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Learning to Search for Targets

– A Deep Reinforcement Learning Approach for Partially Observable Environments

Inlärd sökning efter mål

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Abstract

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Acknowledgments

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Notation

x	variable
X	random variable
$\mathbb{X}$	set

1 Introduction

In this thesis project, the problem of searching for targets in unknown but familiar environments is addressed. This chapter presents the motivation behind the project, the research questions that are addressed, and the delimitations.

1.1 Motivation

The ability to visually search for things in an environment is fundamental to intelligent behaviour. We humans are constantly looking for things, be it be it the right book in the bookshelf, a certain keyword in an article or blueberries in the forest. In many cases, it is important that this search is strategic, efficient, and fast. Animals need to quickly identify predators, and drivers need to be able to search for pedestrians crossing the road they are driving on.

An intelligent searcher should be able to

Automating the task of searching is of great interest

While searching for targets is often seemingly effortless to humans, it is a complex process. How humans and animals search for things has been extensively studied in neuroscience and neurobiology [12, 36, 35].

Applications such as helping robots and search and rescue mean that it is of great interest to automate visual search. In the computer vision field, there has been several attempts to mimic the way humans search in machines []. Most attempts focus on fully observable scenes where the target is in view and the task is to localize it (object localization). However, in many real-world visual search scenarios the field-of-view is limited. This means that the search process is split into two steps: directing the field of view (covert attention), and locating targets within the view (overt attention). Much work has been focused on latter, locating targets within the field of view [].

When only a fraction of the environment is visible, where to move the field of view becomes an important decision. The characteristics of the searched environment can often be used to find targets quicker. For example, if one is foraging for blueberries it makes sense to search the ground rather than the trees. Similarly, if one is searching a satellite image for boats it is reasonable to focus on ocean shores. If you see a railroad track or the wake of a boat you can usually follow it to find a vehicle. The exact characteristics of the environment need not be constant - forests with blueberries can vary greatly in appearance and boats can be found in all of the seven seas. In many cases, the environment is familiar in that it has characteristics that are similar to previously seen environments. Humans are able to generalize in such cases.

Manually creating search algorithms for such tasks is problematic. The appearance and distribution of targets in an environment varies greatly, and may be subtle. The visual richness of the environment itself is another problem. How can you identify useful hints from the environment to guide covert attention? Doing so manually can be labour intensive, especially if a searcing system should be deployed in many different environments. If one could instead learn the underlying from a limited set of sample environments and generalize to unseen similar environments this problem would be circumvented.

1.2 Aim

The aim of this thesis is to investigate how an agent that learns to search for targets can be implemented. This work tries to address these issues, focusing on strategic scans of larger environments where the field of view is small relative to the environment. This is a problem that has been less studied in the literature than visual search in smaller environments. There are other factors that become increasingly important. The field-of-view of the observer is often limited, and she has to move it efficiently to find the target.

The aim of this thesis is to implement and evaluate an autonomous agent that intelligently searches its environment for targets. The agent should learn common characteristics of environments and utilize this knowledge to search for targets in new environments more effectively. Furthermore, the agent should be able to generalize to unseen environments drawn from the same distribution as the ones it has seen previously.

A specific instance of the visual search problem is considered, where the environment is searched by a pan-tilt camera fixed in place. The camera has a limited view of the environent. Automating this task is of interest for multiple reasons. Manually controlling a camera may be costly, and the performance of a human operator may be suboptimal. Crucial to the problem is generalization.

1.3 Research questions

This thesis will address the following questions:

1. How can a learning agent that does efficient visual search in familiar environments be implemented?

2. How does the learning agent compare to random walk, exhaustive search, a human searcher?

3. How well does the learning agent generalize to unseen but familiar environments?

1.4 Delimitations

This thesis will be focused on the behavioral aspects of the presented problem. We do not focus on difficult detection problems, but rather efficient actions. For this reason, targets will deliberately be made easy to detect. For simplicity, we make the assumption that the searched environment is static.

2 Theory

This chapter introduces relevant theory and related work. Section 2.3.3 gives some background on active vision. Section 2.3.4 describes the problem of visual searching for targets.

2.1 Artificial Neural Network

An artificial neural network (ANN) is a type of universal function approximator. Inspired by biological neurons found in the brains of animals, ANNs are collections of connected nodes. Each node receives a real-valued signal, processes it and signals connected nodes.

This section will introduce three classes of ANNs that are relevant to this work: feed-forward, convolutional, and recurrent neural networks.

