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Learning to Search for Targets

– A Deep Reinforcement Learning Approach for Visual Search in Unknown Environments

Inlärd sökning efter mål

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Abstract

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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 behavior. 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.

Automating visual search is of great interest for several reasons. Visual search is crucial for applications such as search and rescue, surveillance, fire detection, etc. Autonomous vehicles can both reduce risk and potentially exhibit more intelligent searching behavior than human-controlled ones.

However, while visual search is often seemingly effortless to us humans, it is a complex process. Attempts to understand and recreate human visual search in machines has been a big challenge [18]. At the root of the visual search problem is partial observability. A searcher can only perceive, or pay attention to, a limited region of the searched environment at once. Therefore which regions to observe and in what order becomes an important decision.

How humans and animals search for things has been extensively studied in neuroscience [18, 52, 39]. When we search, we use features of the environment to guide our attention [53, 18]. For example, we know to look for berries at the forest floor, and not to look for boats on land. Furthermore, search is not purely reactive but involves the use of memory. We also use memory to take the history of the search into account when deciding where to move our attention [53].

Such features can in some cases be quite subtle and difficult to pick up, even for humans. Manually engineering guidance in accordance with these features can be difficult, especially if a searching system should be deployed in many different environments. Doing so manually can be labour intensive, especially if a searching system should be deployed in many different environments. If one could instead learn the a good searching strategy from a limited set of

sample environments this would be circumvented. Such a system could be taught to search in arbitrary environments without the use of environment-specific rules.

Reinforcement learning [49] is a paradigm that is suited for learning mappings from sensor values to actions. In recent years, reinforcement learning has been combined with deep learning [21] with tremendous success. It has been used to master arcade games [38], board games [47], and even complex real-time strategy games [51]. Several works have also applied reinforcement learning to tasks involving embodied agents with visual input [33, 36, 58, 34]. This makes it interesting to see if deep reinforcement learning can also be applied to visual search.

1.2 Aim

The aim of this thesis is to investigate how an intelligent agent that learns to search for targets can be implemented with deep reinforcement learning. Such an agent should learn the characteristics of the environments it is trained on and utilize this knowledge to effectively search for targets in unseen environments. The goal of the agent is to actively locate a set of targets in its environment. Specifically, we consider scenarios where the agent can only observe a small portion of its environment at any given time through a fixed pan-tilt camera. This means that there are no restrictions in movement. The agent has to actively choose where to look in order to gain new information about the environment.

We postulate that an effective searcher learns how the distribution of targets and prioritizes regions where they are more likely according to previous experience. The distribution of targets may be correlated with the appearance of the searched scene. A good searcher should integrate information over time to build an internal representation of the environment and use it to make informed decisions. The agent should be able to search the environment exhaustively while avoiding visiting the same region twice. Finally, the agent should be able to locate multiple targets while minimizing its path length.

If such a system is to be trained and deployed for a real-world task, there is realistically a limited set of samples to learn from. Therefore it is also of interest to determine how many samples are required to infer how to effectively search in similar environments. While similar problems have been addressed in the past [33, 34], our impression is that this is the first work to address for multiple targets in unseen environments where emphasis is placed on how environment cues can guide search. Our contributions are as follows:

- We provide a set of environments to train and evaluate visual search agents.
- We propose a method for solving the visual search task with reinforcement learning.
- We compare the method to a set of common baseline agents.
- We investigate how well each agent is able to generalize to unseen environments.

1.3 Research questions

This thesis will address the following questions:

1. How can an agent that learns to intelligently search for targets be implemented with reinforcement learning?
2. What is a suitable memory architecture for a visual search agent?
3. How does the learning agent compare to random walk, exhaustive search, a human searcher with prior knowledge of the searched environment?
4. How many training samples are needed for the agent to generalize to unseen in-distribution environments?

1.4 Delimitations

We focus on the behavioral and decision-making aspects of the presented problem, and delimit ourselves from difficult detection problems. For this reason, targets will deliberately be made easy to detect. Furthermore, we make the assumption that the searched environment is static. The appearance of the environment and the location of the targets does not change from one observation to the next.

2 Theory

This chapter introduces background and related work.

2.1 Background

2.1.1 Visual Search

The perceptual task of searching for something in a visual environment is usually referred to as *visual search* [52]. 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.

Two big limitations of performance in visual search are processing power, and limited observability. Vision in humans is foveated - we perceive with different resolutions at different parts of the retina. For computer vision systems, this is typically not a limitation in the sensors. However, processing large images might be too expensive, even for computer systems. In such cases, images have to be attended to one part at a time.

Scanning an environment for targets involves the use of *visual attention*. Humans scan environments by directing their gaze (*overt attention*) and shifts of attention in the current visible region (*covert attention*) [28]. While covert attention tends to be reactionary, overt attention usually integrates more features over time. In this work we focus specifically on the former, moving the gaze to bring targets into view.

Humans control overt attention through both eye movements and head movements. Eye movement is *saccadic* - rapid and almost instant between locations. This is in general not true for computer vision systems: cameras are more often

If the searched environment is a random field, visual search is akin to a random process [39]. Experiments in humans have shown that search in featureless environments is consistent with random walk with no memory. Humans have also been shown to use the history of observations to improve visual search efficiency. Simple memory mechanisms, like some inhibition-of return mechanism [28] that prevents searching visited locations twice, improve search time in random fields considerably.

Natural environments are in fact seldom completely random, and exhibit some structure. When finding targets, there tends to be something that can be learned from previous experience to improve performance. Such regularities can learned and used during future searches.

Improvements in human search performance have been measured when certain locations have higher probabilities of containing targets [18]. Furthermore, if targets usually co-occur with other visible elements they tend to be easier to find [18]. [53]

2.1.2 Active Vision

Much of past and present research in machine perception involves a passive observer which samples and perceives images from a fixed distribution. 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 et al. [2] introduce the *active vision* paradigm. An active vision is defined as a system that involves an observer that has some control over its sensory input. They prove that an active observer can solve several basic vision problems in a more efficient way than a passive one. When the transformation of the observer's view is known, it can uniquely compute shape and motion.

Bajcsy [**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.

