CCPT: Automatic Gameplay Testing and Validation with Curiosity-Conditioned Proximal Trajectories

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Abstract

This paper proposes a novel deep reinforcement learning algorithm to perform automatic analysis and detection of gameplay issues in complex 3D navigation environments. The Curiosity-Conditioned Proximal Trajectories (CCPT) method combines curiosity and imitation learning to train agents to methodically explore in the proximity of known trajectories derived from expert demonstrations. We show how CCPT can explore complex environments, discover gameplay issues and design oversights in the process, and recognize and highlight them directly to game designers. We further demonstrate the effectiveness of the algorithm in a novel 3D navigation environment which reflects the complexity of modern AAA video games. Our results show a higher level of coverage and bug discovery than baselines methods, and it hence can provide a valuable tool for game designers to identify issues in game design automatically.

1 Introduction

Play testing plays a crucial role in the production of modern video games. The presence of gameplay issues and bugs can greatly decrease the overall player experience and therefore is crucial to be kept to a minimum. However, modern video games have grown both in size and complexity and thorough coverage is not often feasible via manual human play testing. The goal of automated gameplay testing is to free some of the human resources to do more “meaningful” testing such as measuring gameplay balance, difficulty, and potential retention rate.

Recently, automated testing approaches have been proposed to mitigate total reliance on human testers by training AI-based agents to explore large game scenes [Gordillo et al., 2021]. Automatic exploration through intrinsic motivation is a step in the right direction, however we argue that it is not enough. First, we need agents capable of learning the world around them, efficiently understanding the difference between different states. Second, we need agents that know the difference between good trajectories and bad trajectories, in order to recognize which paths are “broken” ones.

Therefore, in this paper we propose a novel reinforcement learning (RL) approach able to train agents which can explore and analyze a large 3D environment composed of complex navigation challenges. We call the approach Automatic Gameplay Testing and Validation with Curiosity-Conditioned Proximal Trajectories (CCPT). As shown in Figure 1, our technique use a combination of curiosity, which leads agents to seek novel interactions and to improve exploration, and imitation learning which lets agents explore the proximity of demonstrated trajectories. In particular, we propose an exploration-conditioned intrinsic reward function leading to agents that do not just learn to be curious, but that learn what it means to behave curiously. In fact, we train agents which we can control to behave “target-driven” versus “exploration-driven”. The model enables us not only to find bugs and issues, but to automatically identify, filter and highlight them among the massive quantity of information collected by agents during their interactions with the environment.

Our key contributions are: 1) a new open source environment for complex 3D navigation challenges, suitable as
testbed for training both exploratory and navigation agents; 2) a novel neural network architecture for navigation and exploration agents and an empirical demonstration of its effectiveness; 3) a new exploration algorithm which, thanks to its use of expert demonstrations, is able to deliberately explore the proximity of desired trajectories; and 4) our results show how these approaches can help video game designers automatically detect bugs and issues in complex 3D game scenarios.

2 Related Work

The potential of deep reinforcement learning for video game testing has been gaining interest from both the research and video game communities. Here we review recent work most related to our contributions.

Automated Play Testing. Several recent studies have investigated the use of AI techniques to perform automatic play testing, with a focus on maximizing game state coverage. Many of these recent works heavily rely on classical hand-scripted AI or random exploration [Stahlke et al., 2020; Holmgård et al., 2018]. However, when dealing with complex 3D environments with difficult navigation challenges we argue that these techniques are not readily applicable due to the high-dimensional state-space. The Reveal-More algorithm also uses human demonstrations to guide the random exploration, although in simple 2D dungeon levels [Chang et al., 2019]. Mugrai et al. [2019] developed an algorithm to mimic human behaviour to get more meaningful gameplay testing, but also to aid in the game design.

At the same time, many other works have used reinforcement learning to perform either automatic play testing or complex navigation exploration. Alonso et al. [2021] trained a reinforcement learning agent to navigate a complex 3D environment toward procedurally-generated goals, while Devlin et al. [2021] trained different agents to perform a Turing test to evaluate the human-likeness of trained bots. Closer to our work, Agarwal et al. [2020] trained reinforcement learning agents to perform automated play testing in 2D side-scrolling games, also providing a set of visualizations for level design analysis, and Gordillo et al. [2021] used intrinsic motivation to train many agents to explore a 3D scenario with the aim of finding issues and oversights.