2.1.1 Feed-forward Neural Network

A feed-forward neural network, also called multi-layer perceptron (MLP) defines a mapping $y = f(x;\theta)$. It consists of multiple layers of computational units The value of the parameter θ is learned

[14]

2.1.2 Convolutional Neural Network

Convolutional Neural Networks (CNNs) are designed specifically for processing data with a known grid-like topology, such as images. As the name implies, CNNs employ the convolution operator

$$s(t)$$

[14]

2.1.3 Recurrent Neural Network

Recurrent neural networks (RNNs) are networks designed to process sequential data. RNNs extend ANNs by also including *hidden state* in the network. Information from previous inputs is stored in the hidden state and used to influence the current input and output. This means that a single network can be used for sequences of variable length.

Formally, RNNs operate on a sequence $x^{(1),\dots,x^{\{(\tau)}}$. For each value x_t in the sequence, the hidden state is computed as $h^{(t)} = f(h^{(t-1)}, x^{(t)}; \theta)$. The hidden state is used as a summary of all previous items in the sequence

In practice, conventional RNNs struggle with learning long-term dependencies. During back-propagation, gradients can tend to zero for long sequences, something known as the vanishing gradient problem [14]. An architecture that addresses this issue is long short-term memory (LSTM) [20]. LSTMs have *cells* in the hidden layers of the network which have an input gate, an output gate and a forget gate. These gates control how information flows in the network. By allowing

This makes LSTMs particularly useful for learning over long sequences.

2.2 Reinforcement Learning

Reinforcement learning (RL) [33] is a subfield of machine learning concerned with learning from interaction how to achieve a goal. This section introduces the fundamental concepts of RL.

2.2.1 Partially Observable Markov Decision Processes

The problem of learning from interaction to achieve some goal is often framed as a Markov decision process (MDP). A learning *agent* interacts continually with its *environment*. The agent takes the *state* of the environment as input, and select an *action* to take. This action updates the state of the environment and gives the agent a scalar *reward*. It is assumed that the next state and reward depend only on the previous state and the action taken. This is referred to as the *Markov* property. [21]

In an MDP, the agent can perceive the state of the environment with full certainty. For many problems, including the one we consider here, this is not the case. The agent can only perceive a partial representation of the environment's state. Such a process is referred to as a partially observable Markov decision process (POMDP). A POMDP is formally defined as a 7-tuple $\langle \mathcal{S}, \mathcal{A}, \mathcal{T}, \mathcal{R}, \Omega, \mathcal{O}, \gamma \rangle$, where

- $\mathcal{S}$ is a finite set of states,
- $\mathcal{A}$ is a finite set of actions,
- $\mathcal{T} : \mathcal{S} \times \mathcal{A} \to \Pi(\mathcal{S})$ is a state-transition function,
- $\mathcal{R} : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$ is a reward function,
- Ω is a finite set of observations,
- $\mathcal{O} : \mathcal{S} \times \mathcal{A} \to \Pi(\Omega)$ is an observation function, and
- $\gamma \in [0, 1]$ is a discount factor.

Assume that the environment is in state $s_t \in \mathcal{S}$, and the agent selects action $a_t \in \mathcal{A}$. Then, $T(s_t, a_t, s_{t+1})$ is the probability of ending in state s_{t+1} and $r_t = R(s_t, a_t)$ is the expected reward gained by the agent. The agent also receives an observation $o_t \in \Omega$ with probability $\mathcal{O}(s_{t+1}, a_t, o_t)$. [21] The agent and environment interact over a sequence of discrete time steps $t = 0, 1, \dots, T$, giving rise to an *episode* of length T. At each time step t, the goal of the agent is to select the action that maximizes the expected *discounted return*:

$$\mathbb{E}\left[\sum_{k=0}^{T} \gamma^{k-t-1} r_k\right]$$

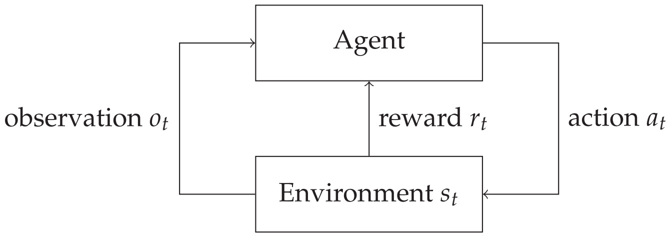

Figure 2.1: Partially observable Markov decision process.

Figure 2.2.1 illustrates the interaction between agent and environment.

