Offline Feature-Based Reinforcement Learning with Preprocessed Image Inputs for Liquid Pouring Control

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Keywords: Offline Reinforcement Learning, Pouring Liquid, Artificial Neural Network, Robust Control, UR5 Robot Manipulator.

Abstract: A method for the creation of a liquid pouring controller is proposed, based on experimental data gathered from a small number of experiments. In a laboratory configuration, a UR5 robot arm equipped with a camera near the end effector holds a container. The camera captures the liquid pouring from the container as the robot adjusts its turning angles to achieve a specific pouring target volume.

The proposed controller applies image analysis in a preprocessing stage to determine the liquid volume pouring from the container at each frame. This calculated volume, in conjunction with an estimated target volume in the receiving container, serves as input for a policy that computes the necessary turning angles for precise liquid pouring. The data received on the physical system is used as Monte-Carlo episodes for training an artificial neural network using a policy gradient method.

Experiments with the proposed method are conducted using a simple simulation. Convergence proves to be fast and the achieved policy is independent of initial and goal volumes.

1 INTRODUCTION

Developing an optimal control for a non-linear system usually requires a detailed model of the plant or process. Reinforcement learning (Sutton and Barto, 2018) is a method used to develop a controller, provided the controlling agent has the opportunity to search and experiment with different actions, receiving respective rewards.

Creating sufficiently detailed models of the system to be controlled is often costly and difficult. Often times, the optimal control (policy) developed using a simulation of the system does not work in practice due to imprecise modeling of the system dynamics and sensor data.

There are different approaches to mitigate the so-called simulation to reality gap (Zhao et al., 2020). One method may be to explicitly simulate the sim-to-reality gap, i.e. by including artificial sensor noise. However, this requires detailed knowledge about the system as a whole to anticipate possible differences between the simulation and the physical system.

Given this problem, it is usually better to collect data and run experiments directly within the physical system. However, this is usually not possible because physical systems are often much slower than simulations and therefore a large number of experiments cannot be carried out, as is often needed in reinforcement learning. In addition, safety aspects often play a role, for example in autonomous driving, robotics or aviation.

Strategies to cope with the problem that simulations sometimes lack necessary precision and physical systems lack proper speed to run many experiments, have been developed. Methods are used in which a teacher demonstrates the experiments. Inverse reinforcement learning (IRL) (Arora and Doshi, 2021), for example, tries to derive a reward function

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Pareigis, S., Hermosilla-Diaz, J., Reyes-Montiel, J., Maaß, F., Haase, H., Mang, M. and Marin-Hernandez, A.
Offline Feature-Based Reinforcement Learning with Preprocessed Image Inputs for Liquid Pouring Control.
DOI: 10.5220/0012235700003543
In *Proceedings of the 20th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2023) - Volume 1*, pages 320-326
ISBN: 978-989-758-670-5; ISSN: 2184-2809

from the demonstrations and use it to train a controller.

We introduce a laboratory setup in which a few predefined experiments are carried out in the task of pouring liquids. The data from those experiments is stored accordingly as described in section 3.1. Later, this data is used to train a reinforcement learning controller in an offline manner. As the training algorithm does not have direct access to the system, exploration becomes impossible.

In the given laboratory setup, a camera is mounted on top of the end effector of a UR5 robot arm. A container with a liquid is held in the end effector. The task is to turn the end effector such that a precise volume of liquid is poured out. The system therefore consists of a camera image as input space, and angles of the end effector (one-dimensional) as output space. A maximal reward is awarded if a given output volume is met precisely.

The proposed controller uses two steps: In the first step, the camera image is analyzed using image processing software. A measure for the liquid quantity leaving the container is calculated. This measure can be considered to be a feature of the liquid as seen in the image.

In the second step, this feature is input into an artificial neural network (ANN) that serves as a policy model for determining pouring angles. This two-step process, utilizing pre-processed images, offers the advantage of a reduced input dimension for the ANN. Consequently, a smaller ANN can be selected, resulting in faster training and inference compared to a high-dimensional input space.

As action space, we use discretized relative turning angles of the end effector. The fact that the angles are chosen to be relative enables the method to be independent of the initial volume in the pouring container. This approach of relative and discretized rotation angles uses our idea from robust autonomous driving, as we presented in (Pareigis and Maaß, 2023).