In a re-visitation of active perception, Bajcsy, Aloimonos and Tsotsos [6] 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.

[6]

Active perception in general relates to the idea of moving a sensor to constrain the interpretation of the environment. Chen et al.[13] survey recent developments in active vision. They refer to the task of finding a given object in a known or unknown environment as object search. This task involves object recognition, localization, sensing control, environment modelling and path planning. Viewpoint selection in object search is similar to that of data acquisition. Visual matching has been shown to be NP complete, with exponential time complexity relative to the size of the image.

2.1.3 Deep Learning

Deep learning is a family of techniques in which hypothesis are represented as computation graphs with tunable weights. The computation graphs are inspired by biological neurons in the brain and are referred to as *neural networks*. Deep neural networks consist of *nodes* arranged in *layers*: one input layer, zero or more hidden layers and one output layer. Each layer receives an input *representation* [8] from the previous layer and outputs a transformed representation to the next layer. Given some input, a neural network optimizes its output representation with regard to some criterion. Usually, a loss function $\mathcal{L}$ is minimized by updating the weights $\mathbf{w}$ of the network with some variant of *gradient descent* with learning rate α:

$$\mathbf{w} \leftarrow \mathbf{w} - \alpha \nabla_{\mathbf{w}} \mathcal{L}(\mathbf{w}) \tag{2.1}$$

The only requirement on the functions computed by each node is that it is differentiable. As long as this holds, layers can be stacked arbitrarily and the gradients can be computed with the chain rule. This way, errors in the output can be passed back through the network (*back-propagation*) and used to update the weights. [44, 21]

The architecture of a neural network imposes some bias onto the learning that its expected to be useful for generalizing to unseen samples. We now describe three neural network architectures that will be used in this work.

2.1.3.1 Feedforward Neural Network

A feed-forward neural network, also known as a multi-layer perceptron (MLP) [21], only has connections in one direction. Each node in the network receives inputs from its predecessors and outputs the result of a function of those inputs. The output y of each node is usually computed by taking the weighted sum of its inputs x and applying some non-linear function

$$y_j = g_j(\mathbf{w}_j^T \mathbf{x}), \tag{2.2}$$

where y_j is the output of node j, g_j is a non-linear *activation function*, $\mathbf{w}_j$ is the vector of weights leading into node j, and $\mathbf{x}$ is the vector of inputs to the node. By convention, each layer also has some *bias* that allows the total weighted input to g_j to be non-zero even when the outputs from the previous layer are zero. The bias is included as an extra input x_0 fixed to 1, and an extra tunable weight $w_{0,j}$. The non-linearity ensures that a network with at least two layers can approximate any continuous function. [44]

2.1.3.2 Convolutional Neural Network

Convolutional neural networks (CNNs) contain spatially local connections. They have patterns of weights, called *kernels*, that are replicated across units in each layer. With some input vector $\mathbf{x}$ of size n and a vector kernel $\mathbf{k}$ of size l, the (discrete) convolution operation $\mathbf{z} = \mathbf{x} * \mathbf{k}$ is defined as

$$z_i = \sum_{j=1}^{l} k_j x_{j+1-\frac{l+1}{s}}, \tag{2.3}$$

where s is the *stride*. This operations can be generalized up to more than one dimension, such as 2 dimensions for images and 3 dimensions for volumes. With multiple input channels, kernels are stacked into a *filter*. The outputs of each kernel are then summed over, giving one output channel per filter.

There are several advantages to using CNNs for structured input data where neighboring values are correlated. Kernels are smaller than the input, which means that fewer parameters have to be stored. These *sparse interactions* give CNNs reduced memory requirements, as well as improved statistical and computational efficiency.

Furthermore, the same parameters are also used for more than one function in the CNN. *Parameter sharing* across input locations mean that layers in a CNN have *equivariance* to translation. The output of one kernel is the same regardless of the input location. This property of CNNs is useful for images where similar features may be useful regardless of their location in the input. [21]

2.1.3.3 Recurrent Neural Network

Recurrent neural networks (RNNs) extend feed-forward networks by allowing cycles in the computation graph. Each cycle has a delay so that some *hidden state* from the previous computation is used as input to the current computation. A recurrent layer with input $\mathbf{x}_t$, output $\mathbf{y}_t$ and hidden state $\mathbf{z}_t$ is defined by

$$\begin{aligned} \mathbf{z}_t &= f_{\mathbf{w}}(\mathbf{z}_{t-1}, \mathbf{x}_t) \\ \mathbf{y}_t &= g_y(\mathbf{W}_{z,y}, \mathbf{z}_t), \end{aligned} \tag{2.4}$$

where $f_{\mathbf{w}}$ is the update process for the hidden state and g_y is the activation function for the hidden layer. This model can be turned into a feed-forward network over a sequence of input vectors $\mathbf{x}_1, \ldots \mathbf{x}_T$ and observed outputs $\mathbf{y}_1, \ldots, \mathbf{y}_T$ by *unrolling* it for T steps. The weights are shared across all time steps. This means that RNNs can operate on inputs of arbitrary lengths. The hidden state is used as a summary of all previous items in the sequence. Thus, RNNs make a Markov assumption. [44]

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 [21]. An architecture that addresses this issue is long short-term memory (LSTM) [27]. LSTMs include a *memory cell* c in the hidden state that is copied from time step to time step, and three soft *gating units* that govern the information flow in the hidden state update process f. This makes LSTMs particularly useful for learning over long sequences.

2.1.4 Reinforcement Learning

Reinforcement learning (RL) [49] is a subfield of machine learning concerned with learning from interaction how to achieve a goal. This section introduces the fundamental concepts of RL.

2.1.4.1 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. [29]

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 $\mathcal{O}(s_{t+1}, a_t, o_t)$. [29] Figure 2.1.4.1 illustrates the interaction between agent and environment.

