Illuminating the Space of Dungeon Maps, Locked-door Missions and Enemy Placement Through MAP-Elites

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ABSTRACT

Procedural Content Generation (PCG) methods are valuable tools to speed up the game development process. Moreover, PCG may also be present in games as features, such as the procedural dungeon generation (PDG) in Moonlighter (Digital Sun, 2018). This paper introduces an extended version of an evolutionary dungeon generator by incorporating a MAP-Elites population. Our dungeon levels are discretized with rooms that may have locked-door missions and enemies within them. We encoded the dungeons through a tree structure to ensure the feasibility of missions. We performed computational and user feedback experiments to evaluate our PDG approach. They show that our approach accurately converges almost the whole MAP-Elite population for most executions. Finally, players’ feedback indicates that they enjoyed the generated levels, and they could not indicate an algorithm as a level generator.

CCS CONCEPTS

• Theory of computation → Evolutionary algorithms; • Computing methodologies → Discrete space search; • Applied computing → Computer games.

KEYWORDS

evolutionary algorithm, map-elites, procedural content generation, level generation, mission generation, video game

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1 INTRODUCTION

Creating game content from scratch is a hardworking task for game designers. Thus, game developers may apply Procedural Content Generation (PCG) to speed up the development process [22]. Some of the many examples of successful games which apply PCG techniques are No Man’s Sky by Hello Games, and Moonlighter by Digital Sun [6, 12]. The latter applies PCG to generate its dungeon levels, a.k.a. Procedural Dungeon Generation (PDG), which is popular both in the research community and game industry [25].

According to van der Linden et al., dungeons are labyrinth environments composed of challenges, rewards, and puzzles interrelated with the playspace and time, where the former is the physical layout where the game takes place [9, 24]. Furthermore, these games present missions, i.e., a set of goals that the player must accomplish [18]. Examples of such a mission are: defeat/kill some enemies, talk to characters, collect some items, collect keys to open locked doors, among others. Locked-door missions are considered puzzles interrelated with the playspace [5, 25].

The present paper approaches the locked-door missions for dungeons, applying PCG by extending the evolutionary algorithm (EA) introduced in Pereira et al. [18]. The previous work presented an EA capable of generating dungeon levels with locked-door missions that match the game designer parameters for levels and missions. Our extended version offers two main contributions from [18] and PDG related works. The first one is to advance from the previous EA by evolving also the enemies distribution through the levels’ rooms. The second contribution is the application of a MAP-Elites algorithm for enhancing Quality Diversity (QD) in content generation, taking into account the level design with lock, keys, and enemies placement. QD algorithms are very relevant for PCG purposes since they can create different content in a single run, according to Gravina et al. [11].

Following the definition of game facets in [16], our approach fits in orchestrating of levels and narrative (as lock and key missions), totaling two creative facets orchestrated concurrently by a single algorithm. Our population has two dimensions and is mapped regarding leniency, as defined by Smith et al. [20], and exploration coefficient, similar to the concept defined by Liapis et al. [15]. The evolutionary parameters are closer to those used by Pereira et al. [18]; however, we added the number of enemies as a parameter, and we replaced the number of generations by time-limit as a stop criterion to ensure most levels converge. Also, besides generating levels to match the entered characteristics, our approach aims to balance the distribution of enemies in the levels and provide more diversity based on leniency and exploration criteria as previously mentioned.

The results show that our algorithm accurately converges all dungeon levels on the MAP-Elites defined for most executions. Furthermore, we evaluated our levels by collecting volunteers’ feedback after playing a game prototype with our levels, and the main feedback was that most of them enjoyed the gameplay. Besides, most players could not point out if an algorithm created the levels.

We structured the paper as follows: Section 2 presents the related works; Section 3 describes the representation of our dungeon levels
and our evolutionary level generation approach; Section 4 presents and discusses the results of our experiments; finally, Section 5 presents the conclusions and future works.

2 RELATED WORKS

Most works on PDG apply search-based approaches in their solutions [25]. Gravina et al. reported that QD approaches are relevant for PCG purposes since they can generate a variety of contents in a single execution without losing quality [11]. Within this class of algorithms, there are the Illumination Algorithms that return sets of the best-found solutions, which are discretized in a map regarding their features [17]. In PCG research, the illumination through MAP-Elites-based approaches has been increasing [11, 25]. We present some related PDG works, in which some of them applied MAP-Elites approaches. Table 1 summarizes the comparison of our paper with related works reviewed through this section.