Since the agent receives partial observations of the environment's state, it has to act under uncertainty. Planning in a POMDP is undecidable, and solving them is often computationally intractable. Approximate solutions are more common, where the agent usually maintains an internal *belief state* [21] which is acts on. The belief state summarizes the agent's previous experience and is therefore dependent on the previous belief state, observation and action. It does not need to summarize the whole history, but generally only the information that helps the agent maximize the expected reward. From here on we will use the belief state and the environment state s interchangably.

2.2.2 Policies and Value Functions

The behaviour of the agent is described by its *policy*. A policy π is a mapping from perceived environment states to actions. Policies are often stochastic and specify probabilities for each action, with $\pi(a|s)$ denoting the probability of taking action a in state s. Most RL solutions methods also approximate a *value function*. A value function v_π estimates how good it is to be in a state. The value function $v_\pi(s)$ is the expected (discounted) return when starting at state s and following policy π until the end of the episode. With a good value function estimate, the policy can select actions so as to maximize the value function. This is referred to as an *action-value* method. [33]

For problems with large state and action spaces, it is common to represent value functions with *function approximation*. In such cases, it is common to encounter states that have never been encountered before. This makes it important that the estimated value function can generalize from seen to unseen states. With examples from the true value function, an approximation can be made with supervised learning methods. We write $\hat{v}(s, w) \approx v_\pi(s)$ for the approximate value of state s with the some weight vector $w \in \mathbb{R}^d$.

An alternative to action-value methods is to approximate the policy itself. *Policy gradient methods* [32] learn a parametrized policy that select actions without a value function. We denote a parametrized policy as $\pi(a|s, \theta)$ with $\theta \in \mathbb{R}^{d'}$ as the parameters to the policy. The policy parameters are usually learned based on the gradient of some performance measure $J(\theta)$. As long as $\pi(a|s, \theta)$ is differentiable with respect to its parameters, the parameters can be updated with *gradient ascent* in J:

$$\theta_{t+1} = \theta_t + \alpha \nabla \hat{J(\theta_t)})$$

Advantages of policy parametrization over action-value methods include stronger convergence guarantees [32] and more flexibility in parametrization [33]. In practice, value functions are often still used to learn the policy parameter, but they are not needed for action selection. Such methods are called *actor-critic* methods, with actor referring to the learned policy and critic referring to the learned value function. In these cases, there might also be some overlap between the weights w of the value function estimate and θ of the policy estimate.

2.2.3 Challenges in Reinforcement Learning

- Exploration and Exploitation
- Sparse Rewards
- Credit Assignment [24]

2.3 Related Work

2.3.1 Deep Reinforcement Learning

As mentioned in Section 2.2.2, policy and value functions are often approximated. Neural networks have good properties for function approximation and have been used for RL with success. One early example is TD-Gammon [34], a neural network trained with RL that reached expert Backgammon performance in the 90s. More recently, the use of deep neural networks has shown tremendous success in RL, giving birth to the field of deep RL.

[4]

[34]

Breakthroughs in computer vision like Mnih et al. (2013) [28] address this by combining deep learning with RL. A CNN is trained to estimate the

Mnih et al. (2015) [29]. . .

Hausknecht and Stone (2017) [16] investigates the effects of adding recurrency to a DQN in order to tackle POMDPs. A LSTM is added after the initial

2.3.2 Proximal Policy Optimization

Proximal policy optimization algorithms. . . [31].

2.3.3 Active Vision

Much of past and present research in machine perception involves a passive observer. Images are passively sampled and perceived. Animal perception, however, is active. We do not only see things, but look for them. One might ask why this is the case, if there is any advantage that an active observer has over a passive one. Aloimonos and Weiss (1988) [2] introduce the paradigm called *active vision*, and prove that an active observer can solve several basic vision problems in a more efficient way than a passive one.

Bajcsy (1988) [**bajcsy_1988**] defines active vision, and perception in general, as a problem of intelligent data acquisition. An active observer needs to define and measure parameters and errors from its scene and feed then back to control the data acquisition process. Bajscy states that one of the difficulties of this problem is that they are scene and context dependent. A thorough understanding of the data acquisition parameters and the goal of the visual processing is needed. One view lacks information that may be present with multiple views. Multiple views also add the time dimension into the problem.