Although our work draws inspiration from Gordillo et al. [2021], they based their approach on count-based exploration that may not be feasible when faced with complex environmental dynamics that, due to the tabular nature of such algorithms, explode in complexity [Strehl and Littman, 2008]. Moreover, the use of a purely exploration-based technique can slow down coverage time, especially if designers want to test a particular part of the environment. Finally, even given good visualizations of the results, this approach does not tell where, when, and how the issues are found, but rather leave the burden of recognizing them to the designers.

Imitation Learning. Similar to Chang et al. [2019], we make use of demonstrations to guide the exploration. However, for this aim we use a state-of-the-art imitation learning algorithm. Imitation learning aims to distill a policy mimicking the behavior of an expert demonstrator from a dataset of demonstrations. It is often assumed that demonstrations come from an expert who is behaving near-optimally. Standard approaches are based on Behavioral Cloning that mainly use supervised learning [Bain and Sammut, 1995; Ross et al., 2011; Knox and Stone, 2009]. Generative Adversarial Imitation Learning (GAIL) is a recent imitation learning technique which is based on a generator-discriminator approach [Ho and Ermon, 2016], as Finn et al. [2016] noticed that imitation learning is closely related to the training of Generative Adversarial Networks (GAN). Based on ideas from GAIL, Peng et al. [2021] proposed the Adversarial Motion Prior (AMP) algorithm, which is a GAN-based imitation learning method that aims to increase stability of adversarial approaches.

Intrinsic motivation. Intrinsic motivation aims to encourage agents to explore the environment states in the absence of an extrinsic reward. The already mentioned count-based exploration is a natural way to do exploration, although for high-dimensional state spaces it can be infeasible [Strehl and Littman, 2008]. Another class of exploration methods rely on errors in predicting dynamics [Pathak et al., 2017; Burda et al., 2018]. These are machine learning techniques for high-dimensional states that aim to push agents to explore never or less-encountered states during training. The interested reader should consult Aubret et al. [2019] for a detailed survey of the state-of-the-art in intrinsic motivation.

3 Proposed Method

This section details our approach to train agents guided by expert priors to find bugs and gameplay issues.

3.1 The Navigation Environment

To validate our approach, and to support continued research, we propose a 3D navigation environment designed to resemble modern AAA game scenarios. A screenshot of the environment is given in Figure 2 together with a top-down view of the whole map. The scene is approximately $500 \times 500 \times 60$ m in size and contains a variety of navigation challenges and dynamic elements such as moving platforms and elevators. Agents wishing to explore all secrets contained in the map must learn complex navigation strategies. Our environment is comparable to recent navigation studies [Gordillo et al., 2021; Devlin et al., 2021; Alonso et al., 2021] and is open source and available for anyone who wants to exploit, contribute, or expand on this research.\footnote{Repository to be published upon acceptance.}

For more details about the navigation mechanics, see the accompanying video included in the Supplementary Material.

Agents spawn in the center of the map and each episode ends after 500 timesteps. There are four goal areas in the environment selected as they are the most difficult spots to reach (indicated by the green arrows in Figure 2(b)). The agent has a total of 10 discrete actions: move forward/backward/left/right, move in one of the 4 diagonal directions, jump, and wait. The agent can also perform a double jump while in the air and climb on surfaces of specific elements located around the map. Moreover, since the intent of the work is to provide an automated way to detect bugs and
glitches in a game scene, we manually introduce such gameplay issues like missing collision boxes and glitches throughout the map.

The state observed by the agent at any instant in time is composed of a local perception in the form of a 3D semantic occupancy map, as well as scalar information about physical attributes of the agent (global position, if is grounded, if is attached to a climbable surface, if it can perform a double jump, its velocity and direction). We show an example 3D semantic occupancy map as inputs to the networks in Figure 3. These maps are a categorical discretization of the space and elements around the agent, and each voxel is defined by the semantic integer value of the type of object at that position.