Table 1: Summarizing of related works on dungeon generation and comparison with this work.

| Work Content Enemy Missions MAP-Elites |
|---------------------------------------|
| [1] Room - - ✓ ✓ |
| [3] Room ✓ - ✓ ✓ |
| [7] Level - ✓ ✓ - |
| [8] Level - ✓ ✓ - |
| [23] Level ✓ ✓ ✓ - |
| [10] Level - ✓ ✓ - |
| [18] Level - ✓ ✓ - |
| [15] Level ✓ ✓ ✓ - |
| Our work Level ✓ ✓ ✓ |

Alvarez et al. extended the Evolutionary Dungeon Design (EDD), a mixed-initiative tool introduced by Baldwin et al., to provide several suggestions of changes presented to the user as a matrix of rooms [1, 2]. This feature was possible due to the Interactive Constrained MAP-Elites (CME), which they introduced. This method can generate suggestions based on the room during the edition process. Each user modification leads to the generation of new suggestions, and it is possible to map the matrix of suggestions into linearity, symmetry, and other specific metrics of the EDD.

Charity et al. introduced an automatic method based on CME to generate rooms for general games based on their mechanics [3]. They applied this approach in four different games with different game mechanics sets by mapping the CME’s matrix according to their mechanics. They also used the General Video Game Artificial Intelligence (GVG-AI) framework to generate the initial population and the framework’s agents in the fitness functions. The fitness functions are based on the survival and conclusion time of the agents. They claim that the generated rooms can be used as game tutorials to teach the players how to use the game mechanics.

Both previous works applied MAP-Elites in their algorithms to generate rooms [1, 3]. We also apply such an approach, but we generate levels instead of rooms. Consequently, we based our MAP-Elites’ feature descriptors on different metrics.

Following, we describe works that tackled the problem of generating levels with missions. Dormans generated dungeons through a Generative Grammar (GG) [7]. The approach creates a graph of missions and applies it to generate the play-space for Action-Adventure games. Later, Dormans used the previous GG and a model-driven approach in a mixed-initiative tool to generate level sketches [8]. The introduced model-driven approach “evolves” the dungeons through model transformations. Similar to Dormans, van der Linden et al. presented a GG-based method for level generation [23]. The work uses gameplay as a vocabulary to control the generative process. The graphs’ nodes express player actions as gameplay design constraints, and they are described semantically, e.g., “fight melee enemy” and “pickup health potion”. Thus, the gameplay grammar allows designers to specify their expected gameplay. This work, like ours, also presents the placement of enemies.

Gellel and Sweetser combined Dormans’ generative grammar with a non-traditional Cellular Automata (CA) [7, 10]. First, the GG creates a string that codifies the locked-door missions and the level rooms. After that, they applied the new CA method based on random neighbor selection to generate the play-space. This method is composed of two rules that place the rooms for each character of the mission string.

So far, the works that generate levels with locked-door missions have applied GG approaches to their solutions. Differently from them, Pereira et al. presented a search-based algorithm for dungeon level generation with locked-door missions for Action-Adventure games [18]. The proposed algorithm is the base for the approach introduced in this paper. The missions’ goal is to collect keys to open locked doors in the levels and find a symbol, similar to Zelda’s triforce. A tree structure represents the dungeon levels to ensure feasibility, and the Genetic Programming approach evolves the levels and missions. The keys are in the trees’ nodes (rooms), and the doors are in the trees’ edges (corridors). We chose to enhance this algorithm in our research, as it creates feasible dungeons, accurate to the designer’s needs, fast, with no need for training, and very few numerical inputs. Our approach goes beyond it by introducing the enemy element in the generation and ensuring QD.

Works like those of van der Linden, Alvarez et al., and Charity perform enemy placement in their approaches [1, 3, 23]. Besides them, Liapis introduced a search-based approach where such property is more important than the previous works. The author presented an approach for dungeon generation composed of two stages applying a FI2Pop GA. The first stage generates dungeon sketches by strategically placing eight segments representing dungeon rooms, which describe impassable (wall), passable rooms and define the number of enemies and rewards in each room. In the second step, each segment becomes a room. Each room evolves independently to create a cavern environment, following connections between the segments and their types. For instance, the enemies are strategically placed around a reward [14].