The agent and environment interact over a sequence of discrete time steps $t = 0, 1, \ldots, T$, 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*:

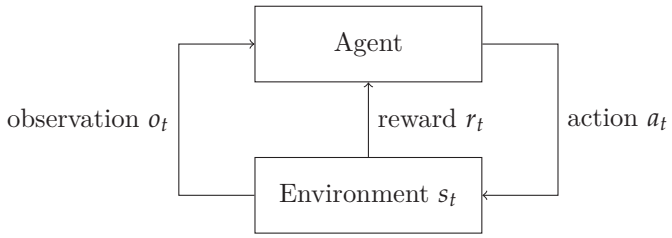


Figure 2.1: Interaction between agent and environment in a partially observable Markov decision process.

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

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 one is often computationally intractable. Approximate solutions are more common, where the agent usually maintains an internal *belief state* [29] which is acts on. The belief state summarizes the agent's previous experience and is therefore dependent on the full *history* of actions and observations. 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 interchangeably.

2.1.4.2 Policies and Value Functions

The behavior 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. [49]

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. There are two common alternative value functions: The *quality function* $Q_\pi(s,a)$ gives the value of state s under policy π where a is the first action taken. Given a quality function, *action-value* methods choose the action greedily at every state as $arg\,max Q_\pi(s,a)$. The *advantage function* $A_\pi(s,a)$ instead represents the relative advantage of actions, $A_\pi = Q_\pi - V_\pi$. [49]

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 $\hat{V}(s,\mathbf{w}) \approx V_\pi(s)$ for the approximate value of state s with some weight vector $\mathbf{w} \in \mathbb{R}^d$. [49]

An alternative to action-value methods is to approximate the policy itself. *Policy gradient methods* [48] learn a parametrized policy that select actions without a value function. We denote a parametrized policy as $\pi(a|s,\boldsymbol{\theta})$ with $\boldsymbol{\theta} \in \mathbb{R}^{d'}$ as the parameters to the policy. The policy parameters are usually learned based on the gradient of some performance measure $J(\boldsymbol{\theta})$. As long as $\pi(a|s,\boldsymbol{\theta})$ is differentiable with respect to its parameters, the parameters can be updated with *gradient ascent* in J:

$$\boldsymbol{\theta}_{t+1} = \boldsymbol{\theta}_t + \alpha \nabla \hat{J(\boldsymbol{\theta}_t)})$$

Advantages of policy parametrization over action-value methods include stronger convergence guarantees [48] and more flexibility in parametrization [49]. 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 $\mathbf{w}$ of the value function estimate and $\boldsymbol{\theta}$ of the policy estimate.

Function approximation includes important aspects of partial observability. If there is a state variable that is not observable, then the parametrization can be chosen such that the approximate value does not depend on that state variable. Because of this, function approximation is applicable to the partially observable case.

2.1.4.3 Design Challenges

One of the challenges that arises in reinforcement learning is the exploration-exploitation trade-off. An RL agent should *exploit* knowledge gained from previous experiences and prefer actions that has yielded reward in the past. It should also *explore* in order to learn better actions to take in the future. Agents that fail to both exploit and explore will lead to failure at the task.

Another challenge is the design of reward signals. For some tasks, like certain video games, the objective is simply to maximize the score obtained. In this case there is an inherent reward signal and the agent achieves its task simply by maximizing this inherent signal. Other times, we have a task we want the agent to solve and have to design a reward signal around that task. Designing rewards is not straight-forward and can often have unintended effects [49]. Special care has to be taken to ensure that the reward encourages the desired behavior.

Here, the problem of *sparse rewards* also comes into play. The agent has to be reward frequently enough to allow it to achieve its goal once. Often it has to incentivize it to achieve its goal efficiently, with multiple different starting conditions. If rewards are too sparse, the agent may explore aimlessly and take too long to find achieve its goal. In such cases, it can be effective to modify the reward to give the agent hints along the way. If the received reward is temporally distant from the action that caused it, the agent may have difficulty connecting the two. This is known as the *credit assignment problem* [32].

In practice, rewards are often designed through trial-and-error. Several iterations of a reward signal are tried until one yields expected and sufficient results.

2.1.4.4 Deep Reinforcement Learning

As mentioned in Section 2.1.4.2, policies 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 [50], a neural network trained with RL that reached expert Backgammon performance in 1995.

More recently, the successes of deep learning have bled over into the field of RL. In 2015, Mnih et al. [38] extend [37] and introduce DQN, which combines deep neural networks with RL. DQN successfully plays Atari games using only visual input. It approximates the quality function $q(s,a)$ with a CNN architecture, and selects actions greedily. To incorporate some memory, images from the 4 previous time steps are stacked and used as input to the neural network. The input is fed through three convolutional layers and a hidden fully connected layer, all with ReLU activation functions. The output layer has one output for each valid action, representing Atari controller buttons.

DQN inspired many several follow-up works which use deep neural networks to approximate policy and value functions. Such methods are often referred to as deep reinforcement learning (deep RL) methods.

2.1.4.5 Proximal Policy Optimization

Proximal policy optimization (PPO) [45] is a family of policy-gradient algorithms. PPO alternates between sampling agent-environment interactions and optimizing the policy. Multiple gradient updates are performed for each batch of samples…

Algorithm 1 Proximal Policy Optimization

for iteration $= 1, 2, \ldots$ **do**
  for actor $= 1, 2, \ldots, N$ **do**
    Run policy $\pi_{\theta_{\text{old}}}$ for T time steps
    Compute advantage estimates $\hat{A}_1, \ldots \hat{A}_T$
  end for
  Optimize surrogate L wrt θ, with K epochs and mini-batch size $M \leqslant NT$
  $\theta_{\text{old}} \leftarrow \theta$
end for

PPO algorithms have turned out to strike a good balance between simplicity, stability and ease of tuning while achieving competitive performance on several tasks [45, 24, 15, 51, 4].

Several papers state this without providing a reference.

2.2 Related Work

To our knowledge, there is no work that considers the exact problem we are looking at. In this section we present work that considers similar tasks, focusing on RL methods.

2.2.1 Object Detection

In computer vision, *object detection* is the task of detecting semantic objects of a certain class in images. Detecting an object entails *recognizing* that it is present in an image, and *localizing* it by determining its bounding box. State of the art object detection use deep learning techniques and usually involve a deep convolutional architecture [57]. Object detectors usually use region proposal networks that consider the whole image and return a set of bounding box candidates. The object recognizer is then run on each region proposal.

