

Assessing Evolutionary Terrain Generation Methods for Curriculum Reinforcement Learning

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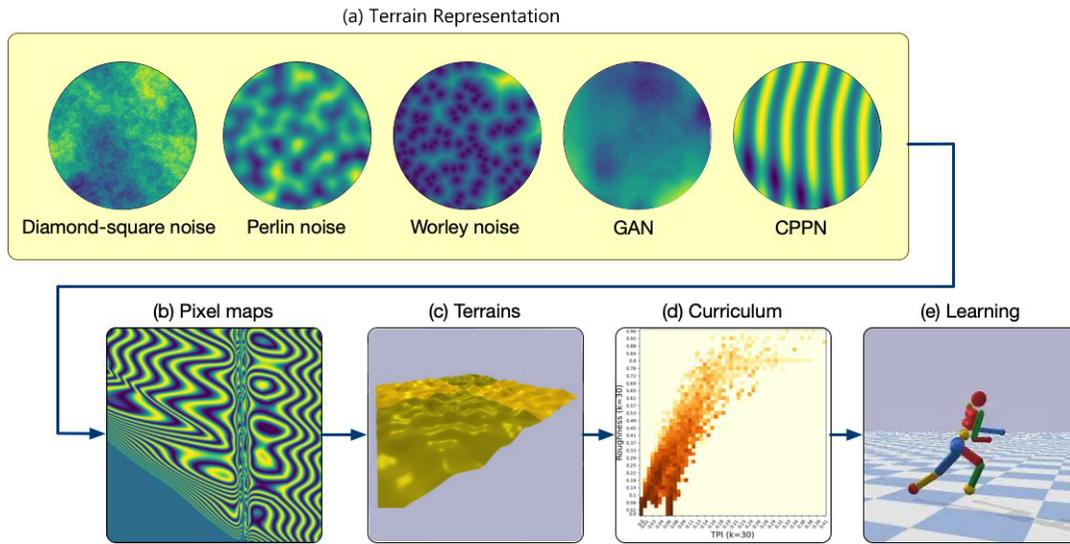


Figure 1: System overview: (a) Evolved terrain representations populate (b) 2D pixel maps and are subsequently turned into (c) terrain meshes which fill a (d) MAP-Elites archive. A bipedal walker is subsequently trained via PPO (e) and its learning performance is used to assess the impact of the various generators.

ABSTRACT

Curriculum learning allows complex tasks to be mastered via incremental progression over ‘stepping stone’ goals towards a final desired behaviour. Typical implementations learn locomotion policies for challenging environments through gradual complexification of a terrain mesh generated through a parameterised noise function. To date, researchers have predominantly generated terrains from a limited range of noise functions, and the effect of the generator on the learning process is underrepresented in the literature. We compare popular noise-based terrain generators to two

indirect encodings, CPPN and GAN. To allow direct comparison between both direct and indirect representations, we assess the impact of a range of representation-agnostic MAP-Elites feature descriptors that compute metrics directly from the generated terrain meshes. Next, performance and coverage are assessed when training a humanoid robot in a physics simulator using the PPO algorithm. Results describe key differences between the generators that inform their use in curriculum learning, and present a range of useful feature descriptors for uptake by the community.

CCS CONCEPTS

• **Theory of computation** → **Reinforcement learning**; • **Computing methodologies** → **Neural networks**; *Learning latent representations*; *Generative and developmental approaches*.

KEYWORDS

reinforcement learning, procedural content generation, CPPN, GAN, representations, quality-diversity, curriculum learning

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1 INTRODUCTION

Curriculum Learning (CL) [5, 24, 34] is a powerful reinforcement learning technique that engenders powerful behaviours by gradually increasing the difficulty of the task to be solved. This incremental approach has numerous benefits including performance and generalisation ability. To maximise the benefit of a curriculum, it is important to have a training environment that increases in complexity proportional to the learning ability of the agent, and contains relevant features to encourage learning. Diverse training examples, presented to the learner in an appropriate order [15], have resulted in the generation of capable, complex behaviours for simulated robots [34, 37], and aided sim2real transfer of those policies to real robot deployments [21].

A typical setup for learning locomotion skills (a popular focus area) involves the creation of a set of terrains of varying difficulty through some terrain generator, typically a parameterised noise function. The terrains are then presented to the agent, generally in order of difficulty, and the agent learns by solving simpler examples to eventually reach a given target behaviour. Noise functions are popular candidate terrain generators, as increasing terrain difficulty can be simply realised by increasing values of the noise parameters. Different generators produce terrains with different geometric features, which has an affect on learning.