As for the orchestration of content, in Liapis et al. [16] review on the topic, none of the presented works that applied the orchestration algorithm also used QD. The same holds for more recent papers focused on the topic of orchestration that we found, like the algorithm of Karavolo et al. [13] for first-person shooter content orchestration or the experiment of Prager et al. on the effects of the combination of visuals and audio facets [19]. Thus, we emphasize
This section describes the representation of our dungeon levels and the MAP-Elites approach we applied to evolve them.

3.1 Representation

One individual in our evolutionary algorithm states a dungeon level, where a tree structure represents such an individual, as shown in Figure 1a. Each node defines a room that encodes its type and position in the dungeon. We have a Key Room (KR), which indicates an available key to open a locked door; a Locked Room (LR) with a locked door; and a Normal Room (NR) that has nothing special.

The node also encodes the number of enemies in that room and the room position concerning the parent node: Right (R), Down (D), and Left (L). We place the room assuming that its parent room (node) is in the north, positioning it (R, D, and L) correctly when decoding the individual into a dungeon level.

To ensure no room overlaps the level, we decode the tree representation (genotype) to a 2D grid (phenotype). If there are overlapping rooms, the branch that causes the overlap is removed from the tree. Thus, we ensure that no level is infeasible following the process of branch removal detailed in [18]. A single key can open a locked door; therefore, the keys are bound with their locks through a shared ID. Rooms can have only a key, only a locker, or none of them; they can never have only one of each or multiples of a kind at the same time. Moreover, our representation does not require keys to be collected and unlocked in a specific sequence.

3.2 Generation Process

Our dungeon generation process evolves tree structures of feasible levels. The parameters that our algorithm receives are the number of rooms, number of keys, number of locks, number of enemies, and linear coefficient (linearity). We designed our approach to evolve dungeons by preserving diversity and optimizing quality. To do so, we applied a MAP-Elites approach for variety by mapping the feature descriptors (or dimensions), weighting the leniency of enemies and exploration coefficient. To measure the leniency of enemies in our levels, we apply the Equation 1 presented by Smith et al. [20]. The leniency is calculated by the number of safe rooms, i.e., without enemies, divided by the total number of rooms.

\[
D_{\text{leniency}} = \frac{\text{Number of Safe Rooms}}{\text{Total Rooms}}
\]

Equation 2 measures our exploration coefficient, inspired by the exploration measure introduced by Liapis et al. [15]. We run a flood fill algorithm between rooms to simulate the map coverage, where the reached rooms represent the required exploration from each starting room and its corresponding goal room.

\[
D_{\text{exploration}} = \frac{1}{\text{\#RR}} \sum_{(r_s,r_g) \in \text{RR}} \frac{\text{Coverage}(r_s,r_g)}{\text{Total Rooms}}
\]

where \text{RR} is the set of pairs of reference rooms containing the pair of starting and goal rooms and all pairs of key and locked rooms; \#RR is the size of \text{RR}; \text{r_s} is the room where the flood fill starts; and; \text{r_g} is the goal room where the algorithm ends.

Since our equations result in values between 0 and 1, we discretized such dimensions. For the leniency dimension, the intervals are (0.5, 0.6), (0.4, 0.5), (0.3, 0.4), (0.2, 0.3), and (0.2, 0.1). Levels with greater leniency values have most rooms without enemies or some of them with several enemies. For exploration coefficient, the intervals are (0.5, 0.6), (0.6, 0.7), (0.7, 0.8), (0.8, 0.9), and (1.0, 0.9). Levels with exploration coefficient values lesser than these lead to rooms much closer to each other. Figure 2 presents our approach’s map.

The proposed MAP-Elites application will map 25 individuals based on the defined intervals. When the map receives a new individual, we must calculate the feature descriptors to place it in the correct entry of the MAP-Elites table. If an individual fills a map cell and a new one hits the same cell, the latter replaces the former if it has a better fitness; otherwise, we discard the new individual.
which are chosen using tournament selection with two competitors. If this level also has keys, we first place them in random rooms, and rebuild the grid. We try to preserve the locks and keys of the initial population by following the initialization algorithm described in [18]. In our case, after stating the intermediate population, we try to swap the selected nodes. After the swap, we remove all overlaps so, we select two rooms to transfer and to receive them. If both rooms have no enemies, nothing is done. If the receiver has enemies and the transferer does not have them, we swap the rooms. Then, we randomly chose from 1 to the transferer’s number of enemies to move to the receiver room.