There are a variety of publications on pouring liquid. We just mention a few which are closely related to our approach.

(Schenck and Fox, 2017) presents a solution for pouring specific amounts of liquids based on imagery, independent of the initial volume of liquid in the source container. A camera films the target container and the images are fed into a two-stage neural network.

(Moradi et al., 2021) apply Soft Actor-Critic (SAC) with an Convolutional Neural Network (CNN) as a reward approximate. The task containes picking up, moving and pouring the entire liquid from one container to another.

An alternative approach employing the Actor-Critic method is presented by (Tamosiunaite et al., 2011). They integrate goal learning through an approximate function and shape learning using a Nonlinear Autoencoder (NAC) and a Probabilistic Inference Optimization (PI2) technique.

While the approaches mentioned earlier demonstrate success within their specific contexts, challenges arise when applying them in real-world scenarios. For instance, the method proposed by (Tamosiunaite et al., 2011) relies on prior knowledge of the robot's liquid quantity, which can vary. To address this limitation, we will employ discretized relative angles as action space, ensuring that the pouring process remains independent of the initial volume in the source container.

Another limitation of both (Schenck and Fox, 2017) and (Moradi et al., 2021) is their reliance on volume estimation of liquid in the recipient container through imagery. Consequently, it becomes essential that the recipient container remains visible from a specific angle or is transparent to allow for accurate liquid volume assessment. This requirement parallels related research on estimating liquid volumes from single images, as observed in works such as (Cobo et al., 2022) and (Liu et al., 2023).

The benefit of just observing the liquid flowing out of the source container as in the proposed setup is, that it can be poured into not or only partially observable containers. Additionally, it could be poured onto surfaces or soils, where no accumulation of liquid would be visible, for example when watering plants.

The experimental setup is described in section 2. Section 3 describes the proposed algorithm in three steps: Data acquisition in section 3.1, the controller architecture in section 3.2, and training the controller in section 3.3. Simple experiments were performed which are described briefly in section 4. Section 5 concludes with a summary and remarks on current work.

2 EXPERIMENTAL SETUP AND REQUIREMENTS

A UR5 robot manipulator is equipped with an end effector holding a container, denoted as C, containing an initial liquid volume of V_{init}. As the end effector is rotated, the liquid pours out. It is assumed that the receiving container, designated as R, is adequately sized to capture all of the poured liquid.

In Figure 1, the side view of the setup is illustrated, along with a reference coordinate system. The Intel RealSense camera is mounted on the robotic wrist and is aligned to capture a continuous video of the liquid as it exits the container.

Figure 2 shows the system from the top and from the front.

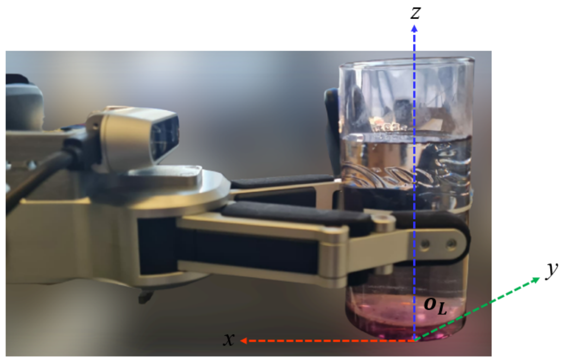


Figure 1: A local reference framework, denoted as O_L, is positioned at the center of the container base. The wrist is initially in position $0°$.

(a) (b)

Figure 2: Experimental design: a) top view of the materials used and b) front view of the pouring process.

The goal is to pour out a certain volume V_G of liquid. This requires an appropriate function $\alpha(t)$ for steering the angle of the end effector in time. This function cannot be computed ahead of time (open loop control) because the initial volume of the liquid in the container C is not known.

Consequently, container C needs to be rotated until the liquid starts pouring out of it. Based on the volume observed by the camera positioned atop the end effector, the angle α must be continuously adjusted as to meet the desired goal volume, denoted as V_G.

A scale is used to measure the weight w of the liquid in the receiving container R at the end of the pouring sequence. This way, the received volume of the liquid can be measured within a certain precision. The current weight of the liquid on the scale may not be used in real-time in the feedback algorithm. It is assumed that the scale may only be read after the pouring process. The reason for this is that an ordinary kitchen scale is used which has a delay and no digital output.