To date, the impact of the chosen terrain generator has not been explored, and this is the focus of our paper. We address the effects of terrain generator on the learning process in two steps. In step 1, we select a varied range of popular terrain generators from the literature, which includes both direct and indirect encodings. Because the difficulty of an indirectly-coded terrain cannot be ascertained *a priori*, we categorise the resulting terrain mesh according to a set of representation-agnostic features selected from related literature. The selected features become feature descriptors in MAP-Elites, providing a diverse set of high-quality terrains. Terrains are evolved to fill the archive and generate one curriculum per generator type. In step two, each curriculum is used to train a bipedal walker, and results compare reachable terrain difficulty and learning speed. Our approach is illustrated in Figure 1.

We present two main original contributions; (i) the selection of appropriate representation-agnostic feature descriptors, including coverage analysis of curricula evolved using those features, and (ii) analysis of the effects of generator type on learning performance and rate. Results show the identification of suitable feature descriptors for representation-agnostic terrain-based curriculum learning, and suggest key differences between the generators, particularly between direct and indirect representations in terms of map coverage. We provide evidence that a multi-generator approach may be beneficial to the generation of curricula that promote rapid learning.

The remainder of the paper is organised as follows; Section 2 presents pertinent background research. Section 3 describes our

methodology. Section 4 presents experiments and results, and Section 5 provides a discussion.

2 BACKGROUND

Reinforcement Learning (RL) [20] is one of the most commonly used methods to train agent behaviours, and is similar conceptually to an evolutionary algorithm which learns by continually interacting with (and being rewarded by) an environment. In this study we use Proximal Policy Optimisation (PPO) [32] due to its ubiquity as a benchmark method to train agents in complex environments. PPO is a policy gradient method that alternates between sampling data through the agent's interaction with the environment and optimising an objective function using stochastic gradient descent. PPOs main advantage over other policy gradient techniques is the use of multiple epochs of mini-batch updates rather than performing one gradient update per data sample.

Curriculum learning [5] is a form of incremental learning [17], designed to address some common challenges with RL [24]. Firstly, it allows for agents to solve very hard problems by progressively building competency in easier versions of the problem [6]. Secondly, it provides a wealth of learning experiences to the agent which can greatly assist with generalisation [16, 19, 25]. Lee et al. [21] demonstrate both of these benefits using a particle filter to update parameters of a noise function-based terrain generator, allowing complex terrains to be navigated by a real quadruped after simulated learning.

A guided curriculum approach [34] incrementally removed supporting forces from a bipedal walker's body before increasing terrain complexity and diversity. Accelerated learning of complex environments is also evidenced with hexapod robots [28]. Miras demonstrated that balancing behaviour could be achieved by training on a tilted plain rather than a flat plain with objects on it, even though balance was not incorporated into the fitness function of the robot [22]. Huizinga [18] found that ordering of sub-tasks towards learning a difficult task is challenging, and instead proposed the Combinatorial Multi-Objective Evolutionary Algorithm (CMOEA) to simultaneously explore all orderings. This is an effective CL method when subtasks can be clearly defined (e.g. jumping, walking). Xie [37] demonstrated the critical role of a curriculum to train three bipedal agents to walk on stepping-stone scenarios, with final terrain complexity and learning rate being superior for curriculum approaches compared to non-curriculum RL. Akkaya [3] presents a CL approach using automatic domain randomization (ADR), demonstrating vastly improved sim2real transfer compared to a non-curriculum baseline. ADR automatically expands the randomisation range parameterising a distribution over environments. Florensa [12] showed that using a curriculum generating network it is possible to train an agent to 'perform a wide set of tasks without requiring any prior knowledge of its environment'. Open-ended curricula [38] can learn on terrains that are continually generated during agent learning [35].

Procedural Content Generation (PCG) originated in computer graphics and video game design. PCG can create large volumes of high-quality content with controllable randomness, including digital objects, landscapes, levels, textures and 3D models. PCG has been readily adopted by the machine learning community [30] to

create a wealth of training data. Rich and diverse environments encourage agent learning and improve robustness [15], with works showing that curriculum learning can train several quadrupedal robot policies in parallel to walk over uneven terrains in simulation [31]. Terrain generators have been previously evolved [14, 26], however these works focus only on a single representation and do not evaluate terrains in an agent-based learning context. Also in an evolutionary context, quality-diversity algorithms [27] present an effective method for storing and traversing a curriculum, shown in both robotics and game-playing contexts [9] [4]. In particular, the use of aligned feature dimensions within MAP-Elites [23] can provide direction to a (stochastic) traversal algorithm.

