Viewpoint Optimization for Autonomous Strawberry Harvesting with Deep Reinforcement Learning

Jonathon Sather
Dept. of Mechanical Engineering
California Polytechnic State University
San Luis Obispo, California 93407, USA
jsather@calpoly.edu

Abstract—Autonomous harvesting may provide a viable solution to mounting labor pressures in the United States’s strawberry industry. However, due to bottlenecks in machine perception and economic viability, a profitable and commercially adopted strawberry harvesting system remains elusive. In this research, we explore the feasibility of using deep reinforcement learning to overcome these bottlenecks and develop a practical algorithm to address the sub-objective of viewpoint optimization, or the development of a control policy to direct a camera to favorable vantage points for autonomous harvesting. We evaluate the algorithm’s performance in a custom, open-source simulated environment and observe affirmative results. Our trained agent yields 8.7 times higher returns than random actions and 8.8 percent faster exploration than our best baseline policy, which uses visual servoing. Visual investigation shows the agent is able fixate on favorable viewpoints, despite having no explicit means to propagate information through time. Overall, we conclude that deep reinforcement learning is a promising area of research to advance the state of the art in autonomous strawberry harvesting.

Keywords—reinforcement learning; deep learning; autonomous harvesting; object recognition

I. INTRODUCTION

Driving down Highway 101 through Santa Maria, California in the springtime, it is hard to ignore the abundance of strawberry fields on both sides of the highway. Each field is populated by dozens of seasonal laborers inching their way down the rows and stooping to manually collect ripe berries—a practice that has been largely unchanged for the past 700 years [1]. Recently, the heavy reliance on human labor has become problematic for the California strawberry industry, as an aging and ever-shrinking workforce continues to drive up costs [2].

A promising idea to address these mounting labor pressures is to use autonomous harvesting to fill the roles of human pickers. In such a system, robots navigate the strawberry field and remove ripe strawberries, eliminating the need for manual labor. While this approach appears sound on paper, strawberry plants present several difficulties for autonomous harvesting systems, including high levels of occlusion, lighting variation, and easily-bruised fruit. Traditional algorithms relying on basic image processing and hard-coded rules have shown to be unsuccessful, either yielding an unacceptably low percentage of ripe strawberries or being too slow for practical usage [3]. More recent strategies making use of specialized hardware or unconventional growing conditions have yet to meet a competitive price point [4]. This suggests that a more sophisticated algorithm for ripe strawberry harvesting not reliant on specialized hardware or growing conditions may be necessary to achieve satisfactory performance at an affordable rate.

Deep reinforcement learning may provide the machinery for a harvesting agent to develop advanced control policies that are infeasible to code by hand while capturing the complex relationships required to reason about the unstructured harvesting environment. However, deep reinforcement learning systems are historically fragile and have seen limited success in real-world settings [5]. In this research, we seek to gain insight on whether deep reinforcement learning could be used to improve the economic viability of autonomous strawberry harvesting systems.

We narrow the scope from the full harvesting process to the sub-objective of viewpoint optimization, or the development of a control policy to direct a camera to favorable vantage points for autonomous harvesting (Figure 1). Viewpoint optimization is a seldom-addressed paradigm that could be prepended to an autonomous harvesting pipeline to simplify
the remaining harvesting steps. Specifically, this research seeks to answer the following questions:

1. How well can a deep reinforcement learning solution for viewpoint optimization perform with respect to its own reward scheme in a simulated harvesting environment?
2. How useful would such a policy be in a practical (non-simulated) autonomous harvesting application?
3. Can we gain insight on reinforcement learning’s potential for the full autonomous harvesting process?

Our general approach is as follows. We develop a novel application of Deep Deterministic Policy Gradients (DDPG) [6] that leverages a pretrained object detector to provide reward feedback and facilitate autonomous training. To collect training images for the object detector, we propose a labor efficient data collection procedure, which makes the entire process require minimal human interaction in a real-world setting. We then create a multi-purpose simulated harvesting environment using ROS [7] and Gazebo [8] and evaluate our algorithms’ performance in a virtual setting. The code for the simulated environment is made publicly available[^1] and we encourage other researchers to adapt it for their own projects.