It is furthermore assumed, that a simulation of the setup is not available within a reasonable precision. Only basic experiments with the real setup can be performed. These experiments will take some time and are slow to perform. However, experiments with the real setup provide a ground truth dependency between images, pouring angles and output volume.

The task shall be to design a set of experiments with the laboratory setup and use this data in an offline manner to develop a controller which will then be able to pour out liquids with a given goal volume V_G.

3 CONTROLLER ARCHITECTURE

First, the method to collect data from the real laboratory setup is described. In section 3.2 the architecture of the controller is presented. Section 3.3 describes the training and setup of the controller.

3.1 Data Acquisition

The laboratory setup as shown in figure 2 is prepared with an arbitrary amount V_{init} of initial liquid in the container C inside the gripper of the UR5. The angle α is initially set to 0. The recipient (a regular coffee cup) is initially empty and the scale is set to zero.

A pre-programmed movement of the end effector is applied. The movement results from the function

$$\alpha(t) := \lambda \cdot e^{-(\gamma\cdot(t-\beta)^2)} \qquad (1)$$

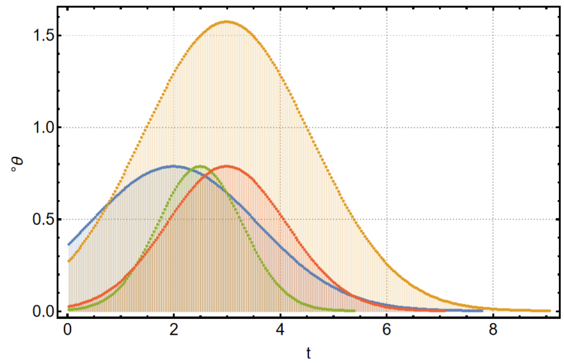
applied to the angle of the end effector. λ, γ and β are parameters to change the height and duration of the curve. Figure 3 shows different angle curves in time for various parameters λ, γ and β.

Basically, any kind of angle curve in time which starts at angle 0 and returns to angle 0 could be used for these experiments, e.g. $\lambda \sin(\gamma \cdot t)$. However, equation (1) has the advantage that the acceleration is slow so as not to create unnecessary turbulence in the liquid while pouring out.

After returning to zero, the resulting weight on the scale is read and registered. Subsequently, one single experiment consisting of a sequence of angles, camera frames and a resulting weight shall be called *experimental episode E*.

During each *experimental episode* the images taken from the camera together with the respective angle α are stored. This way each *experimental episode E* leads to a list L_E of the following format:

$$L_E = \{(\text{Image}_i, \alpha(i)) \,|\, i = 0, 1, 2, \cdots\}.$$



(a)

Figure 3: Different angle functions in time as applied to the end effector. These curves have the property that they increase the angles very slowly in order to generate waves as few as possible.

A typical frame rate for storing images from the camera and respective angle could be 30 fps.

In each *experimental episode* the resulting weight as read on the scale w_E is also stored, such that a data set

$$E = (L_E, w_E)$$

is obtained for every *experimental episode*.

3.2 Controller Architecture

We propose a two stage setup. In a first stage the volume V_e (estimated volume) of liquid leaving the container as seen in a frame is calculated. OpenCV is used to perform this preprocessing step.

As can be seen in figure 4 (c) and (d), the liquid leaving the container has different forms depending on the volume of the stream. The container always has the same position in the image because the camera is attached to the end effector. The chess pattern in the background is used for demonstration purposes to show the real angle of the end effector.

We propose a measure to describe the amount of liquid leaving the container. Since the real flow of liquid cannot be measured, a 2-dimensional geometric approach is chosen. The details are described in section 3.3.1.

In the second stage, the estimated volume V_e (as described above) of the liquid in each frame is used as an input for a policy network. The policy network receives the estimated volume V_e and a required goal volume D to be filled up as an input. The output of the policy network is a discretized relative angle $\Delta\alpha$, where α is the angle of the actuator of the robot arm which holds the container with the liquid. The control in each time step is then applied as $\alpha \leftarrow \alpha + \Delta\alpha$.