In a re-visitation of active perception, Bajcsy, Aloimonos and Tsotsos (2018) [**bajcsy_aloimonos_tsotsos_2018**] stress that despite recent successes in robotics, artificial intelligence and computer vision, an intelligent agent must include active perception:

> An agent is an active perceiver if it knows why it wishes to sense, and then chooses what to perceive, and determines how, when and where to achieve that perception

[**bajcsy_aloimonos_tsotsos_2018**]

2.3.4 Visual Search

The perceptual task of searching for something in a visual environment is usually referred to as *visual search*. The searched object or feature is the *target*, and the other objects or features in the environment are the *distractors*. This task has been studied extensively in psychology and neuroscience.

Wolfe (2021) [35] describes a model of visual search

Eckstein (2011) [12] reviews efforts from various subfields and identifies a set of mechanisms used to achieve efficient visual search. Knowledge about the target, distractor, background statistical properties, location probabilities, contextual cues, rewards and target prevalence are all identified as useful. This is motivated with evidence from psychology as well as neural correlates.

Visual search is not always instant, and can in fact often be slow. This is in part due to processing: our visual system cannot process the entire visual field and

Wolfe and Horowitz (2017) [**wolfe_horowitz_2017**] identify and measure a set of factors that guide attention in visual search. One of these is bottom-up guidance, in which some visual properties of the scene draw more attention than others. Another is top-down guidance, which is user driven and directed to objects with known features of desired targets. Scene guidance is also identified, in which attributes of the scene guide attention to areas likely to contain targets.

These works ground the task considered in this project in psychology.

2.3.5 Object Detection

A similar problem can be found in the computer vision literature under *object detection*. The goal of object detection is to, given an input image, detect instances of semantic objects in it. This includes assigning a bounding box to the objects, and classifying the object. The input image is usually passively sampled, and the whole scene is visible at once.

Caicedo and Lazebnik (2015) [7] propose to use deep reinforcement learning for active object localization in images where the object to be localized is fully visible. An agent is trained to successively improve a bounding box using translating and scaling transformations. They use a reward signal that is proportional to how well the current box covers the target object. An action that improves the region is rewarded with +1, and -1 otherwise. Without this quantization, the difference was small enough to confuse the agent. Binary rewards communicate more clearly which transformations keep the object inside the box and which take the box away from the target. When there is no action that improves the bounding box, the agent may select a trigger action (which would be the only action that does not give a negative reward) which resets the box. This way the agent may select additional bounding boxes. Each trigger modifies the environment by marking it so that the agent may learn to not select the same region twice. This is referred to as an inhibition-of-return mechanism, and is widely used in visual attention models [**[16] in caicedo_active_2015**]. This method has a few shortcomings for the problem considered in this project. The object may not be visible in the initial frame so the agent cannot act in the same way.

A separate field is active object search, which is perhaps most closely related to the problem we consider in this work. In active object search,

A similar work by Ghesu et al. (2016) [**ghesu_artificial_2016**] present an agent for anatomical landmark detection trained with DRL. Different from [7] is that the entire scene is not visible at once. The agent sees a limited region of interest in an image, with its center representing the current position of the agent. The actions available to the agent translate the view up, down, left and aright. A reward is given to the agent that is equal to the supervised relative distance-change to the landmark after each action. Three datasets of 891 anatomical images are used. The agent starts at random positions in the image close to the target landmark and is tasked with moving to the target location. While achieving strong results (90%

success rate), the scenes and targets are all drawn from a distribution with low variance. Most real-world search tasks exhibit larger variance than anatomical images of the human body.

Zhu et al. (2016) [39] create a model for target-driven visual navigation in indooor scenes with DRL. An observer is given a partial image of its scene as well as an image of the target object, and is tasked with navigating to the object n the scene with a minimal number of steps. The agent moves forwards, backwards, and turns left and right at constant step lengths. They use a reward signal with a small time penalty to incentivize task completion in few steps. They compare their approach to random walk and the shortest path and achieve promising results. This setup is quite similar to the one considered in this report, but the authors make a few assumptions that we do not. They a set of 32 scenes, each of which contain a fixed number of object instances. They focus on learning spatial relationships between objects in these specific scenes, and have scene-specific layers to achieve this. Thus, while they show that they can adapt a trained network to a new scene, their approach is unable to zero-shot generalize to new scenes.

A similar work by Ye et al. (2018) [37] integrates an object recognition module with a deep reinforcement learning based visual navigation module. They experiment with a set of reward functions and find that constant time penalizing rewards can be problematic and lead to slow convergence. Their experiments make the same assumptions as [**zhu_target_driven**] - the scenes and targets used during testing have all been seen during training.

2.3.6 Visual Attention

[25]

2.3.7 Coverage Path Planning

[13]

[23]

2.3.8 Visual Navigation

The task we consider bears resemblance to many navigation tasks in robotics. Point navigation is the task of . . . Object navigation is the task of . . . Semantic navigation is the task of . . .

