

Generating Redstone Style Cities in Minecraft

Shuo Huang*, Chengpeng Hu*, Julian Togelius[†], Jialin Liu*

* Guangdong Provincial Key Laboratory of Brain-Inspired Intelligent Computation,

Department of Computer Science and Engineering, Southern University of Science and Technology, Shenzhen 518055, China

[†] Department of Computer Science and Engineering

Tandon School of Engineering, New York University, New York 10012, United States

Abstract—Procedurally generating cities in Minecraft provides players more diverse scenarios and could help understand and improve the design of cities in other digital worlds and the real world. This paper presents a city generator that was submitted as an entry to the 2023 Edition of Minecraft Settlement Generation Competition for Minecraft. The generation procedure is composed of six main steps, namely vegetation clearing, terrain reshaping, building layout generation, route planning, streetlight placement, and wall construction. Three algorithms, including a heuristic-based algorithm, an evolving layout algorithm, and a random one are applied to generate the building layout, thus determining where to place different redstone style buildings, and tested by generating cities on random maps in limited time. Experimental results show that the heuristic-based algorithm is capable of finding an acceptable building layout faster for flat maps, while the evolving layout algorithm performs better in evolving layout for rugged maps. A user study is conducted to compare our generator with outstanding entries of the competition's 2022 edition using the competition's evaluation criteria and shows that our generator performs well in the *adaptation* and *functionality* criteria.

Index Terms—Minecraft, settlement generation, city generation, procedural content generation, competition

I. INTRODUCTION

Minecraft [1] is a 3D sandbox video game widely used in research and education [2]. A well-built city in Minecraft can provide players a better game experience. Recent works focus on procedurally generating terrain and buildings in Minecraft [3], [4]. In the work of [3], generative adversarial network (GAN) is applied to generating terrain with similar features on Minecraft maps of different sizes. Jiang *et al.* [4] employ procedural content generation via reinforcement learning (PC-GRL) [5] to generate 3D mazes in Minecraft.

The Settlement Generation Competition for Minecraft (GDMC) [6] is a city generation competition. Participants are tasked to design a program that takes a Minecraft (version 1.19.2) map and a build area as the input and outputs a version of the same map with a city (or village) on it. The

referees will assess each settlement with four criteria, namely *adaptation*, *functionality*, *believable* and *evocative narrative*, and *visual aesthetic* as described in [6]. The challenges of settlement building in Minecraft are discussed in [7], [8]. Green *et al.* [9] generate buildings with constrained growth and cellular automata, while Barthet *et al.* [10] use an evolutionary algorithm. Merino *et al.* [11] generate buildings based on individual aesthetic choice and interactive evolution. In [12], a needs-based agent is presented that simulates the development process of a village. Demke *et al.* [13] design a multi-agent story-based settlement generator.

Following the rules of GDMC, this paper designs a city generator using redstone buildings (i.e., buildings with inner redstone designs) as components. Redstone is a mineral that can transit redstone signals, which can be used to simulate electrical signals, between blocks. Redstone design makes the city show a scientific style. Three building layout generation algorithms are integrated into our generator and compared by generating cities on maps with different sizes in limited time. A user study is conducted to compare our work with some outstanding ones from the 2022 edition of GDMC.

II. GENERATION PROCESS

The city generation process consists of six main steps: vegetation clearing, terrain reshaping, building layout generation, route planning, streetlight placement, and wall construction as illustrated in Fig. 1. First, we clear the trees and reshape the terrain to get more building area. Then, the whole city is divided into an outer and an inner part. The outer part is used for constructing walls and the inner part is left for placing buildings. After determining the locations of buildings, some important nodes are connected by roads to provide more accessible connections among different parts of the city. Finally, some streetlights are placed in the inner city to offer enough lighting. The following details the steps.

Vegetation clearing: In some maps, trees occupy plenty of space. As enough building space is necessary for placing buildings, our generator clears all the trees.