After the crossover and mutation operators, we repair the new individuals regarding the distribution of enemies. The crossover may generate levels that have more or fewer than the associated input parameter. On the other hand, the mutation may transfer enemies to rooms that cannot have them, i.e., the goal room. If there are enemies in this room, we remove them. When the number of enemies is higher, we remove them, prioritizing the rooms with more of them. If the number of enemies is lesser, we add them, prioritizing the non-empty rooms with fewer enemies.

Finally, the new individuals in the intermediate population are evaluated using an extended version of the fitness function in [18]. Our function calculates three fitness factors. First, we measure the distance of the input parameters and the generated level, i.e., how much closer is a generated level from the designer’s input:

\[ f_{\text{goal}} = \text{abs}(\text{Grooms} - \text{Lrooms}) + \text{abs}(\text{Gkeys} - \text{Lkeys}) + \text{abs}(\text{Glocks} - \text{Llocks}) + \text{abs}(\text{Glinear\_coefficient} - \text{Llinear\_coefficient}) + \text{abs}(\text{Lrooms} - \text{Lneeded\_rooms}) + \text{abs}(\text{Llocks} - \text{Lneeded\_locks}) \]

where \( G \) is the set of the goals and \( L \) is the set of the level’s attributes (number of rooms, number of keys, number of locks, and linear coefficient); \( \text{needed\_rooms} \) is calculated by an adaptation of a Depth-First Search algorithm, and; \( \text{needed\_locks} \) calculated by an adaptation of an A* algorithm, both algorithms are described in [18].

The second factor is an extension of the enemy sparsity equation introduced by Summerville et al. to evaluate the distribution of enemies in the 2D maps [21]. This function encourages the dispersion of enemies in the levels’ rooms (larger values mean more dispersion):

\[ f_{\text{esp}} = \frac{\sum_{e \in E} (e_x - \mu_x)^2 + (e_y - \mu_y)^2}{\text{Number of Enemies}} \]

where \( e_x \) and \( e_y \) are the x-position and y-position of an enemy \( e \), \( \mu_x \) and \( \mu_y \) are the average x-position and y-position of all enemies, and \( E \) is the set of enemies. In the third term, we calculate the standard deviation of enemies in the rooms. This function encourages that the rooms have a balanced number of enemies (lower values imply enemies are evenly distributed):

\[ f_{\text{std}} = \frac{1}{N - 2} \sum_{r \in R} (r_{\text{enemies}} - \mu_{\text{enemies}})^2 \]

where \( r \) is a room in the set of rooms \( R \), \( r_{\text{enemies}} \) is the number of enemies of a room, \( \mu_{\text{enemies}} \) is the average number of enemies in the rooms, and \( N \) is the number of rooms. We subtract the starting and the goal rooms since they cannot have enemies. The final fitness expression follows:

\[ L_{\text{fitness}} = f_{\text{goal}} - f_{\text{esp}} + f_{\text{std}} \]
We subtract the enemy sparsity $f_{es}$, because higher values are better for such metric, and we aim to minimize $f_{goal}$ and $f_{std}$ as well as our fitness function as a whole.

4 RESULTS

This section reports the computational results achieved by our approach, some level generated, and how human players evaluated our dungeons.

4.1 Performance Results

We defined the evolutionary parameters empirically after comparing some range of values. The results comparing different configurations are available in a Google Sheets spreadsheet\(^1\). After such evaluation, we set the following method’s parameters: 25 individuals for the initial population, 10% for mutation rate, 100 individuals for intermediate population, 2-size for tournament selection, and 60 seconds as stop-criterion.

Next, we collected data from 30 executions of our method for six different sets of parameters to evaluate the algorithm performance. Table 2 shows the average and standard deviation of the fitness for each Elite (entry) of our MAP-Elites population. We observe that the fitness values tend to decrease as leniency decreases, which is expected because there are more safe rooms in L1 levels (50% to 60%) than L2 levels (40% to 50%), less in L3 levels, and so on. Moreover, L2 naturally presents their enemies distributed in more rooms than L1 levels; thus, increasing the enemy sparsity and decreasing the standard deviation of enemies. By comparing tables 2b and 2c, we observe that increasing the linear coefficient decreases the dungeons’ fitness. That means that our algorithm works slightly better for lower linear coefficients.