The only extrinsic reward provided is given when an agent reaches an active goal, for which it receives +10 for each timestep it stays inside this area. With such a sparse reward in such a large environment, agents have very little change of receiving even a single, non-zero reward, thus making training very hard. Moreover, with just the extrinsic reward, even if they learn to reach a goal location, agents will always follow the same trajectory without exploring for new paths. Instead we need agents able to efficiently arrive to a goal area while continuing to search for undiscovered paths, thus combining rewards for both exploration and imitation.

### 3.2 The CCPT Algorithm

In this section we detail the algorithm used to generate agents to perform automated play testing. We devise our method following a main idea: train agents which explore in the proximity of trajectories predefined by an expert in order to automatically identify overlooked issues. We define agents composed of navigation, imitation, exploration sub-modules which contribute to the reward function used to drive policy learning.

**Navigation Module.** The navigation module is defined by the policy. As shown in Figure 3(a), the policy takes as input both the global information and the local perception defined by the semantic occupancy map. It also takes an auxiliary input that defines the level of exploration followed in a particular episode. Since it is a fundamental part of the reward function, we defer the description of how this affects training to the section Reward Function below. To encode the global 3D position (X, Y, Z) of the agent we use positional embeddings of Vaswani et al. [2017]:

$$
P_{\text{pos}}(i) = \sin \left( \frac{\text{pos}}{10000^{\frac{i}{d}}} \right),
\quad P_{\text{pos}}(i+1) = \cos \left( \frac{\text{pos}}{10000^{\frac{i}{d}}} \right),
$$  \hfill (1)

where $\text{pos}$ is the integer position, $i \in \{0, 1, 2\}$ is the coordinate being encoded, and $d$ is the embedding size. We claim that the use of such an embedding is crucial for training agents that navigate and explore these environments. In fact, the general way of encoding such information with normalization or with learned embeddings it is not enough to efficiently understand the difference between different states. In Section 4 we support this claim with ablation experiments.

These vectors are concatenated with the other agent inputs and passed through a feedforward network. The semantic occupancy map is instead passed through its own 3D convolutional network. All the processed vectors are then concatenated together and passed through an MLP. The policy is trained using the Proximal Policy Optimization (PPO) algorithm [Schulman et al., 2017].

**Imitation Module.** The imitation module trains the agent to follow the expert trajectories and to guide play testing toward a particular area. We use the AMP algorithm [Peng et al., 2021], which is built on top of GAIL [Ho and Ermon, 2016]. Given a set of expert demonstrations $M$, the goal is to learn to measure the similarity between the policy and the demonstrations, and to then update the policy via forward-RL. The objective is modeled as a discriminator $D(s, a)$ trained to predict whether a given state-action pair $(s, a)$ is sampled from the demonstration set or generated by running the policy. AMP adopts the loss function proposed for the least-square GAN [Mao et al., 2017]:

$$
\mathcal{L}_{\text{AMP}} = \arg \min_D \mathbb{E}_{d^M(s, a)} [ (D(s, a) - 1)^2 ] + 
\mathbb{E}_{d^\pi(s, a)} [ (D(s, a) + 1)^2 ],
$$  \hfill (2)

where $d^M(s, a)$ and $d^\pi(s, a)$ respectively denote the likelihood of observing a state-action pair in the dataset $M$ or by
following the policy $\pi$. The reward function for training the policy is then given by:
\[
 r_i(s_t, a_t) = \max \{0, 1 - 0.25(D(s_t, a_t) - 1)^2\}.
\]
(3)

To further increase training stability, we apply gradient penalties that penalize nonzero gradients on samples from the dataset [Mescheder et al., 2018].

The state $s$ of the imitation module is described by the local perception of the agent, which is defined by the 3D semantic occupancy map. This is passed through a 3D convolutional network and is concatenated with the action embedding before being fed to a feedforward network, as shown in Figure 3(b).

**Curiosity Module.** The curiosity module is responsible for optimizing coverage of the environment in the neighborhood of expert demonstrations via intrinsic exploration. Instead of using count-based exploration like Gordillo et al. [2021], which can be infeasible for high-dimensional state spaces, we use the Random Network Distillation (RND) algorithm [Burda et al., 2018]. The curiosity module gives an intrinsic reward that is higher for novel and less-encountered states. With this reward we can train agents with forward-RL to increase coverage of the environment.