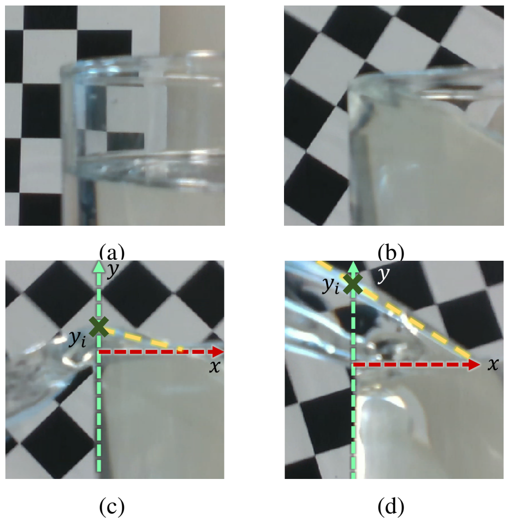


Figure 4: Frames (a) to (d) show the pouring process from the in-hand eye perspective. Pictures (c) and (d) show the different forms of the pouring stream.

The total feedback control setup is then

$$\text{Image} \rightarrow \text{OpenCV} \rightarrow V_e$$

extracting information V_e from the image, and then using V_e and D to receive $\Delta\alpha$

$$(V_e, D) \rightarrow \text{MLP} \rightarrow \Delta\alpha$$

where MLP is a Multilayer Perceptron.

In each frame, the remaining volume D to be poured into the recepient is reduced by the volume V_e of the triangle

$$D \leftarrow (D - V_e) \tag{2}$$

As the current volume in the receiving container cannot be seen by the camera, the variable D serves as an estimation of the remaining volume to be filled up.

3.3 Training of Controller

The data collected from the experimental setup serves as the training data for both components of the controller: first, for estimating the liquid volume in each frame as V_e, and second, for training the angle controller, which takes into account the frame's volume V_e and the remaining goal volume D.

3.3.1 Volumes from Images

OpenCV is used to approximate the volume of the poured liquid in each frame. This is done by calculating the 2d area of the triangle as shown in figure 4 (c) and (d). The y-axis aligns with the left side of the container. The x-axis runs along the top edge of the glass. The yellow dotted line runs along the liquid (intersection x-axis and y-axis). We denote with V_e the area of a triangle (yellow, red and green line) in figure 4 (c) and (d). This way, a finite sequence of values $\{V_e^1, V_e^2, \ldots, V_e^k\}$ is obtained during an experimental episode. All of the values V_e^i contribute to the final output volume w_E of an experimental episode. The contribution of each V_e^i depends on the number of frames and frame rate applied. We define a normalized contribution volume $\hat{V}_e$ of each frame i as

$$\hat{V}_e^i := w_E \cdot \frac{V_e^i}{\sum_{j=1}^{k} V_e^j}$$

Note that the normalized contribution volumes add up to the total volume

$$\sum_{j=1}^{k} \hat{V}_e^i = w_E$$

These normalized contribution volumes are used as an input to the MLP described in the next section.

3.3.2 Offline RL for Angle Control

Policy. The second part of the algorithm consists of a multi-layer perceptron (MLP) which works as a policy

$$\begin{aligned} \pi : O &\longrightarrow \{-10, \ldots, 10\} \\ (v_t, v_{t-1}, v_{t-2}, d) &\mapsto \Delta\alpha \end{aligned}$$

mapping the observation space O to a discretized relative angle $\Delta\alpha$ of the end effector.

Observation Space. The observation space is defined as

$$O := [0, V_{max}]^3 \times [-D_{max}, D_{max}] \quad (3)$$

The observation space $O \subseteq \mathbb{R}^3 \times \mathbb{R}$ is 4-dimensional (four real-valued input neurons) where V_{max} in equation 3 is the maximal normalized contribution volume as measured in phase 1 of the algorithm, and D_{max} is the maximal volume of the receiving container.

The first three arguments v_t, v_{t-1}, v_{t-2} of the observation space are a sequence of the last three normalized contribution volumes as described in section 3.3.1.