Mnih et al. (2016) [27] use a recurrent policy with only RGB images to navigate in a labyrinth. 3D labyrinths are randomly generated, and an agent is tasked with finding objects in them. The same architecture as in [29] is used, but with 256 LSTM cells after the final hidden layer.

Mirowski et al. (2017) [26]...

Henriques and Vedaldi (2018) [18] use a spatial memory...

Gupta et al. (2019) [15] use a latent spatial memory. The They also use a planner that can plan paths given partial information of the environment. This allows the agent to take appearance of visited locations into account when deciding where to look next. The RGB observation is fed through an encoder network that. . . Planning in this fashion s

Dhiman et al. (2019) [11] critically investigate deep RL for navigation. They ask whether DRL algorithms are inherently able to gather and exploit environmental information for during navigation. Experimentally, they find that an agent is able to exploit environment information when trained and tested on the same map. However, when trained and tested on differen maps, it cannot do so succesfully. They further find that, with a single decision point whose correct.

Chaplot et al. (2020) [8] build on the idea of an explicit memory by including environment semantics. . .

2.3.9 Inductive Biases, Overfitting and Generalization in Deep Reinforcement Learning

Kirk et al. (2021) [22] survey generalization in deep RL.

While deep neural networks have proved to be effective function approximators for RL, they are also prone to *overfitting*. High-capacity models trained over a long time may memorize the distribution seen during training rather than general patterns. While studied in supervised learning, overfitting is generally been neglected in deep RL. Training and evaluation stages are typically not separated. Instead, the final return on the training environments is used as a measure of agent performance.

Zhang et al. (2018) [38] study overfitting and generalization in deep RL. With experiments, they show that RL agents are capable of memorizing training data, even when completely random. When the number of training samples exceeds the capacity of the agent, they overfit to them. When exposed to new but statistically similar environments during testing, test performance could vary significantly despite consistent training performance. The authors argue that good generalization requires that the *inductive bias* of the algorithms is compatible with the bias of the problems. The inductive bias refers to a priori algorithmic preferences, like neural network architecture. When comparing MLPs with CNNs, they find that MLPs tend to be better at fitting the training data are worse at generalizing. When rewards are spatially invariant, CNNs generalize much better than MLPs. The authors advocate for carefully designed testing protocols for detecting overfitting. The effectiveness of stochastic-based evaluation depends on the properties of the task. Agents could still learn to overfit to random training data. For this reason, they recommend isolation of statistically tied training and test sets.

In a similar spirit, Cobbe et al. (2019) [10] construct distinct training and test sets to measure generalization in RL. They find that agents can overfit to surprisingly large training sets, and that deep convolutional architectures can improve generalization. Methods from supervised learning, like L2 regularization, dropout, data augmentation and batch normalization are also shown to aid with generalization.

Many current deep RL agents do not optimize the true objective that they are evaluated against, but rather a handcrafted objective that incorporates biases to simplify learning. Stronger biases can lead to faster learning, while weaker biases potentially lead to more general agents. Hessel et al. (2019) [19] investigate the trade-off between generality and performance from the perspective of inductive biases. Through experimentation with common reward sculpting techniques, they find that learned solutions are competitive with domain heuristics like handcrafted objectives. Learned solutions also seem to be better at generalizing to unseen domains. For this reason, they argue for removing biases determined with domain knowledge in future research.

Cobbe et al. (2020) [9] introduce a benchmark for sample efficiency and generalization in RL. They make use of procedural generalization to decide many parameters of the initial state of the environment. This forces agents to learn policies that are robust variation and avoid overfitting. To evaluate sample efficiency of agents in the benchmark, they train and test on the full distribution of states. To evaluate generalization, they fix the number of training samples and then test on held out levels. When an episode ends, a new sample is drawn from the training set. Agents may train for arbitrarily many time steps. The number of training samples required to generalize is dependent on the particulars and difficulty of the environment. The authors choose the training set size to be near the region when generalization begins to take effect. Empirically they find that larger model architectures improve both sample efficiency and generalization. Agents strongly overfit to small training sets and need many samples to generalize. Interestingly, training performance improves as the training set grows past a certain threshold. The authors attribute this to the implicit curriculum of the distribution of levels.

2.3.10 Evaluation of Deep Reinforcement Learning Agents

Anderson et al. (2018) [3] discuss problem statements and evaluation measures for embodied navigation agents. They...