The RND algorithm uses two neural networks: a fixed and randomly initialized target network $\hat{\phi}$ which establishes the prediction problem, and a predictor network $\phi$ trained on data collected by the agent. The predictor network is trained by gradient descent to minimize the expected MSE:
\[
 L^{\text{RND}} = (\phi(s) - \hat{\phi}(s))^2,
\]
(4)
with respect to its parameters. This process distills a randomly initialized neural network into a trained one. The reward $r_c$ of the curiosity module is the same MSE used to train the network:
\[
 r_c(s_t) = (\phi(s_{t+1}) - \hat{\phi}(s_{t+1}))^2.
\]
(5)
The more a state is visited by agents, the closer the output of the predictor network will be to that of the target network for that particular state, lowering the prediction error and thus the reward signal for exploration. States encountered following the expert demonstrations will produce low reward values, while for states encountered less frequently the predictor will not be able to perfectly replicate the target, increasing the reward signal and guiding agents toward undiscovered paths.

As shown in Figure 3(c), both target and predictor networks take as input the global position, encoded with the positional embedding of Equation 1, and the other agent information. These vectors are then concatenated and passed through a feedforward network.

**Reward Function.** The core of the algorithm lies in the reward function. Our aim is to combine the above modules to derive agents that can explore the proximity of expert trajectories. In this work we propose an exploration-conditioned intrinsic reward function. Inspired by works like [de Wolf et al., 2021] and [Gisslén et al., 2021], or in general by goal-conditioned policies [Andrychowicz et al., 2017], our reward function is:
\[
 R(s_t, a_t) = \alpha \cdot r_c(s_{t+1}) + (1 - \alpha) \cdot r_i(s_t, a_t) + r_e(s_t, a_t),
\]
(6)
where $r_c$ is the reward from the curiosity module, $r_i$ is the reward from the imitation module, $r_e$ is the extrinsic reward from the environment, and $\alpha \in [0, 1]$ is a weight hyperparameter that controls the level of exploration versus imitation. The value of $\alpha$ is randomly sampled at the beginning of each episode and remains fixed for all timesteps. If an agent samples a value of $\alpha < 0.5$, the $r_i$ prevails and the reward leads agents to follow the expert demonstrations more closely. When $\alpha = 0$, the reward moves agents toward a perfect replication of expert trajectories. In contrast, if $\alpha > 0.5$ the $r_c$ is dominant and the reward lead the agent to explore more. The greater the $\alpha$ the farther away from expert priors agents explore. When $\alpha = 1$, the agent completely avoids the expert demonstrations, finding completely new ways to arrive to the goal location. The $r_e$ is needed to make agents arrive in the goal area independently of the sampled $\alpha$.

In order for the agent to understand in which way it should behave in a particular episode, the sampled $\alpha$ is part of the state space of the agent. Since $\alpha$ controls the reward that the agent receives, we are basically combining curiosity-driven and goal-conditioned reinforcement learning. In this setting we get a meaningful exploration via curiosity and not just timestep-level randomness, and the result of training is not just a curious agent, but an agent which we can control to behave like the expert or like an explorer just by changing the $\alpha$ in input to the agent.

### 3.3 Highlighting Suspicious Trajectories

The final result of our algorithm is not trained agents, but rather all the information gathered during training. Given the set of all trajectories performed during training, our aim is to find those that evidence game behavior unintended by designers. Since in our case the intended paths are described by the demonstrations, we must find trajectories that arrive at the same goal area defined by experts but are very different from the expected experience.

Thanks to the $\alpha$ component of the reward function in Equation 6, for low $\alpha$ values the agent will revert to following the expert demonstrations very closely, thus lowering the rewards output by the curiosity module for states that are very near to those seen in expert demonstrations. In contrast, as $\alpha$ increases agents will explore more and more, and the rewards output by the curiosity module for states explored in this setting will be kept relatively high with respect to those near to the expert demonstrations.

