Modular Procedural Generation for Voxel Maps

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Abstract—Task environments developed in Minecraft are becoming increasingly popular for artificial intelligence (AI) research. However, most of these are currently constructed manually, thus failing to take advantage of procedural content generation (PCG), a capability unique to virtual task environments. In this paper, we present mcg, an open-source library for facilitating implementing PCG algorithms for voxel-based environments such as Minecraft. The library is designed with human-machine teaming research in mind, and thus takes a ‘top-down’ approach to generation, simultaneously generating low and high level machine-readable representations that are suitable for empirical research. These can be consumed by downstream AI applications that consider human spatial cognition. The benefits of this approach include rapid, scalable, and efficient development of virtual environments, the ability to control the statistics of the environment at a semantic level, and the ability to generate novel environments in response to player actions in real time.

Index Terms—procedural content generation, voxel, minecraft, artificial social intelligence, game design

I. INTRODUCTION

Minecraft [1] has recently emerged as an attractive platform for artificial intelligence (AI) research [2]–[9] owing to its popularity, ease of instrumentation and modification, and its ability to support complex tasks in an open-world environment [10]. A voxel-based game environment such as Minecraft’s is well-suited for designing controlled AI experiments, as it enables researchers to access and manipulate precise details of the environment without having to deal with complications such as curvature or deformable objects. However, most Minecraft environments currently used in AI research [9], [11], [12] are constructed manually, thus failing to fully take advantage of a unique possibility afforded by a virtual environment - namely, the ability to generate environments procedurally.

In this paper, we present mcg, an library for procedurally generating voxel environments for AI research. The library is part of the ToMCAT project\(^1\) which is developing a suite of modular, open-source AI technologies to support human-machine teaming and a Minecraft-based testbed to evaluate them. The design of mcg addresses a number of requirements for AI research that are not sufficiently addressed by existing approaches.

The rest of the paper is organized as follows. In section II, we discuss why procedural content generation (PCG) is particularly important in the context of controlled experimental research. In section III, we describe our approach in relation to other existing work on PCG for AI research in Minecraft. In section IV, we describe how mcg integrates higher-level semantics into the PCG workflow to support human-machine teaming research. In section V, we present the core classes implemented in mcg, and in section VI, a tutorial that illustrates their usage. In section VII, we describe existing and potential integrations with downstream AI applications. Finally, we conclude in section VIII by summarizing progress, noting limitations, and describing our plans for future work.

II. PCG FOR AI RESEARCH

There are a number of reasons to favor procedural content generation over manual environment creation in a research context. We discuss the key ones in this section.

A. Parametric generation.

When designing an environment for human and artificial agents to perform tasks in, it is desirable to have fine-grained control over certain features of the environment, as they can have significant effects on task performance. For example, in a recent simulated urban search and rescue (USAR) experiment [11], there is a direct correlation between the size of the number of rooms in the building and the participants’ performance on the task. Similarly, other factors that influence their performance include the number of victims, their distribution in the building, and the presence and locations of obstacles that inhibit navigation.

Depending on the objectives of the experiment, some of these features will be control variables and others will be independent variables. In the case of features that serve as control variables, it is likely that the values of these variables are settled upon through a process of iterative experimental design. For example, designers of a synthetic USAR task environment (e.g., [11], [12]) will likely need to try a few different values for the number of rooms, the number of victims, the number of blockages, etc. in order to arrive at a configuration that satisfies the experimental requirements.

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\(^1\)https://ml4ai.github.io/tomcat

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A top-down procedural generation approach allows for rapid iteration over these different configurations, resulting in an accelerated experimental design process. As an example, we can go from a gridworld environment with four cells to one with 400 cells simply by changing a single parameter (see Figure 1).

Similarly, randomizing the environment is important for certain types of experiments. Indeed, this can be viewed as a special case of parametric generation, with the random seed serving as the parameter to be varied. In Figure 2, we show four possible dungeon layouts obtained by varying the size and random seed parameters passed to a dungeon world generator implemented using mcg.

B. Controlling the statistics of generated scenes

In experiments where environments matter, they should not be limited to what designers intuitively create. For example, simply saying “maybe this complex needs a cul-de-sac” to investigate how that would affect participants’ frustration levels in USAR scenarios does not lead to careful science. The feature needs to appear in different contexts with well defined probabilities to guard against confounding effects between the presence of the feature and its possibly unique or statistically biased context. While this could be arranged manually, doing so is tedious and harder to get right. On the other hand, specifying the environments procedurally forces researchers to be more clear about the logic of their experiment, makes development easier as modifications can be studied rapidly, and better supports extensions, scaling, and repeatability.