The second argument d of the observation space stands for the volume which remains to be filled up. Initially, if $d = 0$, the controller shall do nothing and stay in the initial position. To activate the controller and start the pouring process, d is set to the desired goal volume

$$d \leftarrow V_G \quad (4)$$

to be poured into the receiving container. In each frame d is reduced according to equation 2. If the remaining volume to be poured is eventually 0, the controller shall rotate the joint back to its initial position.

Since it may happen that the receiving container receives too much liquid, also negative values for d shall be allowed.

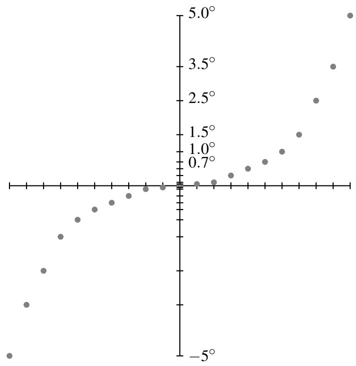


Figure 5: Distribution of the discretization of the relative angles of the end effector. Relative angles close to zero are discretized finer, relative angles close to $-5°$ and $5°$ are discretized coarser.

Action Space. The action space consists of the following 21 output neurons

$$\{i \,|\, i = -10, \cdots, 10\}.$$

Each output neuron is mapped to a discretized relative angle α_i according to figure 5. The relative angle will then be applied to the angle α of the end effector according to $\alpha \leftarrow \alpha + \alpha_i$.

Figure 5 shows the discretization of the relative angles. Relative angles close to zero are discretized finer to allow a control more precise.

Reward. A total reward function denoted as r is established for every completed pouring process. It is presumed that the pouring process concludes either after a predefined number of frames or when all the liquid has been emptied from container C. Let d represent the remaining volume that needs to be filled by the end of the pouring process. When d reaches 0, it signifies that the target volume V_G has been precisely achieved.

Define $r(d)$ as

$$r(d) := e^{-(\delta \cdot d^2)} \quad (5)$$

where $\delta < 1$ is typically a small number which defines the width of the reward function around the desired goal value. Note that a reward is given only at the end of the sequence.

Training. With the defined observation space, action space, and reward structure, a feedback controller can be trained using reinforcement learning techniques. In this scenario, only offline data, as outlined in section 3.1, is accessible, and direct interaction between the agent and the physical system is not possible. Consequently, traditional exploration methods are not viable. Our proposed approach involves employing a policy gradient method based on Monte-Carlo policy gradient techniques, akin to the REINFORCE method as described in (Williams, 1992).

We enrich the sequences obtained from the experiments with the physical system described in section 3.1 to generate training sequences.

Training Data Generation. We propose the following method to generate a sufficiently rich set of training data. A sequence from a single experimental episode E may be used as multiple episodes for training. Given an experimental episode

$$L_E = \{(\text{Image}_i, \alpha(i)) : i\}$$

together with a final volume w_E. Then *training sequences* are generated as follows:

