Hybrid Encoding for Generating Large Scale Game Level Patterns With Local Variations

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Abstract—Generative adversarial networks (GANs) are a powerful indirect genotype-to-phenotype mapping for evolutionary search. Much previous work applying GANs to level generation focuses on fixed-size segments combined into a whole level, but individual segments may not fit together cohesively. In contrast, segments in human designed levels are often repeated, directly or with variation, and organized into patterns (the symmetric eagle in Level 1 of The Legend of Zelda, or repeated pipe motifs in Super Mario Bros.). Such patterns can be produced with compositional pattern producing networks (CPPNs). CPPNs define latent vector GAN inputs as a function of geometry, organizing segments output by a GAN into complete levels. However, collections of latent vectors can also be evolved directly, producing more chaotic levels. We propose a hybrid approach that evolves CPPNs first, but allows latent vectors to evolve later, combining the benefits of both approaches. These approaches are evaluated in Super Mario Bros. and The Legend of Zelda. We previously demonstrated via a quality-diversity algorithm that CPPNs better cover the space of possible levels than directly evolved levels. Here, we show that the hybrid approach first, covers areas that neither of the other methods can, and second, achieves comparable or superior quality (QD) scores.

Index Terms—Compositional pattern producing network (CPPN), generative adversarial network (GAN), indirect encoding, procedural content generation via machine learning.

I. INTRODUCTION

GENERATIVE adversarial networks (GANs [1]), a type of generative neural network trained in an unsupervised way, are capable of reproducing certain aspects of a given training set. For example, they can generate diverse high-resolution samples of a variety of different image classes [2].

Several recent works show that it is possible to learn the structure of video game levels using GANs [3]–[6], but these approaches only generate small level segments. GANs have also generated levels of arbitrary size [7], [8], but global patterns between segments, i.e., symmetry and repetition, are difficult to capture with purely GAN-based approaches [9].

To generate complete levels with global patterns, we combine compositional pattern producing networks (CPPNs [10]) with GANs. A CPPN is a special type of neural network that generates patterns with regularities, such as symmetry, repetition, and repetition with variation. CPPNs have succeeded in many domains [11]–[16].

Our approach, CPPN2GAN, was first introduced in 2020 [17]. It is a directly evolved indirect encoding. An evolved CPPN represents a pattern on the geometry of a level. The CPPN maps coordinates of level segments to vectors in a latent space, where the next level of indirection occurs. These vectors are fed as inputs to a pretrained GAN, which outputs the level segment that belongs at the specified location (see Fig. 1).

This article goes further by hybridizing CPPN2GAN with directly evolved latent vector inputs, a method we called Direct2GAN. The new approach takes inspiration from Hybrid [18], and begins evolution with CPPN genomes, but lets them transition into latent vector genomes to gain the benefits of both approaches. In fact, starting with a CPPN-based focus on global patterns, and only later switching to a vector encoding that allows for local variations, can discover solutions that would not be discovered by either approach in isolation. This combination approach is called CPPNThenDirect2GAN.

We evaluate the three methods using several different evaluation metrics proposed in previous work, and consider both performance as well as their ability to cover the space of possible solutions. We, thus, consider the ability of the different methods to optimize for specific characteristics (controllability), as well as to generate diverse levels, both important qualities of level generators [19]. The quality diversity algorithm MAP-Elites [20] is used to conduct these evaluations. Our experiments reaffirm our previous results [17] with CPPN2GAN and Direct2GAN in Super Mario Bros. and The Legend of Zelda, and we add results both with an additional diversity characterization for each game, and with the newly proposed hybrid CPPNThenDirect2GAN approach. Results show that Direct2GAN is usually inferior to CPPN2GAN, and always inferior to the new CPPNThenDirect2GAN approach in terms of level fitness and coverage of design space. CPPNThenDirect2GAN is as good or better than CPPN2GAN depending on the game and diversity characterization.
Fig. 1. Three Genotype Encodings Applied to Zelda. (a) In CPPN2GAN, the CPPN takes as input the Cartesian coordinates of a level segment \((x, y)\) and its distance from the center \(r\), and for each segment produces a different latent vector \(z\) that is fed into the generator of a GAN pretrained on existing level content. The CPPN also outputs additional information determining whether the room is present, door placement, and other miscellaneous information. The approach captures patterns in the individual level segments, but also creates complete maps with global structure, e.g., imperfect radial symmetry as seen above. (b) In Direc2GAN, one real-valued vector is evolved, which is chopped into one vector per segment. A part of the vector (size 10) is input into the GAN, while additional values specify the presence of a room and miscellaneous information. CPPNs (CPPN2GAN), facilitating the discovery of global patterns, and then later switched to evolving a vector encoding (Direct2GAN) that allows for local variations.

Ultimately, CPPN2GAN and CPPNThenDirect2GAN could be relevant not only for game levels, but other domains requiring large-scale pattern generators, e.g., texture generation, neural architecture search, computer-aided design, etc.