Although we do not focus on difficult recognition problems in this work, the task we consider bears resemblance to object localization. The difference is that images in object detection are passively sampled - they are drawn from some distribution and all are independent. Furthermore, the whole scene that is searched for objects is visible in the image. In *active object detection*, the analyzed images are instead chosen so as to help the detector perform its task better.

Caicedo and Lazebnik [11] 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 given a punishment of -1 otherwise. They find that this reward communicates 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.

A similar work by Ghesu et al. [20] present an agent for anatomical landmark detection trained with DRL. Different from [11] 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 right. 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 a population of anatomical images of the human body.

Chen and Gupta [14] use a spatial memory for context reasoning in object detection. They argue that object detection systems require memory to perform well, Furthermore, they pose that this memory should capture the spatial layout of the scene in order to model object-object relationships. A spatial memory network is proposed, which remembers features and locations of past detections in an image and uses this to improve future ones. A CNN is used to extract features from the memory and used together with the original image as input to a standard region proposal network. The approach gives a small improvement over the standalone region proposal network.

2.2.2 Visual Search and Attention

Minut and Mahadevan[33] propose an sequential model of selective visual attention for visual search tasks. An agent is tasked with finding a particular object in a scene A policy for controlling a fixed pan-tilt-zoom camera is learnt using reinforcement learning. The goal of the agent is to aim the camera at the region where a target is most likely to be found. It has to decide where to fixate next based on visual information only. Despite being limited to a single environment, this is an

Forssén et al [19] implement a mobile robot that searches for specific objects within a cluttered environment.

A similar work by Shubina and Tsotsos [46] consider the problem of visual search in 3D environments with a mobile robot. They use…

Partially observable processes, such as the one we consider in this work, can be seen as hard attention problems. By taking actions, the hard attention can be redirected

Attention has been modelled in machines with success for both language [5] and vision tasks. While overt attention is hard attention, it is also interesting to take inspiration from soft attention, which more closely resemble covert attention.

Mnih et al. [36] take inspiration from visual attention and foveated vision found in humans and propose to use a similar mechanism for computer vision tasks. Applying a CNN to a large images can be expensive, as the complexity scales linearly with the number of images pixels. They propose a recurrent model that extracts information from images by adaptively selecting a sequence of smaller regions to process at high resolution. At each time step, the agent receives an image observation of the environment. Through actions, the agent selects a limited region of this observation to view in high resolution. It is given a reward that is dependent on the task the agent should perform. It can access this image via a bandwidth-limited sensor which it focuses on a limited region. The agent maintains an internal state using an LSTM layer. Though the model is not differentiable, it is trained using RL with a policy gradient method. The authors evaluate the agent for image classification and a game-like task. They find that the model outperforms a similar convolutional architecture for cluttered object classification tasks. This is attributed to its ability to focus its attention on important regions.

Soft attention (Bahdanau [5])…

2.2.3 Visual Navigation

Visual navigation is the process of determining a suitable path between a start point and destination point using visual input [9]. Visual navigation has been studied for use in both autonomous ground vehicles, where obstacles have to be avoided, as well as for unmanned aerial vehicles which typically don't have the problem of avoiding obstacles. The visual search problem can be considered analogous to a visual navigation in unrestricted environments.

Bonin-Font et al. [9] divide visual navigation in map-based and map-less systems. Map-based systems may explore and build a map of their environment They further subdivide map-

based systems into map-less navigation systems into optical flow-based systems, appearance-based systems,

More recently, deep RL seen use for visual navigation as well [55]. The difficulty of hand-engineering In particular, two tasks have been of interest: object (goal) navigation and point (goal) navigation.

Zhu et al. [**zhu_target_driven_2016**] create a model for target-driven visual navigation in indoor 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.

Mnih et al. [35] 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 [38] is used, but with 256 LSTM cells after the final hidden layer. At each episode, a maze is randomly generated with objects that give rewards then traversed scattered around. They train the agent using an actor-critic approach and manage to get the agent to successfully navigate in unseen but similar environments.

Mirowski et al. [34] propose a new approach to tackle a similar maze navigation problem as [35]. They propose a new architecture, that in addition to an image, also observes the reward, velocity and the action from the previous time step. Observing the reward may help the agent learn features of desirable frames, but also limits the set of possible reward signals as the reward has to be present during testing. As in [35], the agent has a recurrent LSTM layer. The architecture is trained using an auxiliary depth prediction objective. The authors argue that understanding the depth of the searched environment helps the agent navigate it better. This agent is evaluated against three baselines on both static and randomly generated maze environments. It is found that an agent that only receives image observations performs worse than one that also has an LSTM layer. Adding the previous reward, action and velocity to the observations bring modest performance improvements. The depth prediction is found to improve performance in all environments, indicating that the correct auxiliary task can help learning.

A similar work by Ye et al. [54] 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 [58] - the scenes and targets used during testing have all been seen during training.

Gupta et al. [22] introduce an agent that navigates in novel environments using a spatial memory. Encoded representations of observed images are placed in a top-down map…

Henriques and Vedaldi [25] argue that autonomous agents must switch from an egocentric representation of their scenes to an allocentric one. They propose a spatial memory which can be updated dynamically during each episode…

Dhiman et al. [17] 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 different maps, it cannot do so successfully. They further find that, with a single decision point whose correct…

Chaplot et al. [12] build on the idea of an explicit memory by including environment semantics…

2.2.4 Memory Architectures

A recurring theme in the related work above is the use of memory architectures. In most cases where active sensing is involved, memory is a requirement for good performance. As mentioned in Section 2.1.4.1, effective behaviour in partially observable processes usually requires some form of memory. Works that don't use memory rely on either full observability, like [11], or low variance so that search can be done reactively, like [20]. For the visual search task we consider here, memory is likely to be important. It is likely that integrating features over time helps with finding targets quicker.

Simple memory mechanisms, like the frame stacking used in [38] can model velocity and work well in certain environments where reactive action is sufficient. Once a task requires integration of features over longer time, more advanced memory is required.