We perform a simple first filtering of trajectories by removing all those gathered with $\alpha < 0.5$. For the the remaining trajectories we exploit the values of the curiosity module. Given all trajectories that arrive at the goal location with $\alpha \geq 0.5$, we compute the average curiosity values along the trajectory from the start to the goal location:
\[
 \hat{r}_c(\theta_t) = \frac{\sum_{t=0}^{T} r_c(s_t)}{T},
\]
(7)
where $\theta_t = (s_0, a_0, ..., s_T, a_T)$ is a trajectory, $T$ is the number of timesteps to arrive to the goal location, and $r_c$ is the reward of the curiosity module at the end of the training. We then define the set $\Theta$ as:
\[
 \Theta = \{\theta_t | \hat{r}_c(\theta_t) > \epsilon\},
\]
(8)
Algorithm 1 Training with CCPT

input: \( M \) dataset of expert demonstrations, \( \epsilon \) filter threshold
\( \pi \leftarrow \text{initialize policy} \)
\( D \leftarrow \text{initialize AMP discriminator} \)
\( \phi \leftarrow \text{initialize RND target network} \)
\( \phi \leftarrow \text{initialize RND predictor network} \)
\( G \leftarrow \text{initialize external dataset} \)

while not done do
  for \( i = 1, \ldots, m \) do
    \( B \leftarrow \text{initialize policy experience dataset} \)
    \( \alpha_i \sim [0, 1] \quad \triangleright \text{sample exploration value} \)
    \( \theta_i \sim \pi \quad \triangleright \text{sample trajectory} \)
    for \( t = 1, \ldots, T \) do
      \( r_t^i = \max[0, 1 - 0.25(D(s_t, a_t) - 1)^2] \)
      \( r_t^i = ||(\phi(s_{t+1}) - \phi(s_t))^2|| \)
      \( R^t = r_t - r_t^i + (1 - \alpha_t) \cdot r_t^c + r_t^s \)
    end for
    Store \( R^t \) in \( \theta_i \)
  end for
  Store \( \theta_i \) in \( B \)
  Store \( (\theta_i, \alpha_i) \) in \( G \)
  \( \triangleright \text{store all trajectories in the external dataset} \)
end for
Update \( D \) with \( D^{\text{AMP}} \) with samples from \( B \)
Update \( \phi \) with \( L^{\text{RND}} \) with samples from \( B \)
Update \( \pi \) with \( L^{\text{PPO}} \) with samples from \( B \)
end while
\( \theta \leftarrow \text{initialize set} \)
for trajectory \( \theta_i \in G \mid \alpha_i > 0.5 \) do
  \( r_t^c = \sum_{t=1}^{T} r_t(\theta_i) \)
  if \( r_t^c(\theta_i) > \epsilon \) then
    Store \( \theta_i \) in \( \theta \)
  end if
end for
return \( \theta \) \( \triangleright \text{return set of broken trajectories} \)

Table 1: Quantitative results compared to baselines: using a linear combination of curiosity and imitation; using only imitation learning; and using only curiosity like Gordillo et al. [2021]. Coverage is expressed in million of different states explored during training. The Bugs Found column regards issues found by agents during training, but not necessarily identified as issues, while Bugs Highlighted are issues found and identified as bugs by our model.

|               | Coverage | Bugs Found | Bugs Highlighted |
|---------------|----------|------------|-----------------|
| CCPT          | 1.91     | 13         | 13              |
| Linear Combination | 1.14     | 7          | 7               |
| Only Imitation | 0.84     | 1          | 0               |
| Only Curiosity | 2.39     | 10         | 3               |

4 Experimental Results

In this section we detail experiments that showcase the capability of our algorithm to perform automated play testing. We are interested in three primary research questions: 1) Can CCPT find and highlight bugs and oversights in a complex 3D environment? 2) How does the exploration-conditioned intrinsic reward function improve play testing efficiency? 3) Do our models offer better performance than traditional models used for 3D navigation? For all experiments in this section we used our navigation environment described in Section 3.1. We report on additional experiments using the VizDoom environment [Kempka et al., 2016] and give complete details on hyperparameters used in all experiments in the Supplementary Material.

4.1 Play Testing Performance

To evaluate the ability of CCPT to find and highlight bugs we tested four different goal areas in the environment. These areas represent four of the most difficult spots to reach, with trajectories that include dynamic elements, climbable surfaces and complex navigation challenges. For the goal areas we provide six expert demonstrations for each one showing the intended way to arrive at each specific goal. We then train ten agents in parallel and show the most relevant trajectories found by the algorithm for each area.