II. PREVIOUS AND RELATED WORK

This article combines GANs and CPPNs into a new form of latent variable evolution (LVE).

A. Compositional Pattern Producing Networks

CPPNs [10] are neural networks with various activation functions. They are repeatedly queried across a geometric space of inputs and are well suited to generating patterns, e.g., a CPPN can generate an image by taking pixel coordinates \((x, y)\) as input and outputting intensity values for each corresponding pixel.

CPPNs typically include various activation functions biased towards specific patterns and regularities, e.g., a Gaussian function for symmetry and a periodic sine function for repeating patterns. Repetition with variation (e.g., fingers of a hand) can be created by combining functions (e.g., sine and Gaussian). CPPNs have been adapted to produce a variety of patterns in domains such as 2-D images [11], musical accompaniments [12], 3-D objects [13], animations [16], physical robots [14], particle effects [15], and flowers [21].

CPPNs are traditionally optimized through NeuroEvolution of Augmenting Topologies (NEAT [22]). NEAT optimizes both the neural architecture and weights of networks at the same time. The population starts simple (inputs directly connected to outputs), but mutations later add nodes and connections. NEAT also allows for crossover between structural components with a shared origin. More recently, CPPN-inspired neural networks have also been optimized through gradient descent-based approaches [23], [24].

Evolved CPPNs can create global patterns with complex regularities, but struggle with precise local variations. GANs trained via gradient-descent do not have this problem.

B. Generative Adversarial Networks

The training process of GANs [1] is like a two-player adversarial game in which a generator \(G\) and a discriminator \(D\) are trained at the same time by playing against each other. The discriminator \(D\)’s job is to classify samples as being generated (by \(G\)) or sampled from the training data. The discriminator aims to minimize classification error, but the generator tries to maximize it. Thus, the generator is trained to deceive the discriminator by generating samples that are indistinguishable from the training data. After training, the discriminator \(D\) is discarded, and the generator \(G\) is used to produce novel outputs that capture the fundamental properties present in the training examples. Input to \(G\) is usually some fixed-length vector from a latent space.

Generating content by parts, as is done by our CPPN2GAN approach, has also been investigated with conditional GANs (COCO-GAN [25]). However, in contrast to our approach, in which the CPPN maps coordinates of segments to latent vectors (generating patterns with regularities, such as repetition and symmetry), COCO-GAN is conditioned on fixed coordinates with a common latent vector to produce segments of an image. Convolutional GANs have also been used to generate game levels of arbitrary size out of patches in both Mario [7] and Minecraft [8]. Alternative generators, such as Variational Autoencoders [26] and Bayes nets [27], have also been used to sequentially generate levels one segment at a time.

For a properly trained GAN, sampling latent vectors produces outputs that could pass as real content. However, to find content with certain properties (i.e., specific game difficulty, number of enemies), the latent space needs to be searched.

The first LVE approach [28] trained a GAN on fingerprint images and used evolution to find latent vectors matching subjects in the dataset. Our previous work [17] introduces the first indirectly encoded LVE approach. Instead of searching for latent vectors, parameters for CPPNs are sought. These CPPNs generate a variety of latent vectors conditioned on the locations of level segments.
III. VIDEO GAME DOMAINS

Game data comes from the video game level corpus (VGLC [29]). GAN models from previous work in Super Mario Bros. [30] and The Legend of Zelda [6] are used because they are popular representatives of two distinct genres. Mario is a platformer with linear levels, and Zelda is a dungeon crawler with 2-D levels. Thus, different types of patterns are required in each game, demonstrating the broad applicability of CPPN-ThenDirect2GAN.

A. Super Mario Bros.

Super Mario Bros. (1985) is a platform game that involves moving left to right while running and jumping. Levels are visualized with the Mario AI framework.²

The tile-based level representation from VGLC uses a particular character symbol to represent each possible tile type. The encoding is extended to more accurately reflect the data in the original game, for example by adding different enemy types. The representation of pipes is adjusted to avoid the broken pipes seen in previous work [3]. Instead of using four different tile types for a pipe, a single tile is used as an indicator for the presence of a pipe and extended automatically downward as required. A detailed explanation of all modifications made to the encoding can be found in Ch. 4.3.3.2 of work by Volz [30].

B. The Legend of Zelda

The Legend of Zelda (1986) is an action-adventure dungeon crawler. The main character, Link, explores dungeons full of enemies, traps, and puzzles. In this article, the game is visualized with an ASCII-based Rogue-like game engine used in previous work [6]. Details on the mapping between original VGLC game tiles and Rogue-like tiles can also be found there.

Previous work [6] reduced the large set of tiles inherent to Zelda to a smaller set based on functional requirements. Some Zelda tiles differ in purely aesthetic ways, and others rely on complicated mechanics not implemented in the Rogue-like. The reduced set of tile types is as follows: regular floor tiles, impassable tiles, and tiles that enemies can pass, but Link requires a special item to pass (raft item to cross water tiles). Enemies are not represented in the VGLC data because its authors did not include them.³

IV. APPROACH

The novel approach introduced in this article is a hybrid of CPPN2GAN and Direct2GAN, so each is explained in detail before explaining CPPN-ThenDirect2GAN. All approaches depend on a GAN trained on data for the target game.