Overall, we see that curriculum learning is a powerful technique relevant to both evolutionary algorithms and reinforcement learning. The literature abounds with a smorgasbord of both direct and indirectly-represented generators, including various noise functions as well as CPPNs and GANs. Additionally, we see many different feature dimensions being used to store the curriculum and permit traversal. However, we identify a significant literature gap in that these different selections of generators and features have not yet been compared. In this study we compare popular generators and a set of selected feature descriptors for an evolved MAP-Elites based curriculum. We attempt to inform the selection of appropriate terrain generators and feature dimensions for fellow researchers in the field. We also demonstrate a curriculum learning approach that simultaneously supports both direct and indirect representations, opening up future work in mixed-generator curricula.

3 METHODOLOGY

We follow a three-stage process: (i) decide on features, (ii) evolve curricula (iii) learn on curricula. To allow for the isolated study of generators, we omit other tasks that typically comprise a curriculum (steps, jumps, etc.) and focus purely on locomotion in rough terrains.

3.1 Generators

We select 5 popular and diverse generators from the literature: 3 direct (Perlin noise, Diamond Square Noise, Worley Noise) and two indirect (a GAN, and a CPPN). Each generator mapped to a 256x256 resolution pixel map which is converted to a heightmap and then to a solid terrain mesh for simulation.

3.1.1 Perlin Noise. Perlin noise was applied to fractal Brownian Motion (fBM). The genome was parameterised into scale [1-100], octaves [1-9], persistence [0.1-0.9], lacunarity [1-3] and a random seed [0-100].

3.1.2 Diamond Square Noise. We use a version of the diamond square noise algorithm [13]. The four corner points of the heightmap grid are initialised with a random value between -1 and 1 making a square. The following two steps alternate until all the values of the heightmap are assigned:

Diamond step: for each square in the grid, assign the value of the midpoint of that square to be a random percentage P of the average of the four corner points, plus a random value R between -1 and 1.

Square step: for each diamond in the grid, assign the value of the midpoint of the diamond to be a random percentage P of the

average of the four corner points, plus a random value R between -1 and 1.

After each iteration of these steps, the range of the random value R is reduced using the formula:

$$\frac{-1}{(\text{steps} * D + 1)} \leq R \leq \frac{1}{(\text{steps} * D + 1)}$$

With $D \in [1, 10]$, and steps corresponding to the number of iterations of the above two steps performed. P is computed as:

$$Z \leq P \leq 100 - Z, Z \in [0, 50]$$

The genome is represented by a random seed, the four initial corner values, percentile (Z), and level (D).

3.1.3 Worley Noise. Worley Noise is typically used to generate procedural textures, and is implemented following [36]. The genome for the Worley terrain generator consists of a seed for randomisation, the number of feature points $N \in [2, 400]$ and the index of the point sorted by ascending distance to the current point $D \in [0, \frac{N}{4}]$.

3.1.4 GAN. The Deep Convolutional GAN (DCGAN) model was trained on real terrain heightmap data with identical resolution to the humanoid in simulation. The original data was in pointcloud format obtained from the OpenTopography website. The ground plane was semantically segmented, and the resulting points interpolated into multiple heightmap patches at the desired resolution. This provided a large amount of high resolution data (30000 256x256 patches) which was used to train the model. The latent vector fed into the generator contained 50 values which formed the genome of the GAN generator.

3.1.5 CPPN. The CPPN terrain generator has 2 inputs corresponding to row and column of the heightmap, and one output for the height value. All remaining CPPN settings were taken from the PicBreeder paper [33].

3.2 Features

We explore a range of generic terrain descriptors for use as MAP-Elites feature descriptors that allow both direct and indirect generators to be compared. Features were aligned to terrain traversability to provide continuity to the final generated curricula, with enough variation to create diversity in the population. Features originate from a range of non-RL, non-evolutionary fields, mainly from surveying where they are used to categorise real terrains. We use:

- (1) Terrain Ruggedness Index (TRI) [29] - measures the average difference between a pixel and its 8 neighbouring pixels.
- (2) Topographic Position Index (TPI) [10] - measures the difference between each pixel and the mean of its 8 neighbouring pixels
- (3) Roughness [11] - measures the maximum difference between a pixel and its 8 neighbouring pixels
- (4) Traversability Estimation Model implemented in [7] - A trained model that predicts the traversability of terrains by outputting a traversability map. This model had been trained on different types of terrains to the terrain generators used in this paper. The orientation input to the model was set to 0 as this was the direction the humanoid traversed.

