A Motion Capture and Imitation Learning-based Approach to Robot Control

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June 21, 2022

Abstract

Imitation Learning is a discipline of Machine Learning primarily concerned with replicating observed behavior of agents known to perform well on a given task, collected in demonstration data sets. In an industrial robotics context this presents the opportunity to replace explicit programming of behavior with demonstrations of the task to be performed. Motion capture is one of the methods for recording such data. It enables lesser model complexity compared to more indirect observation modalities such as visual data, yet requires additional data pre-processing if signals beyond a time series of effector positions and orientations are relevant to the task at hand. In this paper, an approach for motion capture-based imitation learning and implicit control signal estimation is introduced and evaluated on an object throwing task.

Keywords Imitation Learning · Motion capture · Robotics · Artificial neural networks · RNN

1 Introduction

Manipulator arms and other types of robots have become ubiquitous in modern industry and their use has been proliferating for decades, yet even now the primary method for programming these devices remains procedural code, hand-crafted by specially trained technicians and engineers. This significantly increases the cost and complexity of commissioning process nodes that utilize industrial robots. To this end, various alternative approaches grounded in machine learning have been proposed. Perhaps the most commonly studied are methods that fall under the umbrella of reinforcement learning, which optimize an agent acting on its environment through the use of an explicitly specified reward function [Sutton and Barto, 2018]. While offering strong theoretical guarantees of convergence, they require interaction with the environment for learning to occur. Furthermore, in practical settings the reward function for many tasks is very sparse, leading to large search spaces and inefficient exploration [Hester et al., 2018]. Finally, the reward function for a task may be unknown or difficult to specify analytically [Abbeel and Ng, 2004].

Imitation learning is a broad field of study in its own right that promises to overcome some or all of the aforementioned challenges, provided that it is possible to obtain a corpus of demonstrations showing how the task is to be accomplished. When dealing with industrial robotics, this is often the case as the tasks we wish to execute are ones that human operators already routinely perform. Therefore, we have developed an approach for recording actions taken by humans in the physical environment, programmatically producing a training data set structured in the form of explicit demonstrations augmented with additional, extrapolated state inputs and control signals, and training artificial neural network models to reproduce the trajectories therein as motion plans.

Given the inherent trade-off between task specificity and required model complexity when it comes to observation data modality and model output, motion capture has been selected as a convenient middle ground. It does not require a simulated environment as approaches that involve virtual reality do [Zhang et al., 2018, Dyrstad et al., 2018], obviates any issues that may come with having to learn motions in robot configuration space by operating in Cartesian coordinates,

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and does not necessitate the use of complex image processing layers as found in models with visual input modalities [Liu et al., 2018, Zhang et al., 2018]. The main drawbacks of this approach are that it requires motion capture equipment, which is more expensive than conventional video cameras, and Cartesian motion plans need an additional conversion step into joint space trajectories before it is possible to execute them on a real robot. Given the intended application of this system – programming robots to perform tasks in an industrial environment – the advantages of compact models, rapid training times and results that are possible to evaluate ahead of time were deemed to outweigh the drawbacks.

To help guide the development process and serve as a means of evaluation, a sample use case was selected – object throwing with the goal of extending the robot's reach and improving cycle times. While on the surface the task is almost entirely defined by elementary ballistics that can be programmed explicitly, it serves as a convenient benchmark for robot programming by way of demonstrations. The task was deemed sufficiently non-trivial when considered from the perspective of a Markov decision process or time-series model only given limited information about system state at any given time step, while also being suitable for intuitive evaluation by human observers due to its intuitively straightforward nature. Furthermore, the relationship between release position, velocity and target coordinates provides an obvious way to quantitatively evaluate model performance against training and validation data – extrapolated throw accuracy.

2 Preliminaries

In this article, an *agent* can be taken to mean the part of the system that acts based on state or observation information s in an *environment*, according to a *policy* π which is specified by a parametric *model* – a function $\pi_\theta(s)$ with parameters θ tuned in optimization and produces an output *action* a. In practice this means that references to the agent, model and policy are almost interchangeable in most contexts. A formalism common in both reinforcement and imitation learning contexts is the *Markov decision process* (MDP), formally given by [Attia and Dayan, 2018]

$$MDP = (S, A, T, R, I) \tag{1}$$

where S is the set of states s, A is the (formally discrete) set of actions a, $T : S \times A \to S$ is a state transition function that encapsulates the environment, $R : S \to \mathbb{R}$ is a reward function associated with each state and $I = p(s_0 \in S)$ represents the initial state distribution. In many imitation learning-related cases a reward function need not specified or considered. Moreover, if one is willing to break with the strict formal definition and give up the use of mathematical tools defined only on finite probability distributions, continuous action spaces can also be considered.