A. GAN Training Details

The Mario and Zelda models are the same as used in our previous work [17] but details of their training are repeated here. Both models are Wasserstein GANs [31] differing only in the size of their latent vector inputs (10 for Zelda, 30 for Mario), and the depth of the final output layer (3 for Zelda, 13 for Mario). Their architecture otherwise matches that shown in Fig. 1. Output depth corresponds to the number of possible tiles for the game. The other output dimensions are 32 × 32, which is larger than the 2-D region needed to render a level segment. The upper left corner of the output region is treated as a generated level, and the rest is ignored.

To encode levels for training, each tile type is converted to a one-hot encoded vector before being input into the discriminator. The generator also outputs levels in the one-hot encoded format. Mario or Zelda levels in this format are sent to the Mario AI framework or Rogue-like engine for rendering.

GAN input files for Mario were created by processing all 12 overworld level files from VGLC for Super Mario Bros. The GAN expects to always see a rectangular input of the same size, so each input was generated by sliding a 28 (wide) × 14 (high) window over the level from left to right, one tile at a time, where 28 tiles is the width of the screen in Mario.

GAN input for Zelda was created from the 18 dungeons in VGLC for The Legend of Zelda, but the training samples are the individual rooms in the dungeons, which are 16 (wide) × 11 (high) tiles. Many rooms are repeated within and across dungeons, so only unique rooms were included in the training set (only 38 samples). Training samples are simpler than the raw VGLC rooms because the various tile types are reduced to a set of just three as described in Section III-B. Doors were transformed into walls because door placement is not handled by the GAN, but rather by evolution, as described in the following.

B. Level Generation: CPPN2GAN

To generate a level using CPPN2GAN, the CPPN is given responsibility for generating latent vector inputs for the GAN as a function of segment position within the larger level.

For Mario, the only input is the x-coordinate of the segment, scaled to [−1, 1]. For a level of three segments, the CPPN inputs would be −1, 0, and 1. CPPN output is an entire latent vector. Each latent vector is fed to the GAN to generate the segment at that position in the level.

Zelda’s 2-D dungeons are more complicated. For the overall shape to be interesting, some rooms need to be missing. Also, dungeons are typically more interesting if they are maze-like, so simply connecting all adjacent rooms would be boring. How maze-like a dungeon is also depends on its start and end points. These additional issues are global design issues, and so are handled by the CPPN (see Fig. 1), which defines global patterns, rather than the GAN, which generates individual rooms.

Thus, CPPNs for Zelda generate latent vector inputs and additional values that determine the layout and connectivity of the rooms. Zelda CPPNs take inputs of x- and y-coordinates scaled to [−1, 1]. A radial distance input is also included to encourage radial patterns, which is common in CPPNs [11]. For each set of CPPN inputs, the output is a latent vector along with seven additional numbers: room presence, right door presence, down door presence, right door type, down door type, raft preference, and start/end preference.

²[Online]. Available: https://github.com/amidos2006/Mario-AI-Framework
³Pseudorandomly placed enemies appear in visualizations as a red “e.”
Room presence determines the presence/absence of a room based on whether the number is positive. If a room is present and has a neighboring room in the given direction, then positive right/down door presence values place a door in the wall heading right/down. Whenever a door is placed, a door is also placed in the opposite direction within the connecting room (so top/left door outputs are not needed). For variety, the right/down door type determines the types of doors, based on different number ranges for each door type: $[-1, 0]$ for plain, $(0, 0.25]$ for puzzle-locked, $(0.25, 0.5]$ for soft-locked, $(0.5, 0.75]$ for bomb-able passage, and $(0.75, 1.0]$ for locked. Puzzle-locked doors are a new addition to this article, which were absent in the initial paper on CPPN2GAN [17]. A puzzle-locked door is opened by pushing a special block in the room in a certain direction. The remaining door types were present in previous work [17]: Soft-locked doors only open when all enemies in the room are killed, bomb-able passages are secret walls that can be bombed to create a door, and locked doors need a key. Enough keys to pair with all locked doors are placed at random locations in the dungeon. However, to assure that the genotype-to-phenotype mapping is deterministic, the pseudorandom generator responsible for placing keys is initialized using the bit representation of the corresponding right or down door type output as a seed. Puzzle blocks are placed pseudorandomly in the same manner.

Raft preference is another addition absent in the previous CPPN2GAN paper [17], though rafts were included in the Graph GAN paper [6] that introduced this Rogue-like Zelda domain. The raft item allows Link to traverse a single water tile, but is only available in one room in each dungeon. The room with the highest raft preference value is the one where the raft is pseudorandomly placed. The raft can greatly increase the amount of back-tracking required in some dungeons.