Hausknecht and Stone [23] investigate the effects of adding memory in the form of a recurrent step to DQN in order to tackle POMDPs. They use the same convolutional network as [38], but only use the most recent frame as input and replace the hidden layer with a recurrent LSTM. It is found that the agent is able to integrate information over time and achieves comparable performance to the original DQN agent. Several other works use a recurrent step to solve tasks that require memory, like [36] and [35].

Recurrent neural networks can in theory remember anything, but have practical issues like the the ones described in Section 2.1.3.3. Furthermore, they might not be easily trained for all tasks. Memory architectures that are specialized for particular tasks, like [], have the potential to be more useful and give better performance.

Anderson et al. [3] emphasize the importance of memory mechanisms that support the construction of rich internal representations environments in navigation agents. Simple agents that are purely reactive and act on the sensory input at the current time step only work for simple tasks. Augmentations like recurrent update mechanisms add more potential. More advanced memory mechanisms can be important for better navigation. The nature of the internal representation is central to the study of embodied navigation.

One interesting example of such a memory is

Oh et al. [40] use a differentiable retrieval memory. The memory contains a mechanism for retrieving memory contents based on the current context of the agent.

Parisotto and Salakhutdinov [42] propose a structured memory…

2.2.5 Benchmarking Environments

- What is contained in an environment (represents a Markov Decision Process).
- What is a good benchmarking environment
- Should list some common environments and explain why they are not satisfactory
- Motivate why we create our own (higher variance, agent's can not rely on memorizing environments)

2.2.6 Generalization and Inductive Bias

In RL, generalization refers to an agents ability to act well in environments that have not been seen during training. This is vital if RL is to be applied to real-world problems where conditions are diverse and unpredictable. Agents have to be robust to such variations without being trained on them (*zero-shot* policy transfer). In the case of visual search, we want a system that can search in novel environments by generalizing from those seen during training.

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 and generalization has generally been neglected in deep RL [31]. Training and evaluation stages are typically not separated. Instead, the final return on the training environments is used as a measure of agent performance. This results in agents that perform badly on environments that are only slightly different from those seen during training.

Zhang et al. [56] 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. [16] 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. [26] 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. [15] introduce a benchmark for sample efficiency and generalization in RL. They make use of procedural generalization, dependent on a random seed, 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 limit 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.

Kirk et al. [31] survey generalization in deep RL. They propose a formalism for collections of problems called contextual CMDPs. A CMDP which is an MDP $\mathcal{M}$ (or POMDP) where the state can be decomposed into $s = \langle c, s' \rangle$, where $s \in \mathcal{S}$ is the underlying state and $c \in \mathcal{C}$ is the *context*. The context takes the role of a seed and determines the sample drawn from the underlying distribution of task instances. In a CMDP, separate train and test tasks can be

defined by creating $\mathcal{C}_{\text{train}} \subset \mathcal{C}$ and $\mathcal{C}_{\text{test}} \subset \mathcal{C}$ such that $\mathcal{C}_{\text{train}} \cap \mathcal{C}_{\text{test}} = \varnothing$. They conclude that strong generalization requires

2.2.7 Evaluation of Agents

A problem in state-of-the art RL is reproducibility. There is often non-determinism, both in the methods and environments used. Furthermore, many methods have intrinsic variance which can make published results difficult to interpret. This has meant that reproducing state-of-the-art deep RL results is difficult.

Henderson et al. [24] discuss this problem from multiple perspectives. Through experimental analysis, they show that:

- In policy gradient methods, hyperparameters and the choice of network architecture for policy and value function approximation can affect performance significantly. They find that ReLU activations tend to perform best across environments and algorithms. For PPO, the use of large networks may require changing other hyperparameters like learning rate.
- Rescaling rewards can have a large effect, although it is difficult to predict how.
- Variance between random seeds in stochastic environments affects performance of algorithms, and give learning curves that do not fall within the same distribution. This suggests that selecting the top N trials or average over a small number of trials N can be misleading. They suggest to compare performance over many different random seeds.
- For certain environments, learning curves can indicate successful optimization but the learned behavior may not be satisfactory. It is therefore important to not only show returns, but also demonstrations of the learned policy in action.
- Implementation differences that are not reflected in publications can have a dramatic impact on performance. It is therefore necessary to enumerate implementation details and package code bases with publications. Performance of baseline experiments should also match original baseline publication code.

Due to the unstable nature of RL algorithms, it is often inadequate to just report average return. Henderson et al. [24] propose to include confidence intervals when reporting results. Confidence bounds with sample bootstrapping is used to show that PPO is among the more stable algorithms. Finally, [24] make the point that more emphasis should be placed on applying RL algorithms to real-world tasks. It could be more useful to propose a set of tasks that an algorithm could be used for than to show performance on fictional tasks.

A similar work by Agarwal et al. [1] criticizes the heavy use of point estimates of aggregate performance. They show that conclusions drawn from point estimates can be very different from those drawn from more thorough statistical analysis. The popularity of more challenging benchmarks has lead to longer training times. This has made it less feasible to measure performance over many training runs, which in turn has led to a shift to only evaluating a small number of runs per task. Like [24], they advocate for the use of performance metrics that take uncertainty in results into account. They propose the following set of metrics that better reflect performance across a handful of runs:

- Uncertainty in aggregate performance should be reported through interval estimates via stratified bootstrap confidence intervals.
- Variability in performance across tasks should be reported through performance profiles (score distributions).

- Aggregate metrics for summarizing performance across tasks should be reported through interquartile mean (IQM) across all runs.

Anderson et al. [3] discuss problem statements and evaluation measures for embodied navigation agents, and make a set of recommendations. A navigation agent should be equipped with a special action that indicates that it has concluded the episode. The agent should be evaluated at the time this action is made, and not at some more favorable time step. Proximity to a goal should be measured using geodesic distance, the shortest distance in the environment. They recommend success weighted by (normalized inverse) path length (SPL) as the primary measure of navigation performance. With N test episodes, SPL is computed as

$$\frac{1}{N}\sum_{i=1}^{N} S_i \frac{l_i}{\max(p_i, l_i)} \tag{2.5}$$

where S_i is a binary indicator of success, l_i is the shortest path distance from the agent's starting position to the goal, and p_i is the length of the path actually taken in the episode. If 50% of test episode are successful and the agent takes the optimal path in all of them, its SPL is 0.5. By measuring SPL of human subjects, what is a good score can be calibrated.