Batra et al. (2020) [5] do something similar. . .

A problem in RL is reproducibility. There is often non-determinism, both in the methods and environments used. This has meant that reproducing state-of-the-art deep RL results is difficult. [17] Henderson et al. (2018) suggest to make future results in deep RL more reproducible.

A similar work by Agarwal et al. (2022) [1] criticises the heavy use of point estimates of aggregate performance. They advocate for a set of performance metrics that take uncertainty in results into account.

3 Method

In this chapter, the method used is described. Section 3.1 formalizes the problem solved. Section 3.2 details the environment used to evaluate solutions. Section 3.3 describes the baseline learning method. Section 3.4 describes the approach used to solve the problem with a learning agent. Section 3.5 describes the experiments conducted to answer research questions 2 and 3.

3.1 Problem Statement

Formally, the searched environment contains a scene with a set of targets. The scene is described by a Euclidean space. In the scene, there are N targets, each described by a subspace. At any given time the agent observes a subspace of the scene, which we call the view. This observation is given in the form of an image. Through a finite set of actions, the agent can transform its view. With a final trigger action, the agent can indicate that there is a target in the view. The goal of the agent is to bring all targets into the view and indicate that they have been found. This is to be done with a minimal number of actions. This corresponds to changing the field of perception.

We denote the task by $\langle \mathcal{M}, \mathcal{T}_0 \rangle$, where $\mathcal{M}$ is a POMDP and $\mathcal{T}_0$ is the probability distribution on the initial states.

3.2 Environment

To train an test an agent for the problem, we use three environments of varying difficulty. In each environment there is a scene with a background of distractors and a foreground of targets. The scenes are drawn from some unknown distribution. The background and foreground are assumed to be correlated. This means that by looking at the background, an agent should sometimes be able to deduce a suitable action. All scenes are assumed to be static in that the actions of the agent do not affect their appearance.

The scenes of each environment are discretized into a grid. We use the same action space, reward signal for all environments. The action space is

$$\mathcal{A} = \{\texttt{UP}, \texttt{DOWN}, \texttt{LEFT}, \texttt{RIGHT}, \texttt{TRIGGER}\},$$

where UP, DOWN, LEFT, and RIGHT translate the view and TRIGGER indicates that a target is in view.

We experiment with two rewards signals. The first reward signal is defined as

$$\mathcal{R}_1(s_t, a_t) = \begin{cases} 10 & \text{if } a_t = \texttt{TRIGGER} \text{ and a target is in view,} \\ -1 & \text{otherwise.} \end{cases}$$

We argue that R_1 provides a suitable inductive bias for the task at hand. Early experiments show that a constant reward of $r_t = -1$ that simply incentivizes the agent to complete the episode as quickly as possible don't converge for large state spaces. The reward for finding a target speeds up training. Targets should be triggered when in view, but triggers when targets are out of view should be penalized. The constant penalty of -1 in all other cases assures that the agent is rewarded for quick episode completion. This reward signal is maximized when the targets are found as quickly as possible.

The second reward signal is defined as

$$\mathcal{R}_2(s_t, a_t) = \begin{cases} 10 & \text{if } a_t = \texttt{TRIGGER} \text{ and a target is in view,} \\ 1 & \text{if } a_t \text{ moves the view closer to the nearest target, and} \\ -1 & \text{otherwise.} \end{cases}$$

R_2 uses the supervised distance between targets and the agent which is available during training time. We hypothesize that this reward speeds up training time and may help the agent pick out correlations between scene and target probability quicker. However, it can never yield policies that search optimally nor exhaustively as these will not be rewarded.

The observation o_t contains

- an RGB image $x_t \in \mathbb{R}^{3 \times W \times H}$ of the currently visible region of the scene, and
- the current position of the agent $p_t \in \mathbb{R}^{W \times H}$.

To incentivize finding targets quickly, the reward signal is set to -1 for each time step. Since viewing a window twice is redundant, such actions are punished by setting the reward to -2. If the agent selects the trigger action when a target overlaps with the window, the reward is set to 5. When all targets have been triggered, or when 1000 time steps have passed, the episode ends.

Averaged over all possible samples, the probability of targets should be uniform over the scene.

The first environment is the simplest environment. The scene is a two-dimensional discrete Euclidean space. The appearance of the scene is given by a 256x256 RGB image. The agent observes a 64x64 sub-image at each time step. In the image there are three Gaussian kernels with random positions. The height of the kernel is indicated by a higher intensity in the blue channel. Targets are 1x1 pixels in the red channel. The locations of the targets are randomized weighted by the height of the Gaussian kernels. This means that the more intense the blue channel, the higher the probability of a target. The idea with this environment is to test that the method learns what we want it to learn. It is easy to determine whether the agent acts well in this environment. Our feeling is that this is something that previous similar works has not done.