The final output for start/end preference determines which rooms are the start/end rooms of the dungeon. Across all rooms, the one whose start/end preference is smallest is the starting room, and the one with the largest output is the final goal room, designated by the presence of a Triforce item. This approach to generating complete levels is compared with the control approach described next.

### C. Level Generation: Direct2GAN

Direct2GAN evolves levels consisting of $S$ segments for a GAN expecting latent inputs of size $Z$ by evolving real-valued genome vectors of length $S \times Z$. Each genome is chopped into individual GAN inputs at level generation.

This approach requires a convention as to how different segments are combined into one level. For Mario’s linear levels, adjacent GAN inputs from the combined vector correspond to adjacent segments in the generated level. The combined vector is processed left to right to produce segments left to right.

To generate 2-D Zelda dungeons, individual segments of the linear genome are mapped to a 2-D grid in row-major order: processing genome from left to right generates top row from left to right, then moves to next row down and so on. For fair comparison with CPPN2GAN, each portion of a genome corresponding to a single room contains not only the latent vector inputs, but the seven additional numbers for controlling global structure and connectivity: room presence, right door presence, down door presence, right door type, down door type, raft preference, and start/end preference. Therefore, an $M \times N$ room grid requires genomes of length $M \times N \times (Z + 7)$. Such massive genomes induce large search spaces that are difficult to search, but they have the benefit of easily allowing arbitrary variation in any area of the genome. Therefore, CPPNThenDirect2GAN was developed to take advantage of the benefits of both CPPN2GAN and Direct2GAN.

### D. Level Generation: CPPNThenDirect2GAN

This hybrid approach is inspired by the HybrID algorithm [18]. HybrID was used with HyperNEAT [32], an indirect encoding that evolves CPPNs, which in turn define the weights of a predefined neural network architecture. The benefit of evolving with CPPNs is that they easily impose global patterns of symmetry and repetition. However, localized variation is harder for a CPPN to represent. In contrast, localized variation is easy to produce given a directly encoded genome that simply represents each network weight individually. HybrID begins evolution using CPPNs, so that useful global patterns can be easily found. However, at some point during evolution the CPPNs are discarded, leaving only the directly encoded collection of weights they produced to evolve further.

CPPNThenDirect2GAN works in a similar fashion. At initialization, all individuals in the population are CPPNs evolved with CPPN2GAN. An additional mutation operator is introduced that switches a CPPN to the Direct2GAN representation, which is the output of the CPPN queried at all coordinates (as described earlier). This individual is then further evolved by the Direct2GAN approach. This operation has a low probability, since genomes can never switch back to an indirectly encoded CPPN once they switch to a direct vector format.

In HybrID [18], the transition from indirect to direct encoding occurred at a particular generation. In contrast, our hybrid approach transforms offspring based on random chance and, thus, allows for mixed populations. The now directly encoded offspring undergoes mutation after the transition in order to differentiate the generated level from that of its CPPN parent. The mixed population assures that CPPN genotypes persist as long as they are useful. Although it is possible for directly encoded genotypes to completely take over the population, this did not occur in any of the experiments described in the following.

### V. EXPERIMENTS

The experiments below demonstrate the expressive range of these game level encodings using the Quality Diversity algorithm MAP-Elites [20], which divides the search space into phenotypically distinct bins.

### A. MAP-Elites

Instead of only optimizing toward an objective, as in standard evolutionary algorithms, MAP-Elites (Multidimensional Archive of Phenotypic Elites [20]) collects a diversity of quality
artefacts that differ along $N$ predefined dimensions. MAP-Elites discretizes the space of artefacts into bins and, given some objective, maintains the highest performing individual for each bin in the $N$-dimensional behavior space.

First an initial 100 random individuals are placed in bins based on their attributes. Each bin only holds one individual, so individuals with higher fitness replace less fit individuals. Once the initial population is generated, solutions are uniformly sampled from the bins and undergo crossover and/or mutation to generate new individuals. These newly created individuals also replace less fit individuals as appropriate, or end up occupying new bins, so that a variety of niches is represented, but only by the best examples discovered so far. Our experiments generate 100 000 individuals per run after the initial population is generated.

There are many ways of defining a binning scheme to characterize diversity in a domain. The initial study introducing CPPN2GAN [17] used one binning scheme with each game, but because the performance of a given encoding depends on the binning scheme, this article uses two different binning schemes for each game to better explore the tradeoffs between the encodings being studied. A fitness measure is also required (in the following section), and is consistent in each of the games studied.

B. Dimensions of Variation Within Levels

Two binning schemes were used on Mario levels. One from previous work [17] and one new for this article. Both are based on measurements of the following three quantities: decoration frequency, space coverage, and leniency. These measures were inspired by a study on evaluation measures for platformer games [33]. Each measure expresses different characteristics of a level:

1) decoration frequency: Percentage of nonstandard tiles$^4$;
2) space coverage: Percentage of tiles Mario can stand on$^5$;
3) leniency: Average of leniency values$^6$ across all tiles.