Terrain reshaping: The ideal area for placing buildings is a flat area, where all the blocks have about the same elevation. Therefore, we use a rule-based strategy to reshape the terrain (cf. Algorithm 1).

Building layout generation: After preserving enough empty place, the generator determines the layout of a set of

This work was supported in part by the Guangdong Provincial Key Laboratory (Grant No. 2020B121201001), the Program for Guangdong Introducing Innovative and Entrepreneurial Teams (Grant No. 2017ZT07X386), the Research Institute of Trustworthy Autonomous Systems and the SUSTech Undergraduate Teaching Quality and Reform Project (Grant No. SJZLGC202101). Corresponding author: Jialin Liu (liujl@sustech.edu.cn).

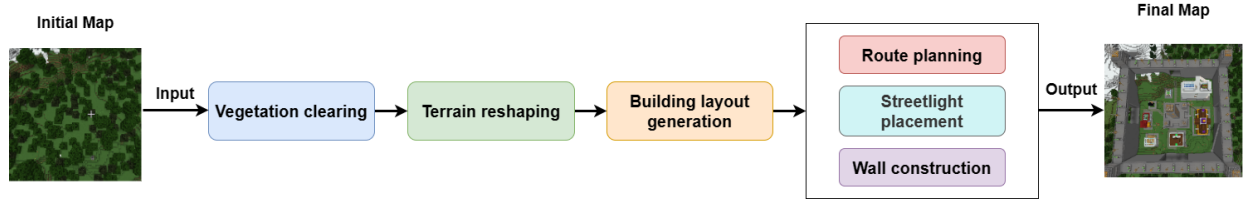


Fig. 1. Main steps of our city generator.

Algorithm 1: Terrain reshaping

Data: Width of the building area w , Length of the building area l , Most common block of the building area's ground gb , Function used to compare two blocks' altitude $compareAltitude$

```

1  $A \leftarrow$  building area's altitude map
2  $mean \leftarrow$  average of  $A$ 
3 for  $x = 1$  to  $w$  do
4   for  $z = 1$  to  $l$  do
5      $score \leftarrow compareAltitude(x,z)$ 
6     if  $score = 3$  then
7       change block in  $(x, A[x][z]-1, z)$  to air
8       change block in  $(x, A[x][z]-2, z)$  to  $gb$ 
9     end
10    if  $score = -3$  then
11      change block in  $(x, A[x][z], z)$  to  $gb$ 
12    end
13  end
14 end
15 return  $buildArea$ 

```

TABLE II
BUILDING REWARDS FOR DIFFERENT BUILDINGS

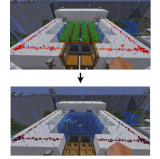
Building	Reward
Dorm	493
Church	416
Munition Factory	119
Monument	625
Shop	182
HIM Statue	35
Enderman Statue	25
Trampoline	35
Enchanting Room	121



(a) Enchanting table



(b) Light



(c) Farm

Fig. 2. Redstone designs.

redstone style buildings pre-designed. Some buildings involve some redstone design as shown in Fig. 2.

The layout generation is modelled as an optimization problem. The terrains are categorized into 5 types, including plain, common land, water, artificial blocks, and blocks around the artificial blocks. The costs and rewards of placing buildings on different terrain type are shown in Table I and Table II. The Monument offers an additional bonus: the closer it is to the city's center point, the greater the reward is. There is a minimum distance between each pair of buildings. The reward after deducting the cost is the score for placing a building.

TABLE I
BUILDING COST ON DIFFERENT TYPE OF TERRAIN.

Category	Cost
Water	10
Plain	0
Artificial blocks	10000
Blocks around the artificial	50
Common land	The sum of its gradient

Search-based algorithms can be applied to optimize the layout aiming at maximizing the reward. Three algorithms are

tested, namely a heuristic-based layout generation algorithm, an evolving layout algorithm, and random placement. Algorithm 2 details the heuristic-based layout generation process. It generates many layouts heuristically and returns the one with the highest score. When generating a layout, it adds buildings one by one until the score is no more increased by adding new buildings. Algorithm 3 details the process of evolving layout. In an $m * n$ map, every position (x, z) can be represented by a positive integer $k = x * n + z$. The number of buildings needed to be placed, num , can be input by users. A solution s is made up of num positive integers. If a solution breaks the rule of minimum distance between two buildings, only one of them would be placed on the map. A solution can be transformed into a layout. The fitness is the total score of the layout. The initial population is generated randomly. Random placement algorithm uses num random numbers to represent the positions of buildings in one layout. Many layouts would be generated and the best one would be chosen.