Batra et al. [7] revisit the problem of evaluating embodied navigation agents. They note some issues with the SPL metric. It fails to consider the fact that some failures are less of a failure than others. Some failures might in fact be close to reaching the goal while some fail completely. The binary success introduces high variance in average SPL computation. Furthermore, SPL is not particularly suitable for comparison across different datasets, as obtaining a high SPL is more difficult for short paths than for long paths. They suggest that SPL should be replaced by some metric that takes these issues into account. However, to our knowledge such a metric is yet to be proposed and widely adopted.

3 Method

In this chapter, the method used is described. Section 3.1 formalizes the problem solved. Section 3.4 details the environment used to evaluate solutions. Section 3.3 describes the baseline learning method. Section 3.2 describes the approach used to solve the problem with a learning agent. Section 3.5 describes the experiments conducted to answer research questions 3 and 4.

3.1 Problem Statement

We can now formally define the problem of searching for targets in unknown environments, adopting the CMDP formalism [31].

Let the task be a contextual POMDP $\mathcal{M}$ where the state includes the context c, which we refer to as the *seed*. The state includes a space $S \subset \mathbb{R}^d$ which we refer to as the *scene*. At each timestep, the agent perceives a subspace $V \subset S$ of the environment which we refer to as the *view*.

The actions in $\mathcal{A}$ transform the view into a different subset of the scene. In the scene, there is a set of N targets $T = \{t_0, t_1, \dots t_N | t_i \in S\}$. If $T \cap V \neq \varnothing$ there are $h = |T \cap V|$ targets in view. With a final trigger action, the agent can indicate that there is one or more target in the view. The goal of the agent is to select actions that bring each target into view and indicate that they are visible with the trigger action, while minimizing the number of actions taken.

The observations $o \in \Omega$ are tuples $o = \langle x, p \rangle$. Here, $x \in \mathbb{R}^{3 \times W \times H}$ is an RGB image representing the current view, and $p \in S$ is the position of the agent which uniquely identifies the view. The seed c determines the initial view V, the location of the targets T, the initial position p_0 as well as the image observations x_t at each position p_t.

3.2 Approach

To design an agent that effectively solves the task, we draw inspiration from several previous works and adapt them to better suit this particular task. The final agent should be able to recognize targets, regardless of where they appear in view. It should also be able to integrate features over time in order to remember which locations have been visited. Remembering features of of these locations may also be of importance, as it can provide clues for what is in their proximity.

With this in mind, we use an episodic spatial memory that stores the agent's belief state. The architecture of the neural network is presented in Figure X.

Due to time constraints and the advantages described in Section 2.1.4.2, we limit our approaches to policy gradients. Specifically, we use an actor-critic method. The policy and value function are approximated using a multi-headed neural network. The neural network of the agent is split into four parts: A feature extraction network is connected to a recurrent network. The recurrent network is in turn is connected to an actor network head and a critic network head, which approximate the policy and value function respectively.

Describe approach once it is fully decided. Will be a (spatial) memory that allows for reasoning over the whole explored scene.

3.3 Baselines

We compare our approach to three different baselines. The first baseline is the agent from [38], modified to be trainable with an actor-critic algorithm. This has previously been used as a baseline in [34] and [15]. The agent receives only image observations, and uses a convolutional neural network with three layers for feature extraction.

The second baseline is a recurrent version of the first baseline, the same architecture used in [35], [34],and [22]. After the initial CNN there is an LSTM layer with 256 cells.

The third baseline also uses the position of the agent, which is encoded as one one-hot vector per dimension. The encoded positions are concatenated together with the output of the CNN and used as input to the LSTM layer. Including position should help the agent avoid revisiting previous locations and understand which parts of the scene are yet to be explored.

All three baselines use the same architecture for the policy and value heads as our approach. With these three baselines, we can clearly see what role the observations and memory plays for the search task.

3.4 Environments

To train an test an agent for the problem, we use three different environments. The three environments have different characteristics to test the applicability of the evaluated approaches to different search problems. In each environment there is a scene with a background of distractors and a foreground of targets. The first two environments approximate the problem of searching with a pan-tilt camera with a 2D environment. The third environment uses a simulated 3D environment with a perspective projection camera.

As [15, 35], we leverage procedural generation in all environments. The seed determines the appearance of the scene, the location of the targets and the initial position of the agent. Furthermore, the appearance of the scenes and the location of targets are correlated to some degree in all environments. This means that the agent should be able to search more efficiently using knowledge from the scene.

The observations are

$$o = \langle x, p \rangle \in \Omega, x \in \mathbb{R}^{3\times 64\times 64}, p \in 0, \ldots, 15^2$$

The agent always moves in a 16×16 grid. For the position part of the observations, we assume the presence of some oracle. In many realistic scenarios it is possible to determine the global position of an agent (GPS, pan/tilt, etc.). If how each action moves the agent is well-defined, we do not need the position at all. We can use relative positions instead of absolute ones. Some of the baselines do not use the position.

The action space is the same in all environments:

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

`UP`, `DOWN`, `LEFT`, and `RIGHT` move the view one step in each direction. The `TRIGGER` is used to indicate that a target is in view.

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

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

with $h = |T \cap V|$. We argue that this reward provides a suitable inductive bias for the task at hand. Early experiments show that a constant reward of $r_t = -1$ that simply incentivize the agent to complete the episode as quickly as possible converge too slowly for large state spaces. The reward for finding a target speeds up training without deviating from the goal of the task - 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.

