing tacit human knowledge. Due to its unwieldy nature, this type of intelligence is often dismissed by machine learning methods because of its need for computationally tractable models. By imposing the physical constraints of the robot onto the human, we utilize the human's neuro-plasticity to create path planning data that is compatible with the robot's degrees of freedom, thereby making it feasible to directly use machine learning to identify features of expert strategies.

This neuro-plasticity is closely related to the phenomenon of homuncular flexibility that was first observed by Jaron Lanier (Lanier) and Tom Furness, pioneers in Virtual Reality (VR) during the wave of wide spread enthusiasm in the medium in the 1980's and 1990's. Through a simple software error, an avatar was created with an accidentally huge arm, but Lanier and Furness observed that human users were able to control it intuitively and with accuracy. They did not conduct scientific studies regarding further use of these "weird avatars", and further research subsided as public interest and funding in VR waned in the late 1990's and 2000s. Basic research in homuncular flexibility has been conducted by Steptoe et al (2013) at the University of Barcelona and Won et al., (2014, 2015) at Stanford, demonstrating the ability of novice operators to control non-human limbs such as a third arm. This phenomenon has not been mentioned for manufacturing until very recently, when Lipton et al. (2017) described it in a paper describing teleoperations for a manufacturing robot. Lipton et al. used the concept to inspire improvements in the mapping of robotic constraints in teleoperations.

Method

We are investigating the digitization of expert human motion data for integration with machine learning to increase the adaptability of robots within the same class of tasks, such as spraying differently shaped coupons using thermal spray. The goal is to resolve a key supervised learning bottleneck; the need for large amounts of labeled and trust worthy training data. Other efforts have evaluated the feasibility of teaching robots to play a musical instrument, such as bow control for a violin (Percival et al., 2011). This is essentially the problem of controlling a non-linear dynamical system, with some physical models consisting of non-deterministic elements. Percival et al use humans to label the results of violin playing as training data, akin to using the human as an evaluator. The current project goes beyond the state of the art by capturing human motion for use directly as training data, akin to a master/apprentice model with the human as a master and a thermal spray robot as the apprentice.

Because human physiology have a different set of constraints as the degrees of freedom of a robotic arm, human movement cannot be used directly to control and train the robot. Instead, human movement needs to be mapped to movements that the robot is capable of performing. In other words, the physical constraints of the robot must be incorporated into training data. To side step the need for formally modelling robotic constraints, we are using the phenomenon of homuncular flexibility, the innate human physiological ability to adapt and control non-human embodiments.

We have obtained and customized a Universal Robot Description Format (URDF) model of a robotic arm platform that describes its mass, dimensions, and degrees of freedom, and successfully loaded the model into a physics simulator that provides support for the HTC Vive VR headset. We have further customized a virtual environment that allows a human to control the robotic arm using the VR hand controllers. This represents the first building block for the envisioned pipeline.

Future Work

While the human has an innate sense of proprioception, i.e. the relative position of one's body parts, center of gravity, movement and inertia, current cues for the evaluate of the virtual robot is limited to visual display of the position of the robotic parts and their physical constraints. This is quite limiting since the human operator tends to focus on the task at hand rather than actively managing proprioception. In a notional pick-and-place task where the operator is tasked with picking up an object and placing it within a target, the human tends to keep their eyes on the target of interest, rather than location of their hand. Due to the current restriction to visual feedback, anecdotally, operators easily lose track of when their physical movements are uncoupled with the virtual movements of the robot due to a violation of a physical constraint. Further, there are currently no cues or feedback mechanism for the human operator on the center of gravity or forces and inertia related to movement. Thus, we are investigating the use of additional visual, audio, and haptic feedback to alert coupling/decoupling of human and robot physical movements as well as other physical dimensions of interest.

Lastly, we are in the process of implementing data collection mechanisms, evaluating a combination of motion capture, VR equipment location, and user behaviors such as button presses. The collected data can then be used as training data to feed a deep learning neuro network so that a robot can rapidly plan a path for spraying a novel shape, mimicking human experts.

Discussion

VR based robot interfaces have existed since early 1980's. NASA-Ames and JPL used VR for telerobotics of remotely deployed robots (Stark 1987). Takahashi et al (1992) proposed a VR interface for the human operator to record robotic assembly tasks using the VPL Dataglove so that the robot can later replicate the operator's movements. Miner et al. (1994) added to this discipline by adding task level representations and voice commands using the software platform CimStation running on SGI workstations. The idea of utilizing a human within VR or Augmented Reality (AR) to control a robot is not new. However, it has only been applied to teleoperations and script-based programming. It has not been applied for generating training data for machine learning to incorporate generalizable path planning strategies.

We believe it is technically feasible because many components necessary for this effort have been successfully developed in isolation. Recent developments in commercial off the shelf (COTS) VR hardware and software ecosystem, Robot simulator platforms, physics engines, machine learning tools, and readily available robot descriptions within standardized formats are all enabling technologies that provide the ripe landscape to implement the described concepts.

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