Once generated, a terrain mesh is tagged with values for each feature descriptor. Settings for kernel size are determined in Section 4. Roughness, TPI and TRI use a stride length of 2. The average of the output from each feature was taken as the overall measure. Initial experimentation found that an archive discretisation of 50 bins per descriptor presented meaningful but achievable differences between terrains in neighbouring cells.

3.3 Evolutionary Algorithm

We evolve curriculums for each generator, and compare different pairs of feature dimensions. Per treatment, we run MAP-Elites for 5000 generations, with 100 random initial genomes. Per generation, 20 new terrains were generated by randomly selecting from the current members of the archive, mutating, generating feature values, and adding back into the archive as in Figure 2.

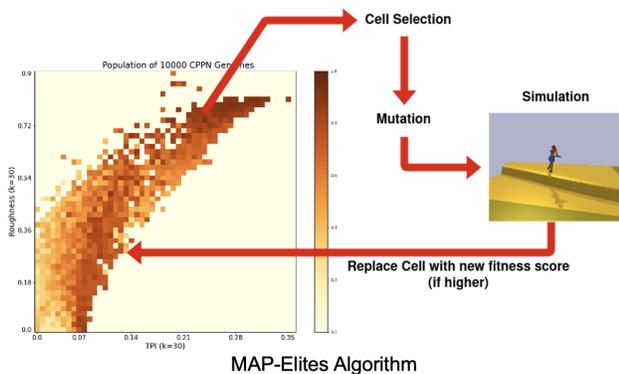


Figure 2: Overview of library generation. Features must be calculate in simulation before the terrain can be added to the library.

For noise emitters, each gene in the genome had a mutation probability of 0.35, and mutation altered the allele by \pm a value taken from a normal distribution with covariance set to 10% of its range. CPPN mutation followed NEAT [33]. The GAN’s latent space was stored in 50 variables, which with $P=0.07$ were mutated by a value taken from a normal distribution with covariance set to 10% of its range (heuristically determined).

Fitness is set to 1.0 - the difficulty of the generated terrain. Difficulty is assessed using the base policy of the Bipedal Walker that is trained on flat ground[8] and simulated in PyBullet. Difficulty of a terrain is calculated as the average distance travelled out of the best 5 of 20 attempts with random joint initialisations, normalised between 0 and 1. The 5 best were taken as some initialisations were too extreme and caused a large amount of noise in the fitness estimation. When replacing individuals in a MAP-Elites cell, we kept the lowest difficulty terrain and deleted the higher difficulty one. This generated a smoother curriculum in terms of fitness, whilst also removing many impossible terrains. A second step removed the remaining impossible terrains, following Algorithm 1. Representative terrains for two generators (CPPN and Perlin noise) that achieve difficulties of ≈ 0.1 , ≈ 0.5 , and ≈ 0.9 are shown in Figure 3.