In practice, early experiments show that even this reward might be too sparse. To speed up training, we experiment with two extensions to the reward:

$$\mathcal{R}'(s_t, a_t) = \begin{cases} 1 & \text{if } a_t \neq \texttt{TRIGGER} \text{ moves the view closer to the nearest target, and} \\ \mathcal{R}(s_t, a_t) & \text{otherwise.} \end{cases}$$

$$\mathcal{R}''(s_t, a_t) = \begin{cases} 1 & \text{if } a_t \neq \texttt{TRIGGER} \text{ moves the view to a previously unseen subspace, and} \\ \mathcal{R}(s_t, a_t) & \text{otherwise.} \end{cases}$$

These three reward signals are interesting to compare for a few reasons. R does not clearly mediate to the agent what actions are desireable until a target is found. It may therefore lead to slow learning, but it also does not steer away from the goal of finding targets quickly. R' uses the supervised distance between targets and the agents, which is available during training. This is similar to the reward used by [11] and [20]. In addition to speeding up learning, we hypothesize that this reward may help the agent pick up correlations between scene appearance and target probability. However, it can never yield policies that search exhaustively as such actions are never rewarded. It may therefore perform worse during testing where the reward is not available to the agent. It will also not learn to take the shortest paths in the general case, as selecting waypoints greedily does not yield optimal paths. R'' strikes a balance between the two other signals by instead encouraging exploration. This should cause the agent to learn to search the environment exhaustively.

The episode is terminated when all targets have been found, or when a certain number of time steps have passed. This number of time steps is set so that the agent can reasonably find the targets with random search, and then gradually improve its policy from there. Terminating episodes early this way is common to speed up training [41].

3.4.1 Gaussian Environment

The first environment is the simplest environment. The scene's appearance is given by a 1024×1024 RGB image. The agent observes a 64×64 sub-image at each time step. Which sub-image is viewed is determined by the position of the agent.

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. Three targets are scattered around the environment, visualized as red squares. The larger the sum of the gaussian kernels, the more likely it is that there is a target present.

The idea with this environment is to test that the method learns what we want it to learn. There is a clear correlation between observations and desirable actions. It is also easy to determine whether the agent acts well in this environment.

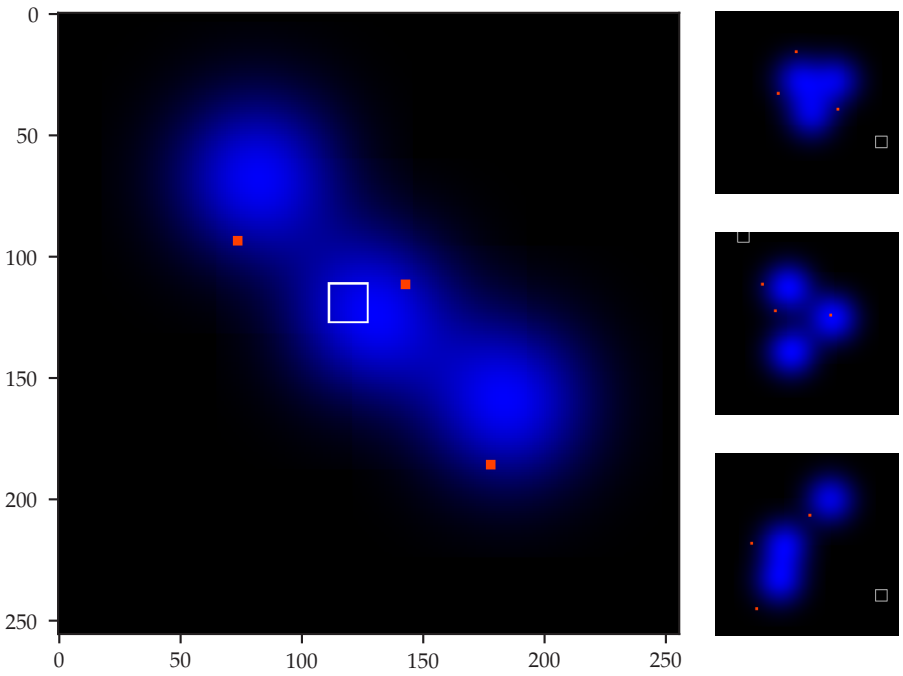


Figure 3.1: Four samples of the first environment. There are three gaussian kernels in the environment, whose heights are indicated by the intensity of the blue channel. There are three targets in the environment, whose location is sampled from the distribution defined by the sum of the three gaussian kernels. The white border indicates the current view.

3.4.2 Terrain Environment

The second environment is intended to look like realistic terrain. As for the gaussian environment, scene's appearance is given by a 1024×1024 RGB image and the agent views a 64×64 sub-image which is translated by the actions. The environment roughly corresponds to a UAV search-and-rescue scenario. It is desirable that a searching agent should learn to not search oceans and lakes, and instead prioritize searching along the edges of land masses.

The scene is generated as follows. Gradient noise is generated and used as a height map. The height map determines the color of the terrain, which is picked to resemble water, sand, grass and rock. The height also correlates to the probability of targets. Specifically, targets are located between shores and mountain bases. There are three targets in each scene.

3.4.3 Camera Environment

The third environment is a three-dimensional version of the second one. The height map is turned into a three-dimensional mesh, and the agent is placed at its center. The agent observes the scene through a pan-tilt perspective camera. Targets are, as before, placed along island edges. The agent is therefore expected to avoid searching the skies and oceans.

This environment is intended to model more realistic scenarios where the image is more difficult to interpret.

The `LEFT` and `RIGHT` actions control the yaw of the camera, while `DOWN` and `UP` control its pitch.