II. RELATED WORK

To the best of our knowledge, this work is the first research exploring viewpoint optimization via reinforcement learning for autonomous harvesting applications (any crop). A related idea is visual servoing [9], which is a class of control algorithms acting on image features that has been applied in the autonomous harvesting domain. Unlike our method, visual servoing typically involves hand-specifying features, whereas our algorithm learns a control policy with a data-driven approach. In [10], Mehta and Burks implement visual servoing by means of two cameras: one in the hand of a citrus harvesting robot and one stationary camera with a wide field of view. The feedback from the cameras is then used to create a perspective image and guide the robotic manipulator towards an artificial citrus fruit. One of the main limitations of this approach is that it requires the target fruit to be visible by the fixed camera, which cannot be guaranteed in unstructured environments.

The main algorithms used in this research are DDPG [6] and You Only Look Once, Version 2 (YOLOv2) [11]. DDPG is an off-policy, actor-critic deep reinforcement learning algorithm that is used as the underlying machinery for the viewpoint optimization problem. YOLOv2 is a single-shot object detection algorithm using convolutional neural networks. It is capable of outputting labeled bounding boxes at above real-time speeds using consumer-level hardware. In this research, we train YOLOv2 to detect strawberries and use its output as a feedback mechanism during the reinforcement learning process.

III. PRELIMINARIES

Reinforcement learning problems are often modeled as a Markov Decision Process (MDP), which describes a discrete-time, stochastic environment with a decision-making agent [12]. MDPs are defined by the 5-tuple \( \{S, A, P, R, \gamma\} \), where:

1. \( s_t \in S \) is the set of all states, each \( s_t \) containing all relevant information about the environment at time \( t \).
2. \( a_t \in A \) is the set of all possible actions in the environment at time \( t \).
3. \( P(s_{t+1}|s_t, a_t) \) is the state-transition probability for state \( s_{t+1} \) given state \( s_t \) and action \( a_t \).
4. \( R(r_t|s_t, a_t) \) is the reward probability for \( r_t \) given state \( s_t \) and action \( a_t \).
5. \( \gamma \in [0,1) \) is the discount factor, which is used to geometrically decay the value of future rewards and often aids in algorithm convergence [13].

The resulting process is characterized by a cyclic interplay between an agent and its environment. At timestep \( t \), an agent observes state \( s_t \) and subsequently takes action \( a_t \) according to its policy \( \pi(a_t|s_t) \). The agent then arrives at state \( s_{t+1} \) through the environment’s dynamics \( P(s_{t+1}|s_t, a_t) \) and receives scalar reward \( r_t \) according to \( R(r_t|s_t, a_t) \). This process repeats, now from \( s_{t+1} \), until a termination criterion is reached.

A roll-out of states and actions from initial state \( s_0 \) until termination is called a trajectory, denoted \( \tau = (s_0, a_0, s_1, a_1, \ldots, s_{T-1}, a_{T-1}) \). We denote the discounted return for a given trajectory as \( R = \sum_{t=0}^{T-1} \gamma^t r_t \). In our problem, the goal of reinforcement learning is discover an optimal policy \( \pi^* \) that maximizes expected return under trajectory distribution \( p_\pi(\tau) \). Formally:

\[
\pi^* = \arg\max_{\pi} \mathbb{E}_{\tau \sim p_\pi(\tau)}[R]
\]

In most practical settings, it is infeasible to explicitly represent the policy or expected return at each \( s \in S \) and \( a \in A \), so it is common to use function approximators to characterize these quantities at regions of interest. DDPG uses neural networks to approximate policy \( \pi_\theta \) and state-action value function \( Q_\theta \approx \mathbb{E}_{\tau \sim p_\pi(\tau)}[R|s_t, a_t] \). During each training iteration, network weights are jointly updated to maximize the reinforcement learning objective using the Deterministic Policy Gradient algorithm [14].

A. A Note on Partial Observability

It is worth noting that while the the foregoing discussion assumes the reinforcement learning problem could be framed as a Markov Decision Process, this is not always the case. In many real-world problems, such as our formulation of viewpoint optimization, each observation taken in the

[^1]: https://github.com/jsather/harvester-sim
Figure 2. Visualization of the state and action space.

environment may not contain all relevant information to maximize expected return. In this case, the environment is said to be partially observed, which often warrants a generalization of the MDP framework [15]. Despite this, we use algorithms designed for fully observed MDPs in a partially observed setting. Although we lose some theoretical support, this simplifies our implementation while still facilitating meaningful insights for reinforcement learning’s promise in autonomous harvesting.