Algorithm 1 Check terrain traversability.

```

procedure CHECK TERRAIN(hm)           ▷ Terrain heightmap
    threshold  $\leftarrow \frac{\text{robotHeight}}{3}$        ▷ max incline in metres
    k  $\leftarrow 26$                              ▷ Approx. step length of robot
    Initialise differences result [hm.rows-k,hm.cols-k]
    for r in [0, hm.rows - kSize) do
        for c in [0, hm.cols - kSize) do
            differences[r,c]  $\leftarrow$ 
                maximum_difference(hm[r:r+k,c:c+k])
        end for
    end for
    return max(differences)  $\leq$  threshold
end procedure

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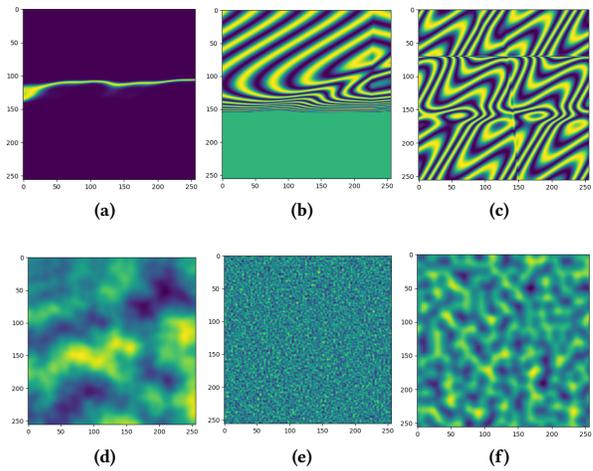


Figure 3: Representative pixel maps with approximate difficulties of 0.1, 0.5, 0.9 respectively (L-R) for (a-c) an indirect representation (CPPN) and (d-f) a direct representation (Perlin noise).

4 EXPERIMENTATION

4.1 Experiment 1: Features and Curriculum

Initial experimentation compared feature descriptors with different kernel sizes to measure their alignment to terrain difficulty (fitness). This alignment was ideal for constraining the solution search space to produce a strong traversability gradient in the MAP-Elites grid. Without a strong gradient, creating an effective curriculum becomes difficult. Roughness, TPI and TRI had similar results with TPI being most correlated. Results are shown in Figure 4. We used TPI in learning experiments as it was most aligned, and use Roughness since TPI and TRI ($k = 30$) were too similar ($r = 0.94/0.95$) to produce sufficient map diversity. A kernel size of 30 was chosen as it had consistently high correlations to terrain difficulty. These features could then be used for arbitrary meshes with confidence that they were meaningful metrics. The traversability model (“Traversability”) had the weakest correlation to difficulty so this was not used further.

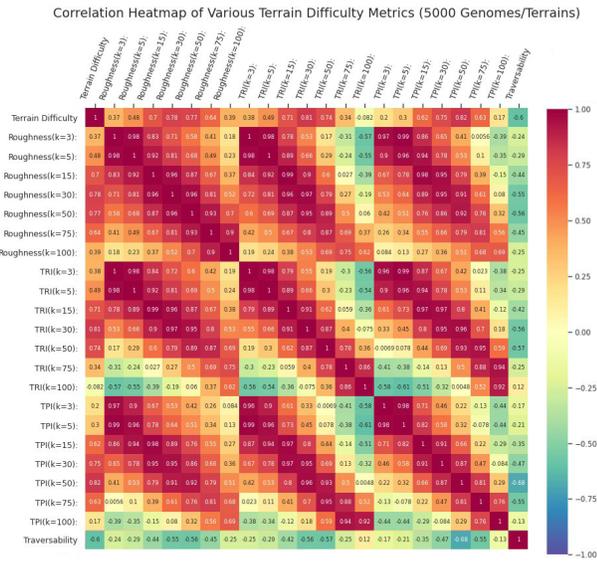
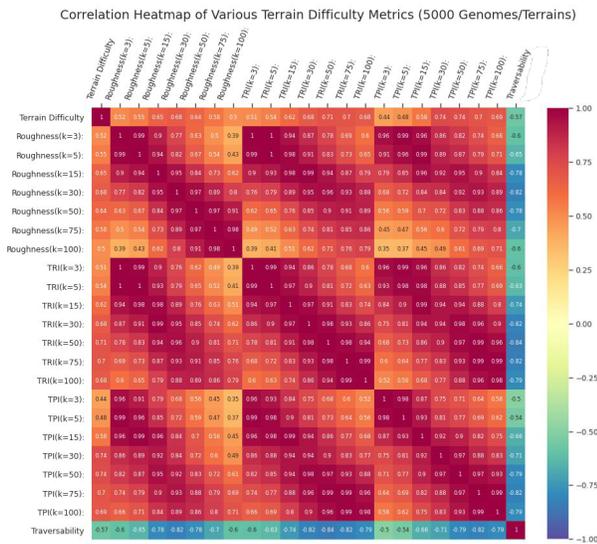


Figure 4: Heatmaps showing Pearson correlation of all considered terrain characterisation features including ground truth: terrain difficulty, for (a) CPPN and (b) Perlin noise.

The coverage of each terrain generator is shown in Figure 5. Pair-wise feature comparisons are shown in Figure 6. All coverage maps show a strong gradient in terrain traversability, with it declining as the map feature values increase. This suggests the chosen features are very representative of traversability. Some variation exists between the different features, but the most significant basis of variation is in the euclidean distance between feature values and (0,0). Each terrain generator presents a characteristic shape and amount of coverage on the map. Table 1 shows the comparative coverage between generators, with CPPN having significantly higher coverage, and able to create more difficult and more diverse terrains than the other generators. Interestingly the other indirect emitter, GAN, presents the lowest coverage of all. The GAN was trained on real