Route planning: After determining the locations of buildings, roads are planned to ensure the accessibility of important areas. Four gates are placed at the closest legal points to the middle positions of four city edges. Roads should connect the four gates and the monument. In addition, the munitions factory is connected to the tower's entrance. All the roads are planned by an A* algorithm, in which the sum of two points'

Algorithm 2: Heuristic-based layout generation.

Data: Number of layouts need to be generated nb ,
Maximum times can be used to add one
building to a layout $maxTry$

```
1  $A \leftarrow$  the altitude map of the inner city
2 for  $i = 1$  to  $nb$  do
3   tempReward  $\leftarrow 0$ 
4   layout  $\leftarrow A$ 
5   maxScore  $\leftarrow 1$ 
6   while  $maxScore > 0$  do
7     maxScore  $\leftarrow -1$ 
8     for  $j = 1$  to  $maxTry$  do
9        $c \leftarrow$  copy of layout
10      randomly place a building  $b$  on  $c$ 
11      score  $\leftarrow$  getReward( $b$ ) - getCost( $b$ )
12      update maxScore
13    end
14    update layout
15    tempReward  $\leftarrow$  tempReward + maxReward
16  end
17  update bestReward
18  update globalLayout
19 end
20 return globalLayout
```

Algorithm 3: Evolving layout.

Data: Size of population $popSize$, Evolutionary
generation $NGeneration$, Mutation rate $pumt$

```
1  $A \leftarrow$  the altitude map of the inner city
2 pop  $\leftarrow$  initial population
3 fitnessList  $\leftarrow []$ 
4 newPop  $\leftarrow []$ 
5 for  $ng = 1$  to  $NGeneration$  do
6   for  $i = 1$  to  $popSize$  do
7     layoutCopy  $\leftarrow A$ 
8     fitnessList[i]  $\leftarrow$  calculateFitness(pop[i],
7     layoutCopy)
9   end
10  parents  $\leftarrow$  selectParents(pop, fitnessList, popSize)
11  for  $i = 1$  to  $popSize$  do
12    Randomly selection parents  $x, y$ 
13    child  $\leftarrow$  reproduce( $x, y$ )
14     $p \leftarrow$  a random number between 0 and 1.
15    if  $p < pumt$  then
16      child  $\leftarrow$  mutate(child)
17    end
18    update(newPop)
19  end
20  pop  $\leftarrow$  newPop
21 end
22 bestSol  $\leftarrow$  the best solution in pop
23 globalLayout  $\leftarrow$  bestSol's corresponding layout
24 return globalLayout
```

difference in x and z values is used to estimate their distance. Finally, roads on the water are transformed into bridges.

Streetlight placement: Streetlights need to be placed in the area with high building density to provide lighting to the city. KMEANS [14] is used to find the most suitable locations for streetlights. However, the returned locations are not always legal. Therefore, breadth first search is applied to the output of KMEANS to determine the final locations of streetlights.

Wall construction: A wall, consisting of the wall base, plane and tower, is built in the outer part of the city to protect the residents. The height of the wall base is adjusted to fit the terrain. Torches and cannons are evenly placed on the plane.

An example of our generator's output is shown in Fig. 4.

III. EXPERIMENTS

Two sets of experiments are designed to test the performance of our generator. One aims at comparing the three building layout generation algorithms in different maps, and the other performs a user study, in which our city generator is compared with two outstanding ones from the 2022 edition of the GDMC.