IV. Method

A. System Setup

We define our environment to consist of a high degree-of-freedom articulated robot with an RGB camera mounted to its end effector, positioned over an outdoor strawberry plant. To avoid plant collisions, we constrain the end-effector to move on a hemisphere of a fixed radius above the strawberry plant as shown in Figure 2. This allows us to define its position by two rotation angles $j = (\theta, \phi)$. The set of all reachable positions combined with the camera images defines our state space, $S = \{J, O\}$. We define our action space as incremental positions on this hemisphere $a = (\Delta\theta, \Delta\phi)$ and use off-the-shelf trajectory planning software and proportional-integral-derivative (PID) joint controllers to move between states.

At each state, we use confidence values from a pretrained strawberry detector and return positive reward if ripe strawberry confidence is above a given threshold. We also penalize invalid actions and impose a light “existence penalty” to instill a notion of urgency in the agent. Intuitively, this reward scheme encourages the agent to move to viewpoints that yield high probability of ripe strawberry detection, which we hope correspond to favorable viewpoints for the harvesting process. Formally, the reward scheme is specified as follows:

$$R(s_t) = \begin{cases} R_{\text{invalid}} & (\theta_t, \phi_t) \notin J \\ R_{\text{detect}} & P_{\text{max}, t} \geq P_{\text{thresh}} \\ R_{\text{exist}} & \text{otherwise} \end{cases}$$

(2)

where $P_{\text{max}, t}$ and $P_{\text{thresh}}$ correspond to the maximum ripe strawberry confidence at timestep $t$ and the ripe strawberry confidence threshold, respectively. In our experiments, we use $R_{\text{detect}} = 1.0$, $R_{\text{invalid}} = -1.0$, $R_{\text{exist}} = -0.1$, and $P_{\text{thresh}} = 0.6$.

B. Detector

Our reward scheme eliminates the need for human feedback during the reinforcement learning process but also introduces the burden of collecting and annotating images for pretraining the strawberry detector. To combat this burden, we develop a labor-efficient data collection procedure that leverages the fact that multiple training images can be annotated per plant given knowledge of its berries 3D poses. This procedure is outlined in Algorithm 1. When collecting the dataset, we annotate both ripe and unripe strawberries and then train the detector on both classes with the hope that it will decrease the frequency of false positive detections.

**Algorithm 1 Detector Data Collection**

```plaintext
initialize dataset $D$
for $i = 0, 1, 2, \ldots$ until num_plants do
  move to next plant
  record location, size, and label of each strawberry
  for $k = 0, 1, 2, \ldots$ until num_views do
    uniformly sample position $j_k$ in workspace $J$
    actuate camera to $j_k$ and capture image $o_k$
    initialize set of valid bounding boxes $B_k$
    for each strawberry
      project 3D pose to bounding box $b$
      if $b$ not occluded then
        $B_k \leftarrow B_k \cup \{b\}$
      end if
    end for
    $D \leftarrow D \cup \{B_k, o_k\}$
  end for
end for
return $D$
```

In a real-world harvesting context, the ground truth 3D strawberry annotations can be obtained by kinesthetically guiding the robot’s end effector around each strawberry to log it’s pose and approximate diameter. In the simulated environment, we replace this step by directly using the ground truth poses and scales of each strawberry. To simplify
the mapping from 3D pose to bounding box, we approximate each strawberry as a perfect sphere. During the annotation step, we check if a given berry is occluded by counting the number of pixels within a color pre-specified color range in the berry’s bounding box. We find this occlusion heuristic results in satisfactory annotations in our simulated environment without requiring manual labelling. However, we note that a more sophisticated occlusion removal strategy may be needed in a real-world setting.

We use Algorithm 1 to collect over 7000 images in the simulated environment, designating 80% of dataset for training/validation and the remaining 20% for testing. We then train YOLOv2 for 50,000 epochs using the Darknet framework [16] with default hyperparameters as specified in [11]. The trained detector is able to perform real-time detections (> 30 frames per second) using a Tesla K80 GPU.

C. Reinforcement Learning

We frame the viewpoint optimization problem as an episode MDP, where each episode the agent is spawned at fixed location $j_0 = (\theta_0, \phi_0)$ relative to an arbitrary strawberry plant. In a real-world harvesting environment, this could be implemented by mounting the manipulator to an unmanned ground vehicle and navigating from plant to plant between episodes. The entire process can be executed without human intervention, provided the robot has equipped with appropriate vision software for autonomous navigation and safe operation. In the simulated environment, this process is mimicked using a generative strawberry plant model to initialize a new plant configuration at the beginning of each episode.