The second environment is intended to look like realistic terrain. The environment has a two-dimensional scene whose appearance is given by a 512x512 image. Gradient noise is generated and used as a height map. The height map determines the color of the terrain. The height also correlates to the probability of targets. Specifically, targets are located between shores and mountain bases. This environment simulates a UAV search-and-rescue scenario.

The third environment is a three-dimensional version of the second one.

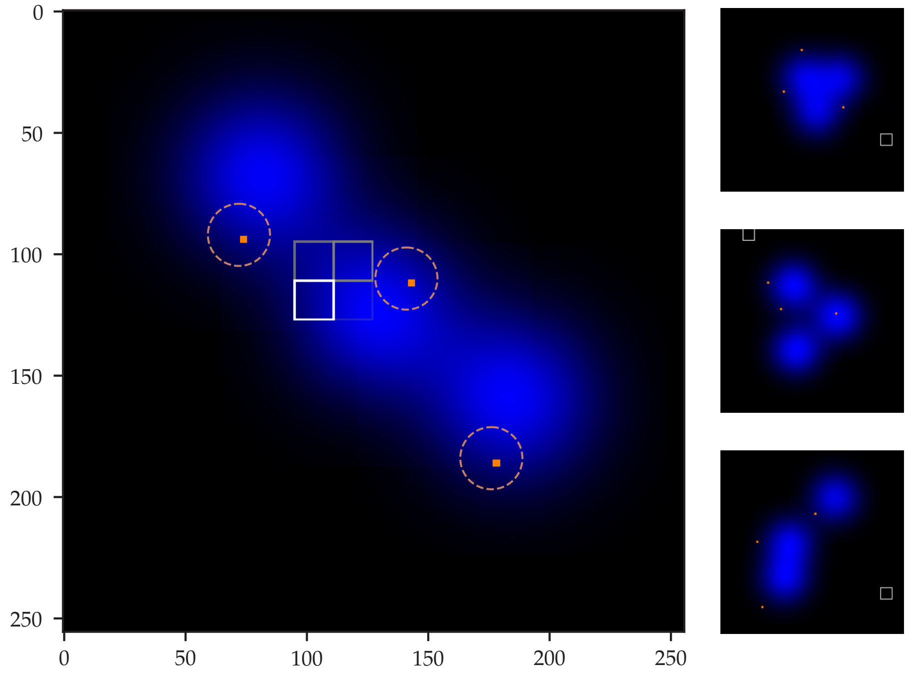

Figure 3.1: Four samples of the first environment. There are three gaussian kernels in the environment, whose height is visualized with the blue channel. There are three targets in the environment, whose location is sampled from the distribution defined by the sum of the three gaussian kernels.

3.3 Baseline

3.4 Approach

We postulate that an effective searcher should be able to:

- Search the scene exhaustively, while avoiding visiting the same location multiple times.
- Learn a probability distribution of targets and its correlation with the appearance of the scene.
- Remember the appearance of previously visited areas in order to prioritize where to go next.

The agent is trained with reinforcement learning using Proximal Policy Optimization [**proxim**] with function approximation using neural networks.

3.4.1 Architectures

The architecture of the neural network is presented in Figure X. The network is split into three main section: the feature extraction, the shared network, and the policy and value heads. In order to be able to use the same extractor for all environments we resize the RGB image to 64×64 pixels.