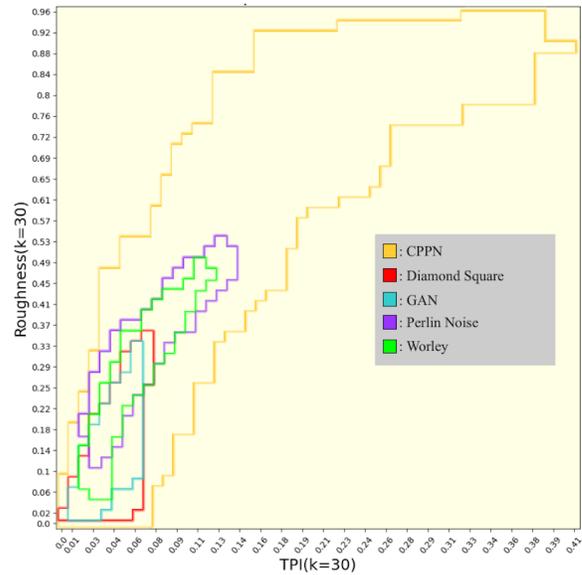


Figure 5: Feature coverage of each generator after each experiment.

terrains and therefore can only output similar meshes. The CPPN is unrestricted in this manner. Perlin noise shows the strongest diagonal mapping to the feature dimensions and presents the best direct encoding, followed by Worley noise. Diamond-square noise can be seen to struggle to generate reasonable values for TPI. Feature ranges were identical between generator coverage maps for fair comparison. While the total terrains in each map vary significantly based on coverage, adjusting feature ranges to account for this does not help learning as terrains with comparable features are similarly traversable and are skipped.

Table 1: Coverage percent of total map for feature combinations with each terrain generator; maps from Figure 5.

Terrain Generator	Roughness/TPI	Roughness/TRI	TPI/TRI
CPPN	23.16%	15.52%	14.92%
GAN	2.48%	2.48%	1.48%
Perlin Noise	3.92%	3.92%	2.80%
Worley Noise	2.88%	1.84%	2.12%
Diamond Square	3.12%	1.36%	1.88%
Combined	23.64%	15.56%	15.56%

4.2 Experiment 2: Bipedal Walker Learning

In the second experiment we carry out a typical learning experiment on the evolved curricula. We trained the walker from the base policy using the PyTorch PPO implementation from SpinningUp [2] with default parameters with a maximum of 30,000 epochs. The base policy provides the prior for IT&E. Traversal of the map is the same Gaussian Process (GP) technique as described by Cully et al. [1], using the same recommended parameters: $\rho = 0.4$, $\alpha = 0.9$, κ

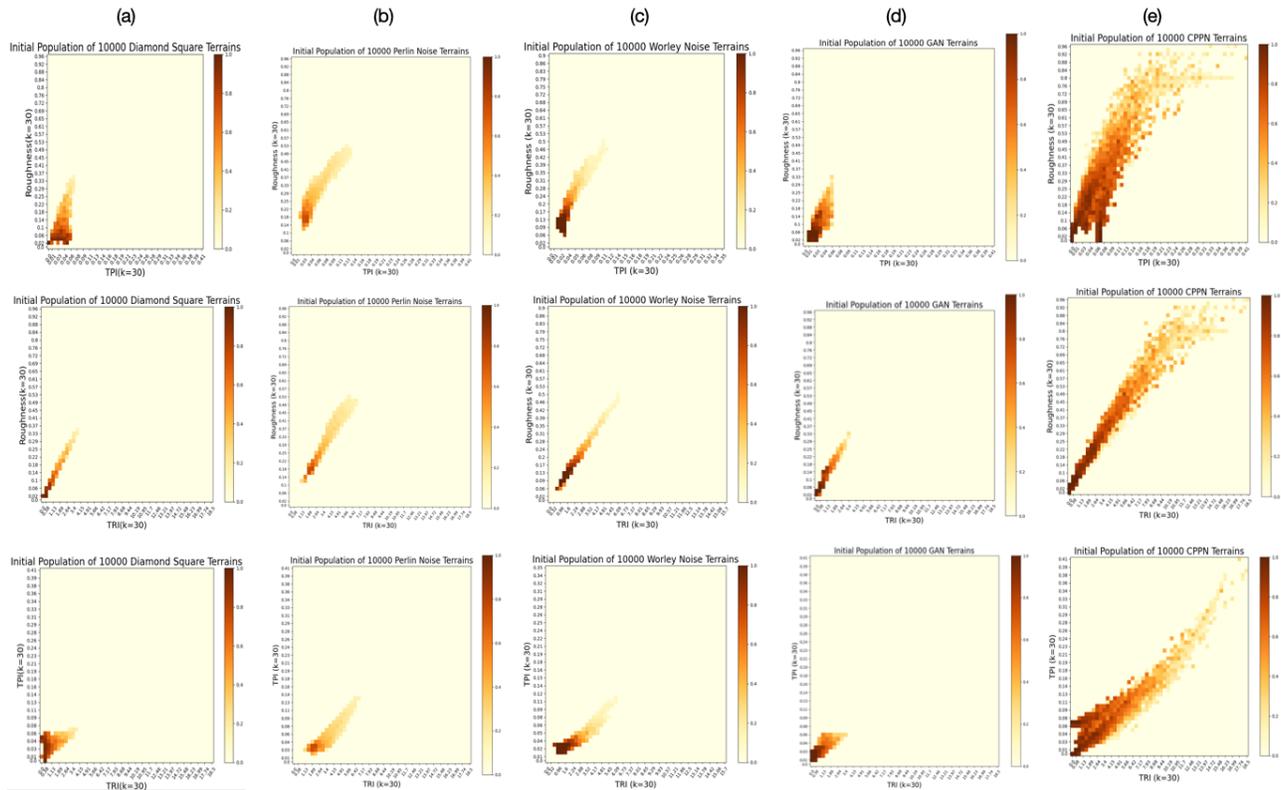


Figure 6: MAP-Elites archive coverage for three combinations of features: TPI/TRI (row 1), roughness/TRI (row 2), roughness/TPI (row 3) for Diamond Square noise (a), Perlin noise (b), Worley noise (c), GAN (d) and CPPN (e) terrain generators after evolution. Colour corresponds to fitness, measured as the average performance of the base policy humanoid traversing each terrain. Dark colours represent fitter behaviours.

$= 0.05$, $\sigma^2_{noise} = 0.001$, and the same covariance function (Matern kernel). PPO trains for 40 epochs at a time until the humanoid reaches the 90% traversability threshold (90% of maximum fitness achieved) or when there had been 100 traversability evaluations on the terrain. Once this condition is met, the GP model finds the highest fitness (easiest) terrain from evaluations with the updated PPO model. However, unlike the original IT&E, our algorithm removes terrains that are estimated by the model to be easier than the terrain just trained on at each update. This ensures that the algorithm incrementally increases difficulty. This also avoids the problem of the curriculum visiting previously easy terrains that may appear hard after learning on complex