Enemies/gaps are negative, power-ups are positive.

All measures focus on visual characteristics, but also relate to how a player can navigate through a level. The previous binning scheme [17] calculated scores for individual segments (10 per level) and then summed across the segments.

Preliminary experiments uncovered reasonable ranges for binning, discretizing each dimension into ten equally sized intervals. Leniency has negative and positive values, so its scores are divided into five negative bins and five nonnegative bins. Negative bins correspond to greater challenges, and nonnegative bins correspond to easier levels. This binning scheme is the Summed Decoration, Space coverage, and Leniency (Sum DSL).

However, one way to hit a target bin in Sum DSL is to repeat a segment with appropriate properties without variation ten times. This type of level might be boring to play and CPPNs have an advantage at generating this type of level, so an alternate binning scheme encouraging more segment diversity within levels was developed: Distinct ASAD.

Distinct ASAD uses Alternating Space coverage, Alternating Decoration frequency, and the number of distinct segments, which is a count of segments that skips repeats. Distinctness directly encourages variation, though two segments are considered distinct for just a single different tile. The alternating dimensions measure how much their quantities fluctuate from segment to segment. Specifically, if $S(i)$ calculates a given score value (e.g., space coverage) for the $i$th segment in the level, then the alternating version of that score is:

$$A_S = \sum_{i=1}^{9} |S(i-1) - S(i)|. \quad (1)$$

Using this formula to distinguish levels from each other encourages more variation in the segments within each level. Both alternating scores are discretized into ten intervals.

For both binning schemes, fitness is the length of the shortest path to beat the level. Maximizing path length favors levels that require jumps, the main mechanic of the game. If no path can be found the level is deemed unsolvable and receives a fitness of 0.

To determine the path, $A^*$ search is performed on the tile-based representation of the level, with a heuristic encouraging heading to the right.

Zelda also uses a binning scheme from previous work [17] and a new one. The old scheme, WWR, is based on Water tile percentage, Wall tile percentage, and the number of Reachable rooms. A room is reachable if it is the start room, or a door connects it to a reachable room. This definition is cheap to compute, but ignores how single rooms can be impassable. Water and wall tile percentages are calculated only with respect to reachable rooms, and only for the $12 \times 7$ floor regions of rooms (surrounding walls ignored). Bins for these dimensions are divided into 10% ranges (10 bins per dimension). Some bins are impossible to fill, because the sum of water and wall percentages must be less than 100%. Floor tiles occupy additional space. For the number of reachable rooms, there is a bin for each number out of 25 (maximum possible number in a $5 \times 5$ grid). Note that in the previous paper [17], experiments were conducted with 100-room dungeons in a $10 \times 10$ grid. The experiments in this article were repeated due to changes in the Zelda level-generation approach mentioned in Section IV-B, but were done with smaller dungeons to reduce computational cost. However, all results presented here are consistent with those from the previous paper.

The new binning scheme for Zelda is Distinct BTR. It encourages more variety in the rooms within each dungeon, and encourages different types of paths through dungeons. The specific bin dimensions are the number of distinct rooms, the number of back-tracked rooms in the $A^*$ solution path, and the number of reachable rooms (as abovementioned). The backtracking dimension deserves some elaboration.

In commercial games, some dungeons can be traversed in a single pass, but others require the player to return to previously visited areas multiple times, e.g., to find a key before backtracking to a room with a locked door, or to find a special item (like the raft) before traversing a particular obstacle. Some players

$^4$breakable tiles, question blocks, pipes, all enemies
$^5$solid and breakable tiles, question blocks, pipes and bullet bills
$^6$1: question blocks; $-0.5$: pipes, bullet bills, gaps in ground; $-1$: moving enemies; 0: remaining
enjoy this type of backtracking, while others find it frustrating, which makes it a good dimension of variation.

The backtracking score is calculated by following the A* path and marking each room the player exits. Exiting a room means another room is being entered. Whenever a newly entered room exists in the set of previously exited rooms, a counter is incremented to measure the amount of backtracking required by the optimal path. If the path revisits a room multiple times, each revisit increments the backtracking count.

The fitness for Zelda dungeons is the percentage of reachable rooms traversed by the A* path from start to goal. The objective is to maximize the number of rooms visited, as exploring is one of the main mechanics of the game. If no path can be found, the dungeon is deemed unsolvable and receives 0 fitness. The A* heuristic used is Manhattan distance to the goal. Since the inclusion of keys makes the state space very large, there is a computation budget of 100 000 states.

**C. Evolution Details**

CPPN2GAN levels are evolved with a variant of NEAT [22] (see Section II-A), specifically MM-NEAT.7 Because CPPNs are being evolved, every neuron in each network can have a different activation function from the following list: sawtooth wave, linear piecewise, id, square wave, cosine, sine, sigmoid, Gaussian, triangle wave, and absolute value.