We use DDPG to train the harvesting agent for viewpoint optimization, as its off-policy nature allows for sample efficient training updates. Sample efficiency is critical due to the large amount of time required for policy execution. Additionally, DDPG has seen success using convolutional neural networks to process raw pixel inputs [6]. The training procedure is shown in Algorithm 2.

For both the actor and critic networks, we use five $3 \times 3 \times 32$ convolutional layers with stride 2 to process the $800 \times 800 \times 3$ raw pixel input. In the actor network, this is followed by two 200-neuron fully connected layers with tanh activations. The critic network has a similar structure, except the first fully connected layer is concatenated with the action input, and the final (scalar) output is a linear activation. The networks use the same uniform initialization scheme and weight regularization as in [6]. Training is performed in batch sizes of 16 and updates are performed with Adam optimizer [17] using learning rates of $1 \times 10^{-4}$ and $1 \times 10^{-3}$ for the actor and critic, respectively, and default values $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\tilde{\epsilon} = 1 \times 10^{-8}$ from the paper. The target networks are updated using Polyak Averaging [18] with mixing parameter $\tau = 1 \times 10^{-3}$. We implement the network architectures using TensorFlow [19] and train for 10,000 episodes in the simulated environment.

**Algorithm 2 DDPG for Viewpoint Optimization**

```
initialize experience replay $\mathcal{D}$
initialize actor and critic networks $Q_\theta$, $\pi_\phi$
initialize targets $Q_{\theta'}$, $\pi_{\phi'}$ with weights $\theta' = \theta$, $\phi' = \phi$
for $i = 0, 1, 2, \ldots$ until num_episodes do
    generate new strawberry plant and reset end-effector
    initialize random process $\epsilon$
    initialize targets $Q_{\theta'}$, $\pi_{\phi'}$
    for $t = 0, 1, 2, \ldots$ until termination do
        Policy execution:
        take action $a_t = \pi_\phi(s_t) + N$
        observe $(s_t, a_t, r_t, s_{t+1})$
        add $(s_t, a_t, r_t, s_{t+1})$ to $\mathcal{D}$
        Training:
        generate new strawberry plant and reset end-effector
        sample mini-batch $(s_i, a_i, r_i, s_{i+1})$ from $\mathcal{D}$
        $y_i = r_i + \gamma Q_\theta(s_{i+1}, \pi_\phi(s_i))$
        $\theta \leftarrow \theta - \epsilon \phi \sum_i \nabla_q ||y_i - Q_\theta(s_i, a_i)||^2$
        $\phi \leftarrow \phi + \epsilon \phi \sum_i \nabla_q Q_{\theta'}(s_i, \pi(s_i))\nabla_\phi \pi_{\phi'}$
        $\theta' \leftarrow \tau \theta + (1 - \tau) \theta'$
        $\phi' \leftarrow \tau \phi + (1 - \tau) \phi'$
    end for
end for
return $\pi_\phi$
```

D. Simulated Environment

We create a simulated environment using Robot Operating System (ROS) [7] and Gazebo [8] with the goal of being sufficiently realistic so that results in the simulated environment are indicative of performance in real-world settings. The virtual world mimics an open strawberry field and consists of a section of a bed with dirt surroundings and a randomly-generated strawberry model. Within the world, we place a “floating arm” harvester centered about the strawberry plant. The arm is modelled after the JACO by Kinova Robotics [20].

Plant models are generated using Gazebo’s native SDF file format with embedded Ruby [21]. This algorithm creates plants based on a simple structural model in which various parameters, such as berry pose, mesh, and ripeness, are sampled to create unique plant configurations on the fly. All of the meshes are custom made, with the exception of the strawberry fruit, which uses down-sampled meshes from the UC Davis Strawberry Database [22].

V. Results

A. Detector Evaluation

We test the learned strawberry detector on 2000 held-out images and compared detections to ground truth values. We evaluate precision and recall on each image using 20
intersection-over-union (IOU) thresholds from 0.05 to 1.00. The resultant precision-recall curve is shown in Figure 3.