environments which require a significant change in policy. The learning process ends when all terrains are used. To assess the performance of each terrain generator’s curriculum map, the hardest terrain successfully traversed at each training epoch was recorded. This is shown in Figure 7, and includes training using a combined map with the highest fitness terrain chosen when grid squares overlap between generators. Hardest terrains are measured in terms of how large their feature values are, which is the euclidean feature distance from (0,0). CPPN and Combined significantly outperform the other four generators with very similar large coverage profiles. CPPN and combined are similar in performance. Diamond Square Noise

and the GAN perform similarly, and have similar coverage maps. Worley and Perlin Noise also obtain a similar final difficulty, and have similarly shaped coverage maps although Perlin covers more of the archive. Learning speed is another key determinant of generator performance – Fig.7. We measure this by designating terrains at a certain Euclidean distance from the top-right corner of the map, and recording the iteration at which the walker learns one of those terrains. Table 2 shows some interesting results. First, the Perlin curriculum learns much faster than the Worley curriculum, despite covering comparable archive area. The high regularity of Perlin Noise may account for this with policies that are more generalisable between Perlin Noise terrains. Second, although CPPN and combined maps achieve comparable difficulty, a combined map that starts on higher-fitness noise terrains before transitioning to CPPN terrains achieves difficulty milestones much faster than the single CPPN generator. The result suggests that combining different generators in a single curriculum may be beneficial, however investigating is out of scope for the current study. Finally, the effect of the map creation and map-traversal algorithm on performance against classic curriculum learning with a single feature (Figure 7(b)). CPPN terrains from the map were sorted by their roughness, and every

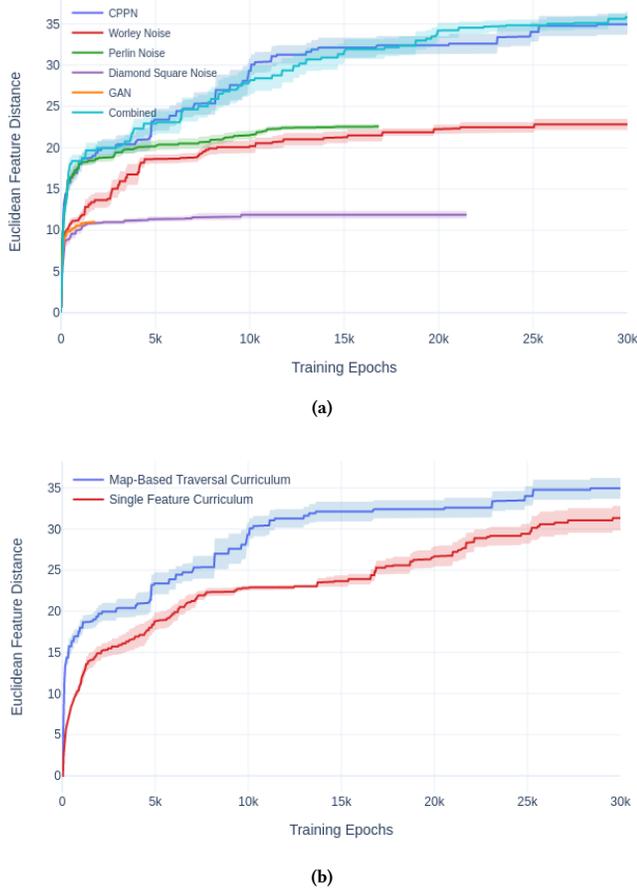


Figure 7: Illustrative performance comparison between (a) the different terrain generators, and (b) CPPN terrains between the proposed map-based curriculum algorithm and incrementally increasing roughness with standard CL, showing the most difficult terrain completed at the current training iteration. Plots finish when 30k epochs is reached or IT&E has excluded all terrains. Averaged over 10 trials, with confidence shown for ± 1 standard error.

fifth terrain was used, similar to standard CL by incrementally increasing a difficulty parameter. This trained much slower and did not succeed on terrains as difficult as in the map-based algorithm.

5 DISCUSSION