Table 1 summarizes the results found for all four areas. CCPT is able to find and highlight different ways of arriving to the same goal area of the expert demonstrations, however taking different paths and using different elements with respect to the intended ones. Compared to the baselines, our CCPT clearly outperforms other methods not only in finding bugs we manually inserted in the environment, but also in highlighting them directly for designers.

Figure 4 shows close-up examples of the CCPT results. Instead of relying on expert demonstrations, the agent took many different paths: in Figure 4(a) the agent uses a missing collision box in a tiny portion of the wall, thus arriving into the goal area by exploiting a slight slope of the wall of a pillar; in Figures 4(b) and 4(c) the agent exploits two oversights that allows it to jump over the wall and skip the main entrance. The first one uses an unintended prop near the wall while the second one exploits a climbable surface and precise double jumps; and in Figure 4(d) the agent exploits a glitch that allows it to perform infinite jumps and to skip the wall like in the previous examples. This last issue is quite interesting as the agent has actually learned to exploit the glitch rather than using it at random.

Such examples can be also found in all of the four goal areas tested in this paper, highlighting the good performance of our algorithm. More high-resolution results are given in the Supplementary Material.

4.2 Evaluating the Reward Function

To evaluate the performance of our exploration-conditioned intrinsic reward function we performed an ablation study using different fixed values of \( \alpha \): \( \alpha = 0.5 \) resulting in an average of \( r_c \) and \( r_i, \alpha = 0.0 \) corresponding to only using imitation, and \( \alpha = 1.0 \) corresponding to only using curiosity.

Table 1 shows the number of points in space covered for the four methods. As expected, agents trained with only imitation learning cover the smallest part of the environment, while those trained with only curiosity cover the most points. However, see that agents trained with our algorithm achieve much better exploration when compared to only imitation learning and average of imitation and curiosity. This is an interesting finding: while they cover a very large portion of the map, agents trained with our reward are still able to follow the ex-
Figure 4: Close-up images illustrating different bugs and gameplay issues found by CCPT. White trajectories indicate expert demonstrations, while the colored ones are those highlighted by CCPT as problematic.

Figure 5: Results of ablation tests. Details in Sections 4.2 and 4.3.

pert demonstrations. This enables us to filter and highlight broken trajectories as described in Section 3.2.

In Figure 5(a) we give a top-down view of the comparison of trajectories found by agents trained with CCPT and those found with the average curiosity and imitation reward. As the plots show, the trajectories found with our reward cover a wider area, finding more differing and varying paths with respect to the baseline. We do not visualize plots for agents training using only the imitation module as they closely resemble the expert demonstrations. We similarly omit plots for pure curiosity since, though it does find various way to arrive in the goal area, without the use of expert demonstrations there is no way to tell if a trajectory is suspicious or similar to expected gameplay experience.

4.3 Ablation Study

We performed a series of ablation tests to better understand the performance of our models. In particular, we claim that the combination of the semantic occupancy map and the positional embeddings described in Section 3.2 is an efficient way to encode environment information when compared to standard navigation and exploration architectures.

In Figure 5(b) we plot map coverage as a function of training steps for different configurations of the policy network architecture. From the plot it is clear that the positional embeddings used to encode the global positions provide an significant boost to the performance compared to using only normalized values as in [Gordillo et al., 2021; Devlin et al., 2021; Alonso et al., 2021] or even to learned embeddings. To the best of our knowledge, this is the first example of using such positional embeddings in deep reinforcement learning. Furthermore, the plot shows that the 3D semantic occupancy map and the relative 3D convolutional network improve the results compared to using only global information and to a ray-casting baseline similar to Gordillo et al. [2021]. The ray-casting approach uses 24 rays cast in various directions and at various heights. Each ray provides two values: the collision distance and the semantic value of the collided object. From the plots it is clear that the combination of positional embeddings and semantic occupancy map that defines our full model clearly outperforms all other ablations.