1. From each Image_i calculate the *normalized contribution volume* of the liquid pouring from the container as described in section 3.3.1 to obain a sequence $\{\hat{V_e^1}, \ldots, \hat{V_e^k}\}$.
2. For each $i = 1, 2, \ldots, k$, calculate the relative angles as $\Delta\alpha(i) := \alpha(i) - \alpha(i-1)$. Apply the discretization of the relative angles as explained in figure 5 to obtain a sequence of values $\Delta\alpha_i \in \{-10, \ldots, 10\}$
3. Choose an initial goal volume V_G for this experimental episode according to the following rule:
$$V_G(\kappa) := \kappa \cdot w_E,\ \kappa = 0.5, \ldots, 1.5. \quad (6)$$
For each κ a different goal volume is created. Therefore, for each κ a different *training sequence* is created. E.g. for $\kappa = 1.0$, the goal volume $V_G(\kappa)$ is equal to the volume w_E from this experimental episode. Therefore a perfect pouring process is obtained which meets exactly the goal volume V_G. For $\kappa = 0.5$, the goal volume $V_G = \frac{w_E}{2}$. This creates a training sequence, where too much liquid is poured into the goal container: $\frac{w_E}{2}$ is desired, but w_E is obtained. For $\kappa = 1.5$ we obtain a training sequence in which too little liquid is poured into the receiving container.
4. Calculate the sequence d_i of remaining liquid volume to be poured. For $i = 0$ choose $d_0 = V_G(\kappa)$ from equation 6 and calculate
$$d_{i+1} := d_i - \hat{V_e^i}$$
to obtain a sequence $\{d_0, d_1, \cdots, d_k\}$.
5. Calculate the reward of the sequence using definition 5
$$R_E := r(d_k)$$
6. To create a baseline, take all total rewards $R_{E,i}$ from all experimental episodes and calculate the mean $\overline{R_E}$ and the variance σ_E to receive normalized rewards
$$\hat{R_{E,i}} := \frac{R_E - \overline{R_E}}{\sigma_E} \quad (7)$$
7. For every state ω_i and action $\Delta\alpha_i$ from the experimental episodes, take the one-hot encoded action $\mathbb{I}_i = (0, \ldots, 0, 1, 0, \ldots, 0) \in \{0,1\}^{21}$, where the 1 stands at the position which represents the action taken in the state ω_i in the experimental episode.
8. Apply a softmax function to the output of the multi-layer perceptron to receive a probability distribution p_i for the 21 possible actions. Train the artificial neural network in the respective state ω_i, applying $\hat{R_{E,i}} \cdot \mathbb{I}_i$, i.e. set the desired output Y (label) of the artificial neural network to
$$Y := (1 - \lambda \cdot \hat{R_{E,i}}) \cdot p_i + \lambda \cdot \hat{R_{E,i}} \cdot \mathbb{I}_i \quad (8)$$
where $\lambda \in (0,1)$ is a learning factor. Use the categorical cross-entropy loss function to train the neural network.
Observe, that equation 8 describes a function $\{-10, \ldots, 10\} \to \mathbb{R}$ in which all values add up to 1, and negative values may occur. This is due to p_i and $\mathbb{I}_i$ being probability distributions, and $\hat{R_{E,i}}$ may be negative.

The training of the multi-layer perceptron is done in adequate batches with samples taken randomly from the experimental episodes.

Observe, that REINFORCE is actually an on-policy method. To use REINFORCE with offline data, usually a correction using importance sampling has to be made to account for the distributional shift, because the sampling data is taken from a different distribution as the one to be corrected for, see e.g. (Liu et al., 2019), (Levine et al., 2020), (Kallus and Uehara, 2020).

In the case described in this paper, the samples from the experimental episodes do not correspond to a particular policy. Therefore corrections cannot be made or are difficult to introduce. The method is expected to work similar to cross-entropy methods, see e.g. (Kroese et al., 2005).

4 EXPERIMENTAL RESULTS

Experiments were conducted using a simple simulation for pouring liquids. The general properties and functioning of the algorithm could thus be proven.

A simulation has been implemented which generates volumes V (corresponding to V_e as described in section 3) of triangles depending linearly on the angle α and the remaining volume in the container.

A multi-layer perceptron with two hidden layers and 2000 parameters is trained. To simplify the experiments, only two actions are used: $\Delta\alpha \in \{-1, 1\}$.

A single *experimental episode* of the robot arm is used as an offline training sequence, creating multiple training sequences by applying random goal volumes according to equation 6.

Experiments show a fast convergence. The resulting policy network pours liquid within the simulation matching an arbitrary given goal volume.

5 CONCLUSION

A method has been outlined for constructing a controller tasked with pouring a specified quantity of liquid into a receiving container.

The approach comprises two primary steps: first, a preprocessing phase that extracts relevant image features, followed by the implementation of a policy network. Importantly, the policy network operates with a low input dimension, as image preprocessing is applied using a separate image processing tool.

In addition, only ground truth data measured from the real laboratory setup is used. Therefore, no simulation of the setup is required to train the policy network. The policy network is trained in an offline manner using the data from the laboratory setup.

A valuable aspect of the proposed approach is its capacity to derive multiple training sequences from a single experimental sequence.

The method presented in this paper exhibits robustness in handling variations in the initial volumes within the source container, achieved through control of relative pouring angles. Moreover, the method exclusively measures the liquid exiting the source container, enabling its applicability in scenarios where the liquid within the target container is not visible or measurable, such as when watering plants.

The method has been implemented within a pouring liquid simulation and shows fast convergence and independence of goal volumes. Next, the data from the physical system will be included to generate a controller for the UR5 robot arm.

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