In this paper we investigated the utility of different feature descriptors for map-based curricula. Using a ground truth of how hard a terrain was for a pre-trained bipedal walker, we showed how several feature descriptors taken from the literature allow for the assessment of meaningful difficulty purely from a terrain mesh. Using pairwise combinations of features as MAP-Elites feature dimensions, we then showed the effect of feature dimension selection on archive coverage and fill pattern.

In a second step, we used our selected feature descriptors to build a MAP-Elites-based curriculum for different terrain generation algorithms, including direct and indirect representation. Using our representation-agnostic feature descriptors, we could directly compare archive properties. We show that CPPNs present the best coverage, and make the most difficult terrains learnable by the agent. GANs were most limited in terms of coverage, with noise generators taking up the middle ground. Perlin and Worley noise in particular presented useful coverage patterns. Interestingly, Perlin noise allowed for much faster learning (achievement of terrain milestones) than Worley. Even more interestingly, we see that a combined map presents significantly faster learning than a pure CPPN map, as it learns first on fitter (easier) terrains (where cells are shared with multiple generators) before transitioning to pure CPPN terrains that the other generators cannot reach.

Future work will investigate this, as well as exploring the effects of hyperparameter tuning (all parameters were set to default), as well as the generalisability of these findings to other high-impact problems. However, purely in terms of learning about how agent-based curriculum RL works, this paper presents several important contributions for the research community. Future work will also apply the methods presented to the training of real robots, where the effect of generator types and the map-based curriculum may be able to contribute in narrowing the sim2real gap in addition to increasing learning speed. Moreover, game-playing agents could benefit from this curriculum technique. Further exploration of feature descriptors should be conducted in different curriculum contexts to measure their influence on policy performance. We hope this will lead to more terrain generator methods used in curriculum learning, as well as more principled selection of generator.

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Table 2: Showing learning speed: the number of training epochs required to learn a designated terrain a given % away from the maximum possible map distance (70.71).

Terrain Generator	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%
CPPN	40	80	120	240	960	4720	7000	9880	13280	-
GAN	40	80	1000	-	-	-	-	-	-	-
Perlin Noise	40	40	160	320	960	8680	-	-	-	-
Worley Noise	40	80	480	2640	4160	14080	-	-	-	-
Diamond Square	80	160	1280	-	-	-	-	-	-	-
Combined	80	120	160	320	440	3720	7280	10280	15040	29000

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