5 Conclusion and Discussion

In this paper we introduced a novel reinforcement learning approach to automatically play test complex 3D scenarios. Curiosity-Conditioned Proximal Trajectories (CCPT) enable developers and designers to specify an area to test in the form of expert demonstrations. CCPT uses a combination of imitation learning and curiosity, driven by what we call an exploration-conditioned intrinsic reward function, to perform exploration in the proximity of the demonstrated trajectories. Our approach is not only able to find glitches and oversights, but can also automatically identify and highlight trajectories containing potential issues. Our results show a high level of coverage and bug discovery in our proposed navigation environment, demonstrating how the particular combination of curiosity and imitation works well for this purpose. We believe that this algorithm will be a useful tool for AAA game designers to automatically identify issues or potential exploits with less reliance on human testers.

A limitation of CCPT applied to automatic gameplay analysis is that we must perform one experiment for each area we want to test. A possible solution would be to provide a large set of demonstrations and to test different areas all at once. However, it is known that GAN-based approaches are susceptible to mode collapse when fit to big datasets. In this setting, the policy is prone to imitate only a small subset of the example behaviors, thus focusing only on one area. Another drawback is that CCPT is not guaranteed to find all the bugs and issues in the environment. In particular, those that are too far from the expert demonstrations can be missed by our agents. One possible solution we are experimenting with is to perform another CCPT iteration using the problem trajectories found in the first iteration as expert demonstrations: since they regard the same area, the policy will not suffer from mode collapse while at the same time increasing exploration.
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1 Hyperparameters

The CCPT hyperparameters and their settings are shown in Table 1. Settings were chosen after a set of preliminary experiments made with different configurations. All training was performed deploying ten agents in parallel on the same machine with an NVIDIA RTX 2080 SUPER GPU with 8GB RAM and a AMD Ryzen 7 3700X 8-Core CPU.

| Navigation module       |       |
|-------------------------|-------|
| Learning rate $\alpha$  | $7e^{-5}$ |
| Discount $\gamma$       | 0.90  |
| Entropy coefficient     | 0.1   |

| Imitation module        |       |
|-------------------------|-------|
| Learning rate $\alpha$  | $7e^{-5}$ |
| Replay buffer size      | 100000 |
| Batch size              | 32    |
| Gradient penalty coeff. | 5.0   |

| Curiosity module        |       |
|-------------------------|-------|
| Learning rate $\alpha$  | $7e^{-5}$ |
| Batch size              | 128   |

Table 1: Hyperparameters of CCPT. Values were chosen after a set of preliminary experiments made with different configurations.

2 Network architectures

This section describes architectural details of each sub-module discussed in section ?? of the main paper.

Navigation Module. The navigation module, shown in figure 1(a), takes three types of inputs:

- the $(X, Y, Z)$ integer global positions that are passed through the positional embedding with size 32 and a fully connected layer of size 512 with ReLu activation;
- the agent info vector (composed of values representing whether the agent is grounded, if it is attached to a climbable surface, if it can perform a double jump, its velocity and direction) is passed through two fully connected layers of sizes 512 and ReLu activations;
- the local semantic 3D occupancy map of size $21 \times 21 \times 21$. The map is a categorical discretization of the space and elements around the agent, and each entry is the semantic integer value of the type of object at that position in $[0, 3]$. A value of 0 means an empty element, a value of 1 means a solid shape (like solid ground, walls, obstacles, moving elements), a value of 2 means a climbable surface and a value of 3 means the agent itself. Each voxel covers a space of $1 \, \text{m} \times 1 \, \text{m} \times 1 \, \text{m}$. The map is passed through a first embedding layer with size 16 and Tanh activation, then through four 3D convolutional layers with 32, 32, 64, 64 channels, each one with kernel size $3 \times 3 \times 3$, stride 2 and ReLu activations.

The outputs of the three branches are concatenated together with the $\alpha$ auxiliary input and the resulting vector is passed through a feed forward network with three fully connected layers with sizes 1024, 512, and 512 and ReLu activations. The final output is defined by another fully connected layer of size 10 and Softmax activation, representing the action probability distribution.

The outputs of the three branches are concatenated together with the $\alpha$ auxiliary input and the resulting vector is passed through a feed forward network with three fully connected layers with sizes 1024, 512, and 512 and ReLu activations. The final output is defined by another fully connected layer of size 10 and Softmax activation, representing the action probability distribution.