The precision-recall curve shows that there is a gradual linear decrease in precision with a large increase in recall as the threshold is lowered from 0.75 to 0.5. Lowering the threshold further results in a sharp decrease in precision and asymptotic recall to 0.5. In reinforcement learning, it is important to have a strong reward signal so that the agent can understand the consequences of its actions. As such, we err on the side of high precision/low recall and select $R_{\text{thresh}} = 0.6$ as our reward threshold, corresponding to a precision of 0.9 and a recall of less than 0.2. While such a low recall may initially raise some red flags, it is important to note that its implications largely depend on the nature of the strawberries that are ignored. For this, we turn to a visual analysis.

Looking at the behavior of the detector frame-by-frame, we note its performance is relatively consistent across the camera images. It appears to prefer strawberries that are closer to the camera and larger, with more red flesh of the strawberry showing corresponding to higher confidence values. The strawberries that are missed by the detector are typically smaller or heavily occluded. Therefore, as a feedback mechanism for viewpoint optimization, the biases exhibited by the detector are likely beneficial. An example annotation is shown in Figure 4.

**B. Policy Performance**

To assess the performance of the learned policy, we compare several performance metrics versus five baseline policies and a “hybrid” policy. These policies are listed below in order of increasing complexity.

1) Random policy, $\pi_1$: At each time step, the agent takes a uniformly sampled action in $\Delta \theta$ and $\Delta \phi$.

2) Random policy with boundary awareness, $\pi_2$: At each time step, the agent takes a uniformly sampled action in $\Delta \theta$ and $\Delta \phi$, taking opposite actions to stay in bounds as needed.

3) Downward heuristic with boundary awareness, $\pi_3$: Given threshold $\phi^* \in (0, \frac{\pi}{2})$. At each time step, the policy selects a downward action along the hemisphere until it reaches threshold $\phi^*$. Once it crosses the threshold, the policy takes random actions in accordance with $\pi_2$.

4) Frozen detector with downward heuristic and boundary awareness, $\pi_4$: At each time step, the policy first runs the pretrained strawberry detector on observation $o_t$, and obtains coordinates $(x_t, y_t)$ of the most confident ripe detection in the image frame. If a ripe strawberry is detected, the policy outputs zero action. Otherwise, the policy moves in accordance with $\pi_3$.

5) Proportional detector with downward heuristic and boundary awareness, $\pi_5$: At each time step, the policy first runs the pretrained strawberry detector on observation $o_t$, and obtains coordinates $(x_t, y_t)$ of the most confident ripe detection in the image frame. If a ripe strawberry is detected, the policy outputs action proportional to the direction of its bounding box in the image plane. Otherwise, the policy moves in accordance with $\pi_3$.

6) Hybrid policy: Given threshold $\phi^* \in (0, \frac{\pi}{2})$. At each time step, the policy selects a downward action along the hemisphere until it reaches threshold $\phi^*$. Once it crosses the threshold, the agent follows the learned policy (DDPG), taking opposite actions to stay in bounds as needed.

Note that for the detector-based policies we use a bounding box threshold of 0.5 to represent a positive detection, instead of 0.6 used to derive the reward values. This prevents the baseline detectors from having “insider knowledge” of the reward scheme and makes the resulting comparison less biased.
We run each of the policies for 100 episodes, recording the reward at each timestep and number of steps per episode. Using this information, we calculate the mean return for each episode and the number of timesteps until first reward, excluding trials without a reward. These data are summarized in Figures 5 and 6.

We observe the trained agent performs 8.8 times better with respect to the reinforcement learning objective than random actions, while it performs on-par with the most proficient baseline. Adding hard-coded heuristics increases return by 2.5 times, making the hybrid policy by-far the best performing of those tested. Looking at mean timesteps until reward, we see an opposite trend when introducing the hybrid policy. In this instance, the trained agent performs better than all baselines by over one timestep, while the hybrid policy only averages nearly six more timesteps than the trained agent. These findings highlight the impact that simple hard-coded rules may incur on a data-driven policy and show that care must be taken to ensure modifications yield one’s desired improvements.

C. Fixation Analysis

After determining a high-reward vantage point for detecting ripe strawberries, it is optimal for an agent to remain fixated at that location for the remainder of the episode. Fixation behaviors can also be detrimental if they occur on a vantage point with low return. In this section, we seek to characterize the learned agent’s fixation tendencies in an attempt to better understand the inner workings of its policy.

To detect instances of fixation, we run the DDPG policy on over 400 plants and track positions and rewards for each episode. We plot the corresponding trajectories on a hemisphere superimposed above the plant models, denoting detection states with a blue star. Examples of these visualizations are shown in Figure 7. We then manually inspect the plots and note trajectories where the agent exhibited fixation behaviors.