One important characteristic of the MDP is that it is history-agnostic – the future state distribution of the system is uniquely defined by its current state. While technically true for physical environments, it is often the case that instead of a complete state representation vector $\mathbf{s}$ we are instead operating on a more limited *observation* $\mathbf{o}$ (often interchangeably referred to as $\mathbf{s}$ for brevity), where each element o_i is given by some function $f_i(\mathbf{s})$. It is therefore possible that historical observations contain information about hidden system state variables even assuming the MDP formalism holds for the underlying environment. An example of this can be the case when individual observations contain only the current position of an object but not its derivatives [Zhang et al., 2018]. In such cases it may prove beneficial to break with the formalism further, by redefining the policy to operate on sequences of $k + 1$ previous states/observations

$$t, k, n \in \mathbb{N}, \pi_\theta : \{(s_n)_{t-k}^t\} \to A \tag{2}$$

which, by allowing for input sequences of variable length, may become a function defined on the entire known state history:

$$\pi_\theta : \{(s_n)_1^t\} \to A \tag{3}$$

These adjustments allow for the employment of sequence-to-sequence predictor architectures also studied in other areas of machine learning such as recurrent neural networks (RNNs) [Rumelhart et al., 1985] and transformers [Vaswani et al., 2017]. Finally, if continuous action spaces are permitted it is no great stretch to also consider cases where the action corresponds to a predicted future state that may be used for static motion planning or in a dynamic error-based controller

$$\pi_\theta : \{(s_n)_1^t\} \to S \tag{4}$$

which, when running the model on its own output, is equivalent to sequence building tasks encountered in domains such as text generation.

3   Related Work

In its simplest and most straightforward form – sometimes referred to as *behavioral cloning* – imitation learning can be reduced to a classification or regression task. Given a set of states and actions or state transitions produced by an unknown expert function, a model (*policy*) is trained to approximate this function. Even with very small parameter counts by modern standards, when combined with artificial neural networks this method has demonstrated some success as far back as the 1980s, provided a task with simple dynamics such as keeping a motor vehicle centered on a road [Pomerleau, 1989].

However, it has since become apparent that pure behavioral cloning suffers from distribution shift – a phenomenon whereby the distribution of states visited by the policy diverges from that of the original training data set by way of incremental error, eventually leading to poor predictions by the model and irrecoverable deviation from the intended task. To improve the ability of policies to recover from this failure mode, various more complex approaches to the task have been proposed. One major direction of research has been the use of inherently robust, composable functions known as *dynamic motion primitives*, employing systems of differential equations and parametric models such as Gaussian basis functions to obviate the problem of distribution shift entirely – ensuring convergence towards the goal through the explicit dynamics of the system [Pastor et al., 2009]. Though showing promising results, it must be noted that the model templates used are quite domain-specific. Others have attempted to use more general-purpose models in conjunction with interactive sampling of the expert response to compensate for distribution shift [Ross et al., 2011]. While theoretically able to guarantee convergence, the major drawback of such methods is that an expert function is required that can be queried numerous times as part of the training process. This severely restricts applicability to practical use cases, since it is impossible to implement when only given a set of pre-recorded demonstrations.

A different means of handling this problem is given by the field of *inverse reinforcement learning* [Abbeel and Ng, 2004]. Rather than attempting to model the expert function directly, it is assumed that the expert is itself acting in accordance with an unknown reward function. An attempt therefore is made to approximate this reward in a way that explains the observed behavior. From there this becomes a classical reinforcement learning problem, and any training method or model architecture developed in the space of this adjacent field of study can be employed. Where early approaches made certain assumptions about the form of this reward function – such as it being linear – more recent work has proposed that generative adversarial networks be used where the discriminator can approximate the class of all possible reward functions fitting the observations over an iterative training process [Ho and Ermon, 2016].

Perhaps the most promising results, however, come from the sequence modelling domain. Recurrent neural networks show up in earlier scientific literature periodically, such as in predicting a time-series of robot end effector loads in an assembly task [Scherzinger et al., 2019] and learning latent action plans from large, uncategorized play data sets [Lynch et al., 2020]. But current state-of-the-art performance across a wide variety of sequence prediction tasks – among them imitation learning in a robotics context – is given by combining a large, universal transformer model with embedding schemes specific to various data modalities [Reed et al., 2022]. These results strongly suggest that structuring one's approach to be compatible with general-purpose sequence predictor algorithms is preferable for ensuring its longevity.