Since we use the Actor-Critic PPO algorithm, we make use of a baseline network that has the same architecture as the policy network.

Imitation Module. The imitation module, shown in figure 1(b), takes two types of inputs:

- the one-hot encoded agent action that is passed through a fully connected layer of size 512 and ReLu activation;
- the local semantic 3D occupancy map. The shape of the map, as well as the architecture of the Conv3D network are the same of the navigation module.

The outputs of the two branches are concatenated together and the resulting vector is passed through a feed forward network with three fully connected layers of size 1024, 512 and 512 with ReLu activations. The final output layer is defined by a fully connected layer with size 1 and Sigmoid activation representing the discriminator probability $D(s, a)$. 
Curiosity Module. The curiosity module, shown in figure 1(c), takes two types of inputs:

- the \((X, Y, Z)\) integer global positions that are passed through the positional embedding with size 32 and a fully connected layer of size 512 with ReLu activation;
- the agent information vector that is passed through two fully connected layers of sizes 512 and ReLu activations.

The outputs of the two branches are concatenated together and the resulting vector is passed through a feed forward network with two fully connected layers of size 1024 and 512 with ReLu activations and a last fully connected layer of size 128 without activation.

3 Additional experiments

This section describes additional experiments on the VizDoom environment \[??\] and also provides more high-resolution visualizations of agents in both the VizDoom environment and our 3D navigation environment described in the main paper.

3.1 VizDoom Experiments

In this section we investigate the robustness of CCPT applied in a real game environment different from our 3D navigation environment. To verify that CCPT can be a useful tool for game development, we applied it to the VizDoom environment, which is a semi-realistic 3D world based on the classic first-person shooter video game Doom \[??\]. The model architectures for all the modules are the same of section \[??\] of the main paper, but replacing the 3D semantic occupancy map and the relative 3D convolutional network with the renderer depth buffer and a 2D convolutional network. The depth buffer has size \(32 \times 32\) and the Conv2D is composed of two 2D convolutional layers with 32 and 64 channels, each one with kernel size \(3 \times 3\), stride 2 and ReLu activation. The action space consists of 6 different actions: move forward, move left, move right, turn left, turn right and jump.

We tested our algorithm on the level shown in figure 2(a). The scene is approximately \(2800 \text{ m} \times 2800 \text{ m} \times 100 \text{ m}\) in size. Since we are interested in coverage testing, we removed all enemies and props. All hyperparameters used in this experiment are the same as those shown in table 1.

For the experiment, we recorded expert demonstrations showing the intended path for arriving at a specific goal area. We then let CCPT run and in the end we visualize the most relevant trajectories highlighted by the algorithm. Figure 2(b) shows some qualitative results in which we can see how the algorithm is perfectly able to find and highlight different ways of arriving to the same goal area with respect to expert trajectories shown in white. In figure 3 we give some close-up examples of specific findings:

- figure 3(a) shows how the agent can arrive at the goal area using a completely different path than the intended one;
- figure 3(b) shows a trajectory similar to the one before, but using an elevated spot that was not meant to be reachable;
- figure 3(c) shows a slight variation of expert demonstrations using a hidden path; and
- figure 3(d) shows how the agent can use a complex path to skip part of the level and arrive in the goal location using a tiny gap between two walls.

3.2 Additional visualizations

Here we provide additional images of the results described in section \[??\] of the main paper. In figure 4 we give visualizations of the results of the four goal area experiments in our 3D navigation environment. Figure 5 shows close-up examples of bugs found and highlighted by the algorithm.
Figure 2: Results of the VizDoom experiment. (a) The explored level. (b) The results of the experiment: trajectories in white are the expert demonstrations, while the colored ones are the results of CCPT.

Figure 3: Close-up images from the VizDoom experiment. Each image represents a different bug or issue found by CCPT. The white trajectories describe the expert demonstrations, while the colored ones are those highlighted by CCPT.

Figure 4: Qualitative visualizations on four different tested areas. The white trajectories indicate the expert demonstrations, while the colored ones are those highlighted by CCPT.
Figure 5: Close-up images of the four area experiments. Each image represents a different bug or issue found by CCPT. The white trajectories indicate expert demonstrations, while the colored ones are those highlighted by CCPT.