Of the 213 trajectories with more than 50 steps, 82 fixate on high-return regions, 64 fixate on low-return regions, and 67 do not appear to fixate. From this, it appears the agent learns the desired fixation behavior, but the policy lacks robustness to extend to all states. We suspect some of the low-return clusters are a pitfall of partial observability: Conflicting interpretations of plant geometry at adjacent viewpoints could result in opposite actions for exploration, even if a ripe strawberry is not in frame.

Next, we investigate the nature of the fixated viewpoints. Using saved plant models from experimental trials, we move the agent to known fixation locations and manually inspect the camera images. On regions with high return, we observe the agent tends to favor viewpoints with ripe strawberries in close proximity with minimal occlusions. Such viewpoints are not only advantageous for detection but likely benefit the remaining steps of the harvesting process, providing better angles for pose prediction and reducing obstacles to simplify planning and execution of harvesting trajectories.

On the other regions, the image contents are more varied, but we notice that several of the viewpoints display ripe, or nearly-ripe, strawberries in frame that were not picked up by the pretrained detector. An example of this phenomenon is shown in Figure 8. In these instances, it is possible that the DDPG policy over-estimates the returns from these viewpoints and thus gravitates towards them. As a whole, it appears that the agent learns to exploit the strengths of the pretrained strawberry detector and generally navigates towards regions where it has a high probability of detection. This is particularly impressive considering the known limitations of partial observability.

VI. Conclusion

A. Contributions

In this research, we formulated a novel application of reinforcement learning to solve the viewpoint optimization problem for autonomous strawberry harvesting. We showed that feedback from a pretrained strawberry detector could be used as an autonomous reward scheme, eliminating the need for a human in the loop during the training process.
In doing so, we developed a labor efficient data collection procedure for capturing and annotating strawberry images to train the strawberry detector. To train and test our algorithms, we created a realistic simulated environment incorporating many harvesting challenges found in real-world contexts.

In Section I, we posed three research questions of increasing generality. First, we wanted to determine how well a reinforcement learning solution for viewpoint optimization could perform in the context of a simulated harvesting environment with respect to the reinforcement learning objective. Our reinforcement learning algorithm was proficient in this regard: In our experiments, we saw that the trained agent was able to achieve episodic returns on par with sophisticated baseline policies, and it’s performance could be significantly improved by hard-coding a few simple heuristics.

Next, we wanted to assess the reinforcement learning algorithm’s utility in real-world harvesting contexts. In this assessment, we not only need to consider how well results in the simulated environment would transfer to real-world settings, but also what additional metrics may be important besides the reinforcement learning objective. We note that the simulated environment, while not perfect, contains many real-world challenges, such as apparent randomness, frequent occlusions, complex textures, shadows, and lighting variation. In Section IV, we considered additional pertinent metrics like time-to-detection and expected return, and observed that the learned agent is generally competent in these areas. Further, we noted that the nature of the agent’s fixated viewpoints not only aids ripe strawberry detection, but also provides favorable angles for pose determination, trajectory planning, and trajectory execution. Therefore, we are optimistic that the viewpoint optimization algorithm would have practical merit in real-world settings.

Finally, we wanted to know if we could gain insight on reinforcement learning’s potential for the full autonomous harvesting process. In our experiments, we witnessed a successful application of reinforcement learning to process high-dimensional sensory input and optimize with respect to an abstract objective specified by a complex reward function. The generality of this approach suggests that the reinforcement learning framework may provide a viable solution to other components of the harvesting process. In the following subsection, we propose several means to extend the scope of our algorithm to increase its utility for harvesting applications.

B. Future Works

The research presented in this paper indicates that reinforcement learning is a promising method to improve the autonomous strawberry harvesting pipeline and serves as a branching-off point for many future developments. In this section, we briefly outline several directions for future work and discuss plans for implementation.

1) Parallelization: Our training procedure consisted of two independent processes: a worker collecting training data and an asynchronous update procedure using samples from the experience replay. In future work, this could be extended to include multiple workers for the data collection process with minimal modifications to the underlying algorithm. In [23], parallelization was used to significantly speed up deep reinforcement learning for a real-world manipulation task. Such a modification is a natural extension to autonomous harvesting since most existing systems already use multiple workers during the harvesting process.