E5 column in Table 2d presents only subpar fitness values, and these results happen mainly due to the high number of locks at such a small level. To be mapped in E5, the map coverage must be 50% up to 60% safe rooms and ensure they present 90% up to 100% over, L2 naturally presents their enemies distributed in more rooms than L1 levels; thus, increasing the enemy sparsity and decreasing the standard deviation of enemies. By comparing tables 2b and 2c, we observe that increasing the linear coefficient decreases the dungeons’ fitness. That means that our algorithm works slightly better for lower linear coefficients.

Finally, the Elite L1-E5 presents the worst fitness value in all the tables. In this case, our algorithm should fill enemies in levels with such a small level. To be mapped in E5, the map coverage must be 50% up to 60% safe rooms and ensure they present 90% up to 100% of exploration coefficient. Our algorithm struggled to find good results for such Elites. Besides, this Elite has poor fitness values, particularly in the tables 2e and 2f. Such a result is an accumulation of bad values of the factors of $f_{goal}$, in which the main one is the

Table 2: Results of fitness obtained after 30 executions of our approach. Each table caption represents a set of parameters: (number of rooms)-(number of keys)-(number of locks)-(number of enemies)-(linear coefficient). Each table cell corresponds to an Elite. Descriptors for leniency values: $L1 = (0.5,0.6), L2 = (0.4,0.5), L3 = (0.3,0.4), L4 = (0.2,0.3), L5 = (0.1,0.2)$. Descriptors for values of exploration coefficient: $E1 = (0.5,0.6), E2 = (0.6,0.7), E3 = (0.7,0.8), E4 = (0.8,0.9), E5 = (0.9,1.0)$.

(a) 15-3-2-20-2.

|       | E1    | E2    | E3    | E4    | E5    |
|-------|-------|-------|-------|-------|-------|
| L1    | 1.02  | 0.48  | 0.48  | 0.85  | 0.96  |
| L2    | 0.33  | 0.25  | 0.23  | 0.85  | 0.49  |
| L3    | 0.90  | 0.02  | 0.00  | 0.90  | 0.90  |
| L4    | -0.12 | -0.21 | -0.22 | -0.01 | 0.03  |
| L5    | 0.05  | -0.15 | -0.10 | 0.15  | 0.30  |

(b) 20-4-4-30-1.

|       | E1    | E2    | E3    | E4    | E5    |
|-------|-------|-------|-------|-------|-------|
| L1    | 0.28  | 0.22  | 0.06  | 0.06  | 0.06  |
| L2    | 0.23  | 0.23  | 0.22  | 0.19  | 0.13  |
| L3    | 0.06  | 0.25  | 0.06  | 0.20  | 0.32  |
| L4    | -0.10 | -0.35 | -0.32 | -0.21 | -0.00 |
| L5    | -0.40 | -0.45 | -0.44 | -0.35 | 0.20  |

(c) 20-4-4-30-2.

|       | E1    | E2    | E3    | E4    | E5    |
|-------|-------|-------|-------|-------|-------|
| L1    | 1.17  | 0.94  | 0.96  | 1.00  | 1.74  |
| L2    | 0.42  | 0.40  | 0.42  | 0.44  | 0.77  |
| L3    | 0.03  | 0.04  | 0.04  | 0.06  | 0.38  |
| L4    | -0.23 | -0.23 | -0.22 | -0.19 | 0.13  |
| L5    | -0.06 | -0.15 | -0.25 | -0.20 | 0.13  |

(d) 25-8-8-40-2.

|       | E1    | E2    | E3    | E4    | E5    |
|-------|-------|-------|-------|-------|-------|
| L1    | 1.47  | 1.23  | 1.35  | 1.76  | 10.79 |
| L2    | 0.71  | 0.63  | 0.66  | 1.07  | 5.82  |
| L3    | 0.43  | 0.36  | 0.39  | 0.80  | 5.42  |
| L4    | 0.05  | -0.01 | 0.02  | 0.43  | 4.93  |
| L5    | -0.02 | -0.04 | -0.09 | 0.33  | 5.12  |

(e) 30-4-4-50-2.