Comparison of layout generation algorithms: The algorithms are tested on the four maps described in Table III. The total score of placing buildings according to the generated layout is computed to assess the corresponding algorithm. The population size, mutation rate and generation number in Algorithm 3 are set as $PopSize = 100$, $Pmut = 0.1$ and $NGeneration = 100$, respectively. Each algorithm is run 30 times. Fig. 3 shows the convergence curves.

TABLE III
MAP MESSAGE

Map	Map size	#Buildings	Ratio of plain
(a)	100	5	60.6%
(b)	100	5	48.2%
(c)	150	9	53.9%
(d)	150	9	25.2%

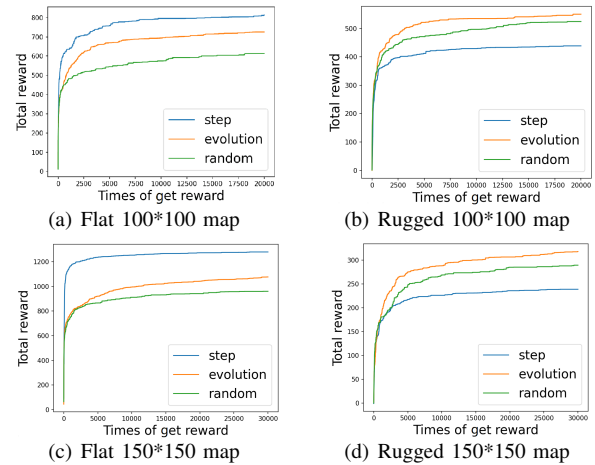


Fig. 3. Comparison among three algorithms on maps with different sizes.

In flat maps like (a) and (c), the heuristic-based layout generation algorithm can find a layout with an acceptable score quickly. It may be explained by the fact that this algorithm guarantees the legality of layout, thus there is no collision among buildings. However, it does not use previously generated layouts well, and performs poorly in some rugged maps like (b) and (d). In contrast, the evolving layout algorithm can generate better new layouts based on the good ones in the population, which significantly increases the efficiency.

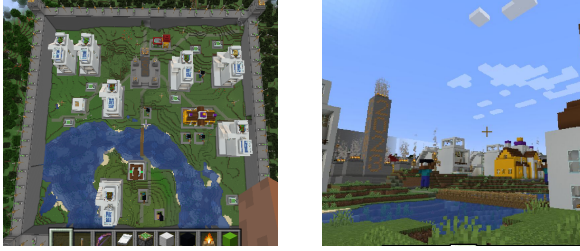


Fig. 4. Final output

User study: A user study is conducted following the evaluation criteria of GDMC to evaluate the performance of our generator. Six undergraduate and graduate students have participated. All of them are between 21 – 26 years old. They all have some basic knowledge of Minecraft. Our generated city is compared with two entries of GDMC’2022: *PandaVision* and *Medieval City* found on the competition website (<https://gendesignmc.engineering.nyu.edu/results>). *Medieval City* is the one with the highest overall score in GDMC’2022. *PandaVision* offers a detailed documentation which facilitate its usage.

Every participant needs to visit each city generated by the three works for at least five minutes in a first view. They are asked to rank the three generators with a score of 1-10 based on their performance on four criteria, *adaptation*, *functionality*, *believable and evocative narrative*, and *visual aesthetic* as in the competition’s official evaluation process. Table IV reports the user study with six participants.

Result shows that our generator performs better in adaptation, probably because it only reshapes the terrain slightly and considers the influence of terrain a lot. *PandaVision* generator flattens the entire building area and lays the stone slab directly, which looks out of place in the environment. The *Medieval City* generator performs badly on functionality. It does not pay enough attention to the accessibility of the city. Some ladders cannot be climbed, and some paths cannot be passed. Our generator outputs maps with poor narrative. That may be blamed to the hidden redstone structures in the buildings, that are hard to be seen by users.

IV. CONCLUSION

This paper designs a redstone style city generator to create a city on given Minecraft maps, as a competition entry to the GDMC’2023. Three algorithms are used to determine the position of buildings and are compared on maps with different sizes and terrain types. Our generator is compared with two

TABLE IV
RESULT OF USER STUDY.