Whenever a new network is generated, is has a 50% chance of being the offspring of two parents rather than a clone. The resulting network then has a 20% chance of having a new node spliced in, 40% chance of creating a new link, and a 30% chance of randomly replacing one neuron’s activation function. There is a per-link perturbation rate of 5%.

For Direct2GAN, real-valued vectors are initialized with random values in the range $[-1, 1]$. When offspring are produced, there is a 50% chance of single-point crossover. Otherwise, the offspring is a clone of one parent. Either way, each real number in the vector then has an independent 30% chance of polynomial mutation [34].

When using CPPNThenDirect2GAN, all genomes start as CPPNs. When bins are randomly sampled to generate offspring, a CPPN or directly encoded vector could be selected. CPPNs have a 30% chance of being converted into directly encoded vectors. This procedure generates a directly-encoded genome that represents the exact same level previously encoded by the CPPN. However, the newly generated vector genome immediately undergoes the mutation for real-valued vectors described earlier, so it will only persist in the archive if the resulting level is an elite. Genomes that are not converted are exposed to the standard mutation probabilities for their encoding as described earlier. Whenever crossover occurs, parents mate in the usual fashion if they are of the same type, but if two parents of different types are selected, then the crossover operation is canceled and the first parent is simply mutated to create a new offspring.

**VI. Results**

This section highlights our most relevant results, but an online appendix contains additional result figures and sample evolved levels.8 [see the Appendix (in supplementary material)].

Fig. 2 shows the average quality diversity (QD) score across 30 runs of each genome encoding for each binning scheme in the two games. QD score [35] is the sum of the fitness scores of all elites in the archive, and gives an indication of both the coverage and quality of solutions. Fig. A.1 [see the Appendix (in supplementary material)] shows the average number of bins filled by each encoding, and is qualitatively similar. In Mario, CPPN2GAN and CPPNThenDirect2GAN are statistically tied in terms of filled bins and QD score, but are significantly better than Direct2GAN ($p < 0.05$) for both binning schemes. The performance in Zelda depends more on the binning scheme. In the WWR scheme from previous work, CPPN2GAN is slightly better than CPPNThenDirect2GAN in terms of filled bins and QD score ($p < 0.05$), though CPPNThenDirect2GAN almost catches up in terms of QD score. Both are far better than Direct2GAN in both metrics ($p < 0.05$). For the new Distinct BTR scheme, CPPNThenDirect2GAN is significantly better than both CPPN2GAN and Direct2GAN in terms of filled bins and QD score ($p < 0.05$). CPPN2GAN and Direct2GAN are statistically tied in terms of filled bins, but Direct2GAN actually has the better QD score ($p < 0.05$).

Fig. 3 analyzes the final archives for Sum DSL. These results reaffirm the dominance of CPPN2GAN over Direct2GAN [17], and demonstrate the qualitative similarity between CPPN2GAN and the new CPPNThenDirect2GAN. For Sum DSL, CPPNs are generally superior, but the new CPPNThenDirect2GAN approach is not hindered by producing directly encoded genomes. Average archive heat maps for each method are in Fig. A.2 [see the Appendix (in supplementary material)]. For each approach, the percentage of beatable levels averages to 97%, though the actual number of beatable levels is much higher for CPPN-based approaches because of the higher number of filled bins.

Fig. 4 shows Distinct ASAD results. Direct2GAN performs even worse in terms of coverage, but there is no difference between CPPN2GAN and CPPNThenDirect2GAN. However, CPPNThenDirect2GAN and Direct2GAN more frequently produce the most fit level as the number of distinct segments increases. Average archive heat maps are in Fig. A.3 [see the Appendix (in supplementary material)]. Direct2GAN averages 97% beatable levels, whereas both CPPN-based approaches average 99% beatable levels.

Fig. 5 shows results for WWR. Although these dungeons are smaller than those from previous work [17], results are consistent with the previous paper. CPPN2GAN is better than Direct2GAN. CPPNThenDirect2GAN is comparable to CPPN2GAN, but is not represented in some bins with many reachable rooms where CPPN2GAN is represented. CPPNThenDirect2GAN is also absent in some bins with few reachable rooms. Direct2GAN is the method most underrepresented across all bins, but sometimes has the fittest solutions. However, CPPNThenDirect2GAN generally has the most best solutions in bins with a large number of reachable rooms. Average heat maps in Fig. A.4 [see the Appendix (in supplementary material)]. Interestingly, only 85% of Direct2GAN levels are

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7[Online]. Available: https://github.com/schrum2/MM-NEAT

8[Online]. Available: https://www.southwestern.edu/~schrum2/SCOPE/cppn-then-direct-to-gan.php
Fig. 2. Average QD Score Across 30 Runs of MAP-Elites. For each MAP-Elites binning scheme in Mario and Zelda, plots of average QD Scores with 95% confidence intervals demonstrate the comparative performance of the three encoding schemes. CPPNThenDirect2GAN is always the best or statistically tied for best (eventually catching up to CPPN2GAN in WWR). Direct2GAN is always worst, except with Distinct BTR, where it beats CPPN2GAN, but is inferior to CPPNThenDirect2GAN.