|       | E1    | E2    | E3    | E4    | E5    |
|-------|-------|-------|-------|-------|-------|
| L1    | 2.41  | 1.69  | 1.60  | 2.04  | 5.33  |
| L2    | 0.64  | 0.53  | 0.55  | 0.72  | 1.49  |
| L3    | 0.06  | 0.04  | 0.06  | 0.20  | 0.53  |
| L4    | -0.31 | -0.35 | -0.32 | -0.21 | -0.00 |
| L5    | -0.40 | -0.45 | -0.44 | -0.35 | 0.20  |

(f) 30-6-6-50-1.5.

|       | E1    | E2    | E3    | E4    | E5    |
|-------|-------|-------|-------|-------|-------|
| L1    | 1.36  | 1.17  | 0.88  | 1.40  | 5.03  |
| L2    | 0.18  | 0.08  | 0.04  | 0.08  | 1.82  |
| L3    | -0.37 | -0.40 | -0.38 | -0.35 | 1.06  |
| L4    | -0.76 | -0.76 | -0.74 | -0.70 | 0.24  |
| L5    | -0.92 | -0.92 | -0.89 | -0.84 | 0.60  |

\(^1\)Link to the spreadsheet: [https://docs.google.com/spreadsheets/d/1QmKPv8KyoavVyoJLWSQqot7oT8vS7lLD47X78HVk](https://docs.google.com/spreadsheets/d/1QmKPv8KyoavVyoJLWSQqot7oT8vS7lLD47X78HVk).
Figure 3: Example of a MAP-Elites population of levels with 20 rooms, 4 keys, 4 locks, 30 enemies, and linear coefficient equal to 2. Each table cell corresponds to an Elite. Descriptors for leniency values: $L_1 = (0.5,0.6)$, $L_2 = (0.4,0.5)$, $L_3 = (0.3,0.4)$, $L_4 = (0.2,0.3)$, $L_5 = (0.1,0.2)$. Descriptors for values of exploration coefficient: $E_1 = (0.5,0.6)$, $E_2 = (0.6,0.7)$, $E_3 = (0.7,0.8)$, $E_4 = (0.8,0.9)$, $E_5 = (0.9,1.0)$. The small squares represent corridors, and the bigger squares represent rooms. The white room with a purple square within it is the start room. The purple room with a white square within it is the goal room. White rooms have no enemies while red rooms have enemies within, the more intense the shade of red, the more enemies there are. Colored corridors are locked, and their keys are colored circles within rooms.

number of rooms. Since our levels are randomly generated in the initial population, the difficulty of generating levels with a higher number of rooms is somewhat expected.

Finally, we test the consistency of the algorithm’s convergence along with generations. Figure 7 shows the evolution of the fitness and its standard error averaged from 100 executions using the inputs: 20 rooms, 4 keys, 4 locks, 30 enemies, and the linear coefficient equal to 2. Moreover, it shows the convergence’s progression over 612 generations, which was the minimum number of generations that the 60s created over the 100 tests (60s being the parameter used for the other tests).

We can observe that the convergence is stable, with little standard error, especially after 500 generations. Our approach can converge to at least one good solution with its initial population (because of the preprocessing to guarantee some elites) and converge in less than 50 generations to an average of good solutions. Besides, with over 500 generations, even the worst elites are good.
Figure 4: Bar charts of answers of the 74 players for 121 levels. Each bar corresponds to the number of levels evaluated for the respective value of the five-point Likert scale. The questions from Section 4.3 were shortened for brevity.

Figure 5: Bar charts of answers for question Q5 ("I liked the challenge of finding the keys to this level") of 57 players for 93 levels. These players answered, through a pre-questionnaire, they enjoy exploring. Each bar corresponds to the number of levels evaluated for the respective value of the five-point Likert scale. Each figure correspond to a descriptors for values of exploration coefficient: E1 = (0.5,0.6), E2 = (0.6,0.7), E3 = (0.7,0.8), E4 = (0.8,0.9), E5 = (0.9,1.0).