Criteria	Redstone Technique	PandaVision	Medieval City
Adaptation	7.67	6.33	7.50
Functionality	7.50	7.33	6.67
Narrative	7.83	8.67	7.67
Aesthetic	7.33	8.50	7.50
Overall	7.58	7.71	7.33

representative entries of the GDMC’2022 and shows competitive performance according to user assessment. As future work, it is worth integrating building generation techniques (such as [9]–[11]) to increase the generator’s performance on *Narrative* and *Aesthetic* criteria while minimizing the human input for designing buildings. More professional participants will be invited to evaluate the generator comprehensively.

REFERENCES

- [1] S. C. Duncan, “Minecraft, beyond construction and survival,” *Well Played: a journal on video games, value and meaning*, vol. 1, no. 1, pp. 1–22, 2011.
- [2] S. Nebel, S. Schneider, and G. D. Rey, “Mining learning and crafting scientific experiments: A literature review on the use of minecraft in education and research,” *Journal of Educational Technology & Society*, vol. 19, no. 2, pp. 355–366, 2016.
- [3] M. Awiszus, F. Schubert, and B. Rosenhahn, “World-GAN: A generative model for minecraft worlds,” in *2021 IEEE Conference on Games (CoG)*. IEEE, 2021, pp. 1–8.
- [4] Z. Jiang, S. Earle, M. Green, and J. Togelius, “Learning controllable 3D level generators,” in *Proceedings of the 17th International Conference on the Foundations of Digital Games*, 2022, pp. 1–9.
- [5] A. Khalifa, P. Bontrager, S. Earle, and J. Togelius, “PCGRL: Procedural content generation via reinforcement learning,” in *Conference on Artificial Intelligence and Interactive Digital Entertainment*, vol. 16, no. 1. AAAI, 2020, pp. 95–101.
- [6] C. Salge, M. C. Green, R. Canaan, and J. Togelius, “Generative design in minecraft (GDMC) settlement generation competition,” in *Proceedings of the 13th International Conference on the Foundations of Digital Games*, 2018, pp. 1–10.
- [7] C. Salge, M. C. Green, R. Canaan, F. Skwarski, R. Fritsch, A. Brightmoore, S. Ye, C. Cao, and J. Togelius, “The AI settlement generation challenge in minecraft: First year report,” *KI-Künstliche Intelligenz*, vol. 34, pp. 19–31, 2020.
- [8] C. Salge, C. Guckelsberger, M. C. Green, R. Canaan, and J. Togelius, “Generative design in minecraft: Chronicle challenge,” in *International Conference on Computational Creativity*, 2019, pp. 311–315.
- [9] M. C. Green, C. Salge, and J. Togelius, “Organic building generation in minecraft,” in *Proceedings of the 14th International Conference on the Foundations of Digital Games*, 2019, pp. 1–7.
- [10] M. Barthet, A. Liapis, and G. N. Yannakakis, “Open-ended evolution for minecraft building generation,” *IEEE Transactions on Games*, pp. 1–10, 2022.
- [11] T. Merino, M. Charity, and J. Togelius, “Interactive latent variable evolution for the generation of minecraft structures,” in *Proceedings of the 18th International Conference on the Foundations of Digital Games*, 2023, pp. 1–8.
- [12] L. Clappers, “Simulation-based believable procedurally generated video-game villages,” Ph.D. dissertation, Thesis, 2021.
- [13] J. Demke, R. Morain, C. Wilhelm, and D. Ventura, “Multi-agent story-based settlement generation,” in *2021 IEEE 33rd International Conference on Tools with Artificial Intelligence (ICTAI)*. IEEE, 2021, pp. 1149–1153.
- [14] J. MacQueen *et al.*, “Some methods for classification and analysis of multivariate observations,” in *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability*, vol. 1, no. 14. Oakland, CA, USA, 1967, pp. 281–297.