When it comes to the use of motion capture data, previous work in the robotics and imitation learning corner is quite sparse, possibly due to the costly and specialized nature of the equipment involved. One previously considered direction has been the use of consumer-grade motion tracking equipment for collecting demonstrations [Jha et al., 2017]. Unlike our work, they employ a single, relatively inexpensive sensor unit to generate the motion tracking data, and the main focus of the work is on accurate extraction of the demonstrations rather than modelling and extrapolation – which is left as something of an afterthought, with cluster and k-nearest interpolation methods used for inference. Outside the imitation learning space, related work has been done in human motion modelling utilizing RNNs trained on motion capture data [Fragkiadaki et al., 2015]. The main difference between research in this direction and our work lies in the fact that we are looking for ways to translate human motion into paths taken by a robot, and do not consider the human kinematic model. Additionally, we place an emphasis on extracting particular implicit signals such as release timing and desired target coordinates.

Meanwhile, optimal execution of object throwing tasks has been previously studied in a reinforcement learning context, such as with *TossingBot* [Zeng et al., 2020]. Their approach is radically different from ours, in that it utilizes a reinforcement learning policy to predict a set of grasp and throw parameters. These serve as inputs for grasping and throwing motion primitives. The throwing primitive itself is not learned, but provided with a release position and velocity, which it then executes. Initial estimates are produced analytically, which are then combined with learned residuals. The main distinction between their work and ours, however, is that of purpose. We do not seek to perfect an approach to throwing in particular, but rather establish a method for using imitation learning to program industrial robots. There is an expectation of being able to further adapt them for a variety of tasks – with throwing serving primarily as a convenient benchmark for progress.

4   Proposed approach

Three crucial decisions need to be made when devising an imitation learning-based approach to robot control:

- Data collection – what will serve as the expert policy? How will data be obtained?
- Model architecture – what type of model template will be used to learn the policy?
- Control method – how will model outputs be used to interface with the robot controller software and hardware?

Considering that the goal of this paper is not to examine any of these sub-problems in detail but rather to come up with a holistic approach to combine all of them, trade-offs that affect more than one step at a time need to be considered. Recording of human performances as the expert data set is also a constraint imposed by the objective we set out to accomplish. Therefore, when selecting the demonstration data modality, three possibilities were examined:

- raw video – using conventional cameras to record a scene and use these observations as model inputs directly;
- motion capture – obtain effector and scene object pose (position and orientation) data with specialized motion capture equipment that consists of multiple cameras tracking highly reflective markers affixed to bodies of interest;
- simulation – using a simulated environment in conjunction with virtual reality (VR) or other human-machine interface to obtain either pose data as with motion capture, or record the configurations of a robot model directly.

Raw video is the most attractive approach from an equipment standpoint – it does not involve motion capture or VR equipment, does not require simulated environments, and in principle presents the possibility of a sensor-to-actuator learned pipeline, if the video data were used directly in the model's input to predict actuator commands. In practice, however, not only does using image data call for the employment of more complex model architectures such as convolutional neural networks, images are inherently 2-dimensional representations of 3-dimensional space, leading to ambiguities in the data – and one quickly runs into difficult issues such as context translation that confound the issue further [Liu et al., 2018].

In contrast, unambiguous pose information is readily obtained with motion capture or simulation. Simulating a robot model very tightly couples the trained model to a specific physical implementation, and reasoning about or debugging model outputs obtained this way is not straightforward. Thus, the main comparison is to be drawn between object pose data as obtained in a simulation and with motion capture.

5   Implementation

The overall approach proposed in this paper can be broken down into three main sections – the collection of observations in the physical environment (5.1), a pipeline for turning raw observation data into structured demonstrations (5.2) and neural network model implementations (5.3). Two general ways to evaluate system performance and obtain design feedback were employed. First, qualitative observations of the generated trajectories were made using spatial visualization in a virtual environment, followed by execution on simulated and real robots (5.4). When satisfactory performance was attained a series of quantitative metrics were computed for comparing system outputs with training and validation datasets on different model architectures and hyperparameter sets (5.5).

5.1   Data collection

5.2   Pre-processing, extraction of implicit control signals

bla bla bla

5.3   Models

bla bla bla

5.4   Visualization and execution

bla bla bla

5.5 Evaluation metrics

bla bla bla

6 Results

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7 Discussion

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