Figure 6: Bar charts of answers for question Q3 ("The challenge was just right") of 43 players for 74 levels. These players answered, through a pre-questionnaire, they enjoy battles. Each bar corresponds to the number of levels evaluated for the respective value of the five-point Likert scale. Each figure correspond to a descriptor for leniency values: L1 = (0.5,0.6), L2 = (0.4,0.5), L3 = (0.3,0.4), L4 = (0.2,0.3), L5 = (0.1,0.2).
We believe this behavior occurs due to the enemy sparsity, since worst and average of elites for each generation, averaged while rooms with enemies tend to be closer to the edges of the levels. The empty rooms (white squares) tend to be closer to each other, however, the player can access all the keys without unlocking any lock to collect the green key and open the goal room. In L2-E2, the player must collect the yellow key and open the yellow door. Nonetheless, this particular feature of chained locked-doors puzzles while not finding it very difficult to find the exit. Thus, the gameplay in the game prototype, using levels procedurally generated by our MAP-Elites approach, advances from the original one in [18].

A total of 96 people played the levels, where 74 answered all the questions. They played 121 levels, randomly selected to feed the game prototype. After finishing a level, the players answered how much they agree or disagree, on a five-point Likert scale, with the following statements:

Q1 The level was fun to play;
Q2 The level was difficult to complete;
Q3 The challenge was just right;
Q4 I liked the amount of exploration available on this level;
Q5 I liked the challenge of finding the keys to this level;
Q6 It was difficult to find the exit/goal of this level;
Q7 The levels I played were created by humans.

Figure 4 presents seven bar charts, each one with the answers to a question. Each chart summarizes their answers by presenting the average (AVG) and standard deviation (SD). The low SD (σ = 1) shows that the responses vary slightly. In Figure 4a, the players had fun while playing 80 out of 121 levels, and only 20 did not enjoy it. Figure 4b shows that most players did not have difficulty completing most of our levels (73 out of 121), and Figure 4c shows the players felt that the challenge of 61 levels was just right, it was not good for 37 levels, and they felt neutral for 23 levels.

Players liked the exploration of 82 levels, as shown in Figure 4d, they did not enjoy only 16 levels, and they were neutral for 23 levels. We observe in Figure 4e that the players liked the locked-doors puzzles in 66 levels; they did not like it in 23 levels and were neutral about it in 32 levels. The players easily found the goal room in 59 levels in Figure 4f; the goal room was difficult to find in only 35 levels. Finally, Figure 4g shows that the players believed that humans created 42 levels, 46 levels were generated by a PCG algorithm, and 33 had no sure.

Therefore, even while playing different levels, most players felt that playing the generated content was fun, with a balanced difficulty that brought a good challenge in combat against enemies and a good feeling of exploration in the dungeons. They liked the locked-doors puzzles while not finding it very difficult to find the exit. Thus, our algorithm was able to bring quality and diversity to the solutions while also creating the content so that players could enjoy exploring by class of exploration with most of them converging very close to the designer’s needs and having interesting contents.

4.3 Gameplay Feedback

Finally, we asked people to play a game prototype with the generated levels, and the players had to answer a questionnaire about each played level. The game prototype is the same introduced by Pereira et al., but our locked-door missions are not generic, which means a key can open only a specific locked door [18]. Also, in our gameplay, the players must defeat enemies to progress, and our rooms may also have blocks that players can use to protect themselves from enemies. Thus, the gameplay in the game prototype, using levels procedurally generated by our MAP-Elites approach, advances from the original one in [18].

Figure 7: Average fitness and standard error of the best, worst and average of elites for each generation, averaged from 100 executions.
coefficient. Most players played E1 levels, and no one played E5 levels; however, most enjoyed playing all the levels independent of the value of the exploration coefficient. Figure 6 shows the feedback of levels of the players that enjoy battling. The results vary more in these charts, with most players playing L4 levels and agreeing with the challenge in the levels they played. Regarding the levels with the remaining leniency values, we cannot declare if they presented the just right amount of challenge, since the number of players who agreed and disagreed with that is too close.

5 CONCLUSION

This paper introduced an illumination approach that extended the work presented by Pereira et al. [18]. Our contributions advance the method by orchestrating enemies within the levels (level facet) and the locked-door missions (narrative facet) through their illumination with the MAP-Elites approach. The experiments show that our evolutionary level generation approach is stable, concerning the standard deviation of the fitness, and converges all the dungeons on the map in many executions. Regarding the experiments with people, the results show that most players positively answered the levels we generated. The players enjoyed the levels created by our algorithms and could not indicate if an algorithm created the levels. Thus, our approach maintains the dungeon quality — once our results corroborate the results of the original method [18] — and goes beyond by providing a set of diverse levels. As future works, we intend to add a novelty score to allow more distinct levels in the map in terms of level structure as proposed in [4].

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