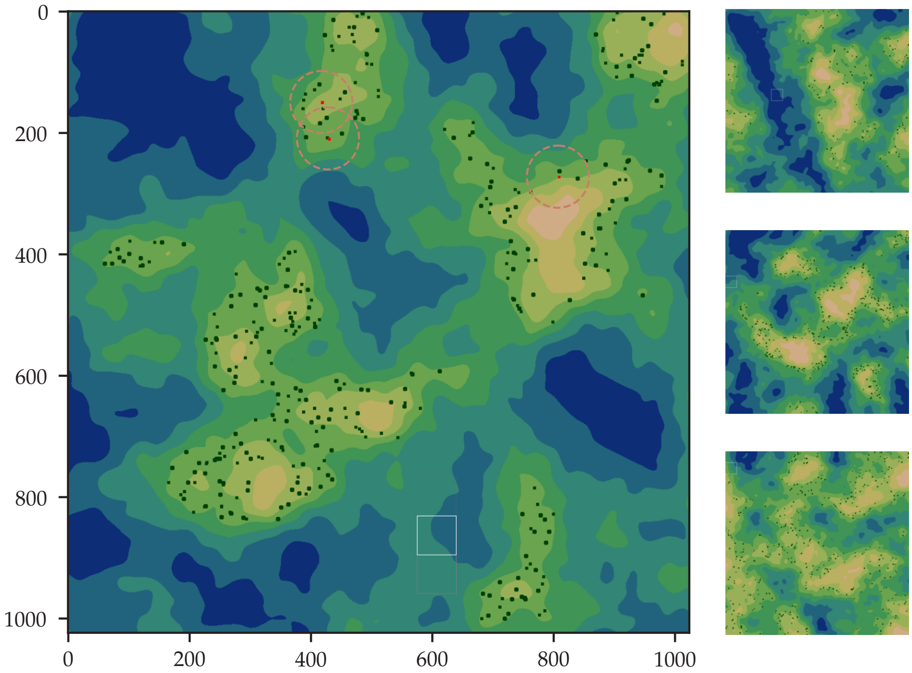

Figure 3.2: Second environment. Terrain seen from above with ocean,

We compare our architecture to three different baselines. As [26], we use a

3.5 Experiments

The first environment was used to determine a good observation space. By just observing the current window, the agent can never learn a suitable policy to solve the problem. This is because it cannot distinguish between equal windows at different locations. Experiments are run with several additional observation types: window position, ... Results of these experiments are presented for this environment only.

The agent was trained using the algorithm described in Section 3.4 for 100 million time steps in all three environments using PPO, PPG and A2C. Hyperparameters are tuned with random search separately for each environment. For all experiments, the average return per episode is reported together with the theoretically optimal reward (obtained with an optimal path). The agent was trained and tested on the full distribution of environments.

With the best performing algorithm we compare three different reward signals. One gives a constant time penalty of -1 to incentivize finding the target quickly. The second gives a constant time penalty of -2 and an exploration bonus of +1 when a new view is reached. The third gives a reward of +1 for moving closer to the target and a penalty of -1 otherwise, as in [7].

Additionally, experiments to eveluate the generalization capability of the agent were conducted. These were conducted on the procedurally generated terrain environment following the approach suggested in **[procgen]**. During training, the seed pool size was fixed to various sizes to limit the training set size. The agent was trained for varying number of timesteps and then tested on the full distribution of environments. This way, we can get a sense of how much data and simulation is required to use the approach for real-world tasks.

All experiments are conducted on an Intel Core i9-10900X CPU and an NVIDIA GeForce RTX 2080 Ti GPU.

For each experiment, we report the mean return and episode length over time during training. We compare the approach to an exhaustive search and a human searcher with prior knowledge of the characteristics of the searched environments. As per [1], we report results across multiple seeds.

3.6 Implementation

The environment is implemented with Gym [6], and the agent is implemented with PyTorch [30]. Proximal policy optimization was implemented following the official implementation by OpenAI. Some necessary modifications were made to allow for recurrent policies.

4 Results

When it comes to hyperparameters, we find that letting the number of rollout steps be substantially lower than the episode length we achieve much more stable training results. Furthermore, increasing the number of weights in the neural network made it more difficult to train.

We find that the hyperparameters from [procgen] perform well, especially when the number of environments is large.

Also, proximal policy optimization was unstable without reward normalization.

This coupled with a sparse reward signal led to many cases where the agent converged towards a poor local optimum (or perhaps never converged at all).

5 Discussion

This chapter contains the following sub-headings.

5.1 Results

5.2 Method

It is worth considering whether using a learning agent like this is suitable for this task. One could imagine that it is possible to compute an optimal strategy for certain environments. However, this quickly falls apart. The dynamics of environments can vary considerably which may drastically affect how a manual approach is implemented.

Another thing worth discussing is the possibility of combining manual search method with reinforcement learning. One could imagine combining a frontier based approach with a learning approach.

In this work, we have only covered searches where the view is transformed in the spatial domain. However, the method could be applied to a broader category of problems. For instance, one could imagine a scenario when searching along the time dimension is useful. If we let the actions be translations arbitrary translations along the time dimensions in, say, a long audio or video file, the agent could learn to look for landmark features in such modalities.

5.3 The work in a wider context

While automated search systems have many positive uses, like XXX, there are certainly other use cases that could be considered negative. Mass surveillance, XXX, are both very relevant today.

6 Conclusion

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