Fig. 3. MAP-Elites archive comparisons across 30 runs of evolution in Mario using Sum DSL. Each subgrid represents a different leniency score. Within each subgrid, summed decoration frequency increases to the right, and summed space coverage increases moving up. (a) Color coding shows whether any of the 30 runs of each method produced an occupant for each bin. Direct2GAN leaves many bins completely absent, but CPPN2GAN and CPPNThenDirect2GAN have similar coverage. (b) Average bin fitness scores across 30 runs of each method were calculated, and the method with the best average fitness is indicated for each bin. Direct2GAN was never the best, though CPPN2GAN and CPPNThenDirect2GAN have a comparable number and spread of best bins, and tie for best in some cases (indicated by “CPPN Tie”).

Fig. 4. MAP-Elites archive comparisons across 30 runs of evolution in Mario using Distinct ASAD. Methods are compared as in Fig. 3, but with Distinct ASAD. Each subgrid now represents the count of distinct segments. In each subgrid, alternating decoration score increases to the right, and alternating space coverage score increases moving up. The upper-left grid is mostly empty, since it is for levels with only one repeated segment, meaning decoration and space coverage scores cannot alternate. (a) Direct2GAN is missing from many bins, but CPPN2GAN and CPPNThenDirect2GAN have identical coverage. (b) Highest scoring levels for fewer distinct segments mostly come from CPPN2GAN, though some CPPNThenDirect2GAN results are mixed in. As number of distinct segments increases, CPPNThenDirect2GAN and Direct2GAN are more prominent.

beatable, whereas 91% of CPPN2GAN and 94% of CPPN-ThenDirect2GAN levels are.

Fig. 6 has Distinct BTR results. Although CPPNThenDirect2GAN occupies more bins than either Direct2GAN or CPPN2GAN, each method occupies some bins that the others do not. However, CPPNThenDirect2GAN fitness is superior to CPPN2GAN in nearly every bin where both are present, and superior to Direct2GAN in some cases too. Average heat maps in Fig. A.5 [see the Appendix (in supplementary material)], Direct2GAN averages 90% beatable levels compared to 99% for both CPPN-based methods. CPPNThenDirect2GAN archives can be analyzed in terms of their genotype composition [see Fig. A.6 in the Appendix (in supplementary material)]. The two Mario binning schemes end up with more CPPNs, and the two Zelda schemes end up with more direct vectors, but no type of genotype goes extinct with any approach. The distribution of genotypes within each archive is fairly consistent for the Mario Sum DSL scheme and both
Fig. 5. MAP-Elites archive comparisons across 30 runs of evolution in *Zelda* using WWR. The three methods are compared as in *Mario*. Each triangular grid corresponds to levels with a particular number of reachable rooms (top-right of grid). Wall percentage increases upwards and water percentage increases to the right. Grids are triangular due to a trade-off between water percentage and wall percentage (sum cannot exceed 100%). (a) Direct2GAN cannot produce levels with only one reachable room, but otherwise has high representation for smaller numbers of reachable rooms and less representation for larger numbers. CPPN2GAN is mostly comparable to CPPNThenDirect2GAN. However, CPPNThenDirect2GAN fails to reach certain bins that CPPN2GAN reaches when the number of reachable rooms is high, and is even sometimes beaten by Direct2GAN when the number of reachable rooms is small. (b) CPPNThenDirect2GAN makes up for less coverage with higher fitness scores in many bins, particularly as the number of reachable rooms grows. Bins with a “Not Hybrid Tie” represent a tie between CPPN2GAN and Direct2GAN. For certain small numbers of reachable rooms there are bins with a three-way tie.

Fig. 6. MAP-Elites archive comparisons across 30 runs of evolution in *Zelda* using Distinct BTR. Methods are compared as in Fig. 5, but with Distinct BTR. The number by each subgrid still represents the number of reachable rooms. Backtracking increases to the right and distinct rooms increases moving up. When there are fewer reachable rooms, less backtracking is possible, hence, the changing subgrid width. (a) Dark blue regions show bins that only CPPNThenDirect2GAN reaches, though each method has some bins to themselves. Direct2GAN backtracks well in dungeons with many distinct rooms, but CPPN2GAN and CPPNThenDirect2GAN dominate bins for smaller numbers of distinct rooms. (b) CPPN2GAN almost never produces the best result for a bin. There are regions where Direct2GAN does best. However, CPPNThenDirect2GAN is a clear winner in terms of the number of best bin occupants, especially as the number of reachable rooms increases. In some rare bins with a “Direct Tie” Direct2GAN and CPPNThenDirect2GAN are both the best.
Fig. 7. Evolved *Zelda* Levels. (a) Direct2GAN generates levels with unique rooms and structure, but struggles to form a cohesive pattern. (b) CPPN2GAN generates levels with symmetry or other global patterns. (c) CPPNThenDirect2GAN generates levels with interesting overall patterns like CPPN2GAN, but can tweak individual rooms like Direct2GAN to increase overall fitness.