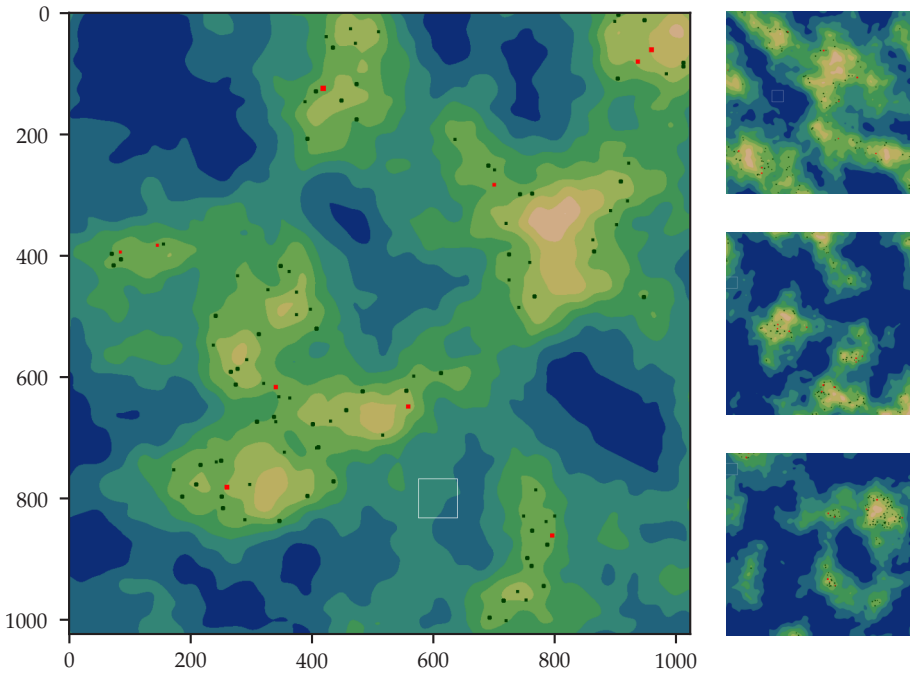


Figure 3.2: Three samples of the terrain environment. Terrain seen from above with red targets scattered along island edges.

3.5 Experiments

To compare our approach to the different baselines, we train and test all agents on all three environments. The agents are trained on the full distribution of environments, We do this for all three reward signals R, R' and R''. All agents are trained for 25 million time steps. They are then tested on 1000 held out samples from each environment.

For each agent, environment, and reward signal we report the average return and episode length over time during training. During testing, we compare the learning agents to random walk, exhaustive search and a human searcher with prior knowledge of the characteristics of the searched environments. We report the SPL metric for all agents, where the shortest path length is the optimal travel distance between the targets and the initial position of the agent. The distance between two points is computed as the minimal number of actions to transform the view between the two.

During testing, we increase the maximum episode length from 1000 time steps to 5000 time steps. This is to give more accurate metrics for episodes that do not terminate within 1000 time steps.

Additionally, we conduct experiments to measure the generalization capabilities of the agents. For this, we use the terrain environment only. The training set size is varied from 100, 1000, 10 000, and 100 000 samples by limiting the seed pool used to generate the environments. We test on held out samples from the full distribution, as done by [15]. This way, we can get a sense of how much data and simulation is required to apply the approach to real-world tasks. For each training set size, we train the agents until convergence. Once again, we compare all three reward signals.

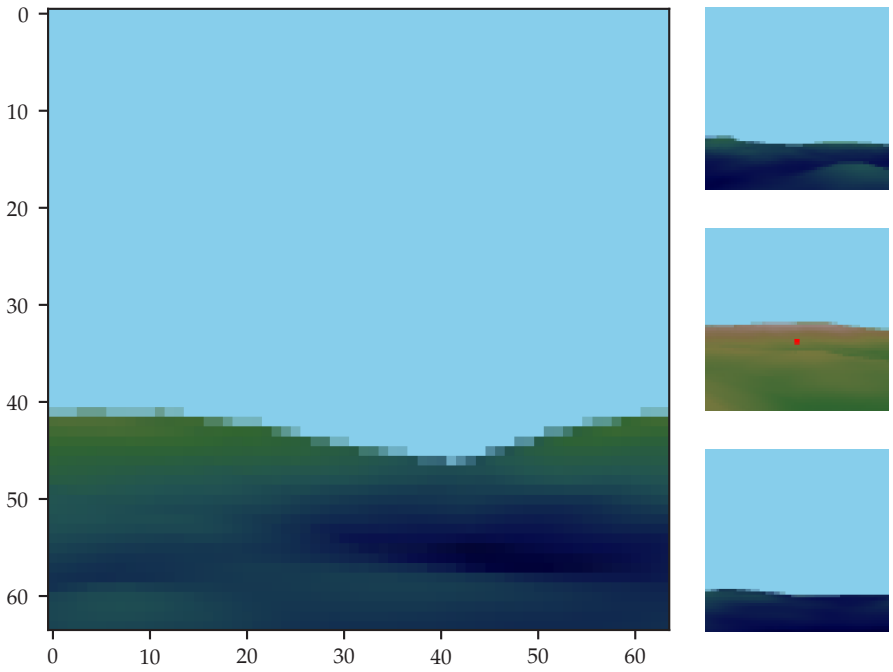


Figure 3.3: Three samples from the camera environment. Terrain seen from a pan-tilt-zoom camera. The pan and tilt of the camera can be adjusted to move the view around. In the mid-right image, a target can be seen.

Following the recommendations of [24] and [1], we report confidence intervals across a handful of seeds. We run all experiments across 3 different runs, and use the aggregate metrics proposed by [1].

We train all agents with PPO [45]. Early experiments show that PPO gives good results, stable learning curves and good sample efficiency, which is in line with results reported by [4]. Furthermore, we use similar hyperparameters as in [15] (Table 3.1). We find that using more parallel environments stabilizes the training. As suggested by [4], we initialize the policy output weights so that their mean is 0 and their standard deviation is low (10^{-2}). The Adam optimizer [30] is used in all experiments.

We normalize the reward to limit the scale of the error derivatives. Early experiments show that this stabilizes training. Similar results have been reported by [4] and [37].

3.6 Implementation

The environment is implemented with Gym [10]. The agent is implemented and RL algorithms are implemented with PyTorch [43] for automatic differentiation of the computation graphs. Proximal policy optimization [45] was implemented following the official implementation by OpenAI. All experiments are conducted on an Intel Core i9-10900X CPU and an NVIDIA GeForce RTX 2080 Ti GPU. The source code for environments, agents and RL algorithms is available at … Add link.

Table 3.1: Hyperparameters used during training.

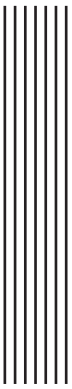
Parameter	**Value**
γ	.999
λ	.95
time steps per rollout	256
epochs per rollout	3
mini-batches per epoch	8
entropy bonus	0.01
clip range	.2
reward normalization	yes
learning rate	5×10^{-4}
parallel environments	64
total time steps	25×10^{6}

4 Results

5 Discussion

This chapter contains the following sub-headings.

6 Conclusion



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