2) Memory Unit: In Section IV, we defined the agent’s “state” to be its raw camera image and its end-effector position. This presents problems in a heavily occluded environments due to partial observability at each timestep, which may lead to sub-optimal actions. If the agent had some mechanism to propagate relevant state information through
time, then it would be able to overcome this limitation. We propose several improvements for future work. First, the state itself could be modified to include additional information from previous state(s). In the simplest case, this could consist of appending the previous position to the current state vector, while a more extreme case is frame stacking. These strategies are limited by their finite horizon and linear memory complexity. A more sophisticated approach would be to provide a framework for the agent to learn which information to propagate through time. Possible frameworks for this include recurrent neural networks [24][25][26] or an external memory unit [27][28].

3) Feature Embedding: For any learning task, it is generally desirable to use the lowest dimensional feature space that contains all relevant information. The high-dimensional camera images seen by our agent contain many redundancies and irrelevant data for viewpoint optimization. In future works, we suggest exploring feature embeddings to exploit this fact and reduce the dimensionality of the state input. Two popular approaches are [29], which uses variational autoencoders and optimal control-inspired constraints to learn a low dimensional embedding, and [30], which uses task-specific images to learn spatial key-points for manipulation. In such an approach, care must be taken to ensure that task relevant information is preserved during the transformation.

4) Reward: A key component of our viewpoint optimization algorithm was the use of a pretrained strawberry detector to determine the utility of the camera observations. For the most part, this reward scheme aligned with our goal of viewpoint optimization, i.e. maximizing rewards generally corresponds to finding a good viewpoint for viewing ripe strawberries. However, there are a few edge cases where the reinforcement learning algorithm could potentially “out-smart” the reward scheme. For instance, there are certain viewpoints where, if given a full view of the strawberry, the detector would predict that it is unripe due to light coloration towards the top. However, if the top of the strawberry is not visible, the detector may indicate that the strawberry is ripe. To exploit this, the agent could learn to predominantly focus on the tips of strawberries to avoid lower returns from additional information. Although we did not directly observe this behavior, it is important to keep in mind ways that the reward scheme could be exploited to derive an unintended policy. In future works we recommend experimenting with other reward metrics to see if performance can be improved.

5) Scope: In Section [1] we defined the overarching goal of this research to gain insight on reinforcement learning’s potential for autonomous harvesting. In addressing this goal, we narrowed the scope of the research to the task of viewpoint optimization, which we identified as a key component in the autonomous harvesting process. Given the success of our approach, a natural progression for future works is to extend the application of reinforcement learning to other aspects of the harvesting process, including pose determination, path planning and execution, and fruit removal. For future works, we recommend exploring techniques like hierarchical or curriculum learning [31][32] to develop complex policies for the full harvesting pipeline.

We reiterate that the most pertinent change of scope is to go beyond the simulated environment and evaluate our algorithms on a physical system. While the simulated environment is convenient and enables a rapid development cycle, without physical testing we can only speculate on reinforcement learning’s utility in real-world harvesting applications. By comparing results between the two domains, we also will be able to improve the simulated environment and better understand its limitations for future research.

REFERENCES

[1] V. Grubinger, “History of the strawberry,” Jun 2012, online; Accessed October 2018. [Online]. Available: https://www.uvm.edu/vtvegandberry/factsheets/strawberryhistory.html

[2] G. Mohan, “As california’s labor shortage grows, farmers race to replace workers with robots,” Jul 2017, online; Accessed October 2018. [Online]. Available: https://www.latimes.com/projects/la-fi-farm-mechanization

[3] C. W. Bac, E. Van Henten, J. Hemming, and Y. Edan, “Harvesting robots for high-value crops: State-of-the-art review and challenges ahead,” Journal of Field Robotics, vol. 31, 07 2014.

[4] D. Charles, “Robots are trying to pick strawberries. so far, they’re not very good at it,” https://www.npr.org, Mar 2018, online; Accessed October 2018.

[5] K. Arulkumaran, M. P. Deisenroth, M. Brundage, and A. A. Bharath, “Deep reinforcement learning: A brief survey,” IEEE Signal Processing Magazine, vol. 34, no. 6, pp. 26–38, Nov 2017.

[6] T. P. Lillicrap, J. J. Hunt, A. Pritzel, N. Heess, T. Erez, Y. Tassa, D. Silver, and D. Wierstra, “Continuous control with deep reinforcement learning,” arXiv preprint arXiv:1509.02971 2015.