*Zelda* schemes [see Fig. A.7 in the Appendix (in supplementary material)]. Oddly, *Mario* Distinct ASAD shows more variation, and some distinct examples are shown in Fig. A.8 [see the Appendix (in supplementary)]. These results show that CPPNThenDirect2GAN is highly adaptable to different diversity characterizations.

Among generated levels, global patterns in *Zelda* dungeons from CPPN2GAN and CPPNThenDirect2GAN stand out immediately. There is often a symmetrical or repeating motif in these dungeons that is missing in results from Direct2GAN. Even when all rooms in a CPPN-generated dungeon are distinct, there is often a theme throughout the dungeon, such as a water-theme, or reuse of maze-like wall obstacles. Some examples are in Fig. 7, with more in the Appendix (supplementary material) (see Fig. A.9).

*Mario* levels produced by CPPNs tend to have too much repetition, except when the number of distinct segments is an explicit dimension of variation. When encouraged to be distinct, CPPN levels have more variety, yet maintain a theme of similar elements. An example of a repeated theme is an arrangement of blocks that presents a particular jumping challenge, but requires a slightly different approach on each occurrence due to small variations. See the Appendix in supplementary material (see Fig. A.10).

VII. DISCUSSION AND FUTURE WORK

Combining multiple GAN-generated segments into a cohesive whole was an under explored research area. Our previous work [17] presented a method for creating large game levels by combining CPPNs with a GAN, revealing a functional relationship between the latent vectors of different game segments, which the CPPN exploits. Compared to a direct representation of multiple latent vectors, CPPN2GAN generates a larger variety of different complete game levels. CPPNThenDirect2GAN incorporates strengths of both approaches.

Our original work showed that CPPN2GAN results often contained repeated segments, and those results are reproduced here. However, the additional experiments in this article demonstrate that CPPN2GAN can generate diverse segments within a single level if distinct segments are a dimension of variation for MAP-Elites. CPPN2GAN levels can easily evolve any number of distinct segments within a level, but Direct2GAN has trouble repeating segments within a level.

The new hybrid approach introduced in this article is CPPNThenDirect2GAN. First, CPPN2GAN introduces global structure and imposes regular patterns in the level. After mutation, Direct2GAN can take over to fine-tune levels and/or introduce more local variety. For the binning schemes in *Mario*, this approach is comparable to CPPN2GAN, which already fills many bins in the archive. However, CPPNThenDirect2GAN produced interesting results in *Zelda*, particularly in the new Distinct BTR scheme where it outperformed both Direct2GAN and CPPN2GAN. Specifically, CPPNThenDirect2GAN filled many bins that neither of the other methods filled, and had the most fit levels in many bins as well.

However, Direct2GAN reaches some bins that CPPNThenDirect2GAN could not. These bins might be reachable if CPPNThenDirect2GAN genomes were not forced to start as CPPNs. Starting as a CPPN may introduce a bias toward patterns that is so strong that subsequent direct vector manipulation has trouble breaking the patterns. Therefore, the initial population could simply be a combination of CPPN and direct genomes. In fact, the archive size could be doubled to allow separate archives for direct and CPPN genomes, with the benefit of CPPNs occasionally mutating into direct vectors.

CPPNThenDirect2GAN is inspired by HybrID [18], but later research introduced Offset-HybrID [36]: instead of transitioning to direct vectors, one is evolved with each CPPN. Vector components are offsets added to CPPN output. Applied to game levels, this approach would still generate large-scale patterns while also allowing local variation.

But direct, hybrid, and offset genomes cannot scale to arbitrary sizes; a major benefit of CPPNs. Plain CPPN2GAN could enable levels with components generated as needed: levels would never stop growing. This would be especially useful for exploration games, as new segments can be served by CPPN2GAN whenever new areas of the map are discovered. Evaluating this special scenario, and finding a way to incorporate the benefits of directly encoded components, is an interesting area for future work. Further work is also planned on characterizing different binning schemes
and their relationship to the performance of different level generators.

Modifications to the training process are also possible. Our GAN was pretrained and only CPPNs evolved. Instead, a discriminator could decide whether global patterns are similar to original levels via adversarial training against the complete CPPN2GAN network. Training could be end-to-end or by alternating between the CPPN and the generator. The generator could even be represented by an autoencoder or some other non-GAN approach. The resulting samples should be able to reproduce both global and local patterns in complete game levels rather than just in individual segments.

VIII. CONCLUSION

CPPNThenDirect2GAN is a new hybrid approach combining the benefits of CPPN2GAN and Direct2GAN. Whereas CPPN2GAN generates global patterns with GAN-generated segments, CPPNThenDirect2GAN allows for additional variation in segments, increasing the expressive range of generated levels in some situations, e.g., Zelda. CPPNThenDirect2GAN could be useful in other game domains and situations requiring global organization of GAN-generated segments.

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