C. Changing the world in response to player action

The ToMCAT project is mandated to support a large range of behavioral psychology studies into team performance. It is easy to construct scenarios where we will need to change the Minecraft environment as a function of what the human players are doing, their affective state, brain activity (using EEG or fNIRS equipment), and where they are in the virtual environment. As such, it is not predictable where, and hence precisely what the needed modification will be. For example, suppose we are interested in how robust a team’s performance is to unexpected events such as a room collapse specifically when the team members cannot see each other. To do this, we would need to programatically collapse a room in the task environment according to a defined stochastic process, but only when they are out of view of each other. In particular, the room that needs to collapse is not known in advance. While we could have a single room collapse model manually specified for each room, the awkwardness of this approach amplifies with each additional changeable feature. For example, a second room collapse entails being ready for any two rooms to change in any order.

Currently, mcg supports this kind of programmatic change in a scalable manner, since the high-level representation it outputs provides semantic ‘hooks’ that a Minecraft mod can leverage to preserve the desired collapse models across task environments with different numbers of rooms, varied room layouts, and scenarios in which different numbers of rooms will need to be collapsed. While the existing executables built using mcg write files to disk, it is conceivable that the library could be used to provide a ‘PCG as a service’ program that can generate complex environment specifications on the fly.
D. Task environments as code

Initially, the task environments for the ToMCAT project were built manually, rather than procedurally. As the experimental design evolved, it became quickly apparent that we would need to keep track of the different versions of the task environment, so that (i) it would be easy to revert back to an older version if necessary, and (ii) the version could be added to the provenance for a given experimental trial.

While source code management (SCM) systems (e.g., git [14]) excel at version management, they are designed for text files rather than binary files such as the ones corresponding to the manually-constructed Minecraft environments. Managing binary files (especially ones that are liable to change frequently, as is the case with an iterative experimental design process) with SCM systems results in the source code repository getting bloated, hindering developer productivity and collaboration.

For these reasons above, we decided to maintain versions of the binary save files on a public server that developers could access. However, we soon realized that this approach had its own share of problems, the most troublesome of which was the fact that every change to the environment required manually uploading the updated binary files to our server, making it easy for the environment to get out of sync with the source code of the ToMCAT Minecraft mod.

Switching to procedurally generated environments addresses all of these issues - taking an ‘environment as code’ approach allows us to effectively leverage SCM systems to manage environment versions, making tasks like reverting back to a previous version or comparing versions much easier than with manually constructed environments. In addition, we no longer have to worry about manually synchronizing the task environment and the code that interacts with it - the SCM system takes care of this for us.

III. Decoupled PCG for rapid iteration

There exists prior work on procedural generation to support AI experiments in Minecraft. Notably, Project Malmo [2] provides a declarative XML-based API to specify ‘missions’, including the parametric generation and placement of individual blocks, entities, and simple structures such as spheres and cuboids. In addition, it supports implementing custom procedural generation algorithms as Java classes in the Malmo mod and exposing them via the XML API.

However, the procedural generation capabilities in Project Malmo are tightly coupled with Minecraft itself - to view the results of a procedurally generation algorithm implemented in a Malmo class, one would need to recompile the Malmo mod and relaunch Minecraft with it loaded. This process is fairly slow and does not fit well into a workflow that involves the need for rapid iteration through environments. Ideally, there should be a way to visualize the outputs of procedural generation without having to launch the full game.

In contrast, our library is decoupled from Minecraft - it outputs declarative specifications of an environment that can be consumed by other downstream applications, including a Minecraft mod that can translate the specification into ingame entities, blocks, and structures. The data structures and algorithms in our library are general enough that they could be used for any other voxel-based environment - the only things that would need to be modified are the labels for the block and entity types.

IV. Connection to human spatial cognition

One of the primary motivations for developing mcg was to explicitly inject high-level semantic information (labels of relevant locations and structures, layout and topology, etc.) into the generation process. The Malmo API and the Minecraft Forge event bus give us access to low-level information about the positions of the player and individual blocks in the environment. However, humans tend to reason about their environment at a high level of abstraction. For example, a human carrying out tasks in a Minecraft environment will tend to think about ‘rooms’ and ‘buildings’ rather than the individual blocks that the structures are comprised of.

Furthermore, humans rely on high-level spatial representations of their environment for navigation [15]. These representations have been hypothesized to take the form of Euclidean maps [16] or graph-like representations [17], though there is evidence that both representations may be simultaneously maintained and used in different contexts [18].

One way to incorporate high-level semantics is by manually specifying location boundaries, labels, and hierarchies after an environment is built. However, this method is prone to human error and bottlenecked by the time it takes for humans to annotate regions and identify area boundaries in a prebuilt map. This method will certainly not scale to large or stochastically generated maps.

In contrast, the mcg library takes a ‘top-down’ approach, producing the following machine-readable representations simultaneously, in lockstep with each other:

- **High-Level Representation (HLR)**: Also known as a ‘semantic map’, this is a JSON file that contains information about the labels and locations of areas, their connections with each other, and their hierarchical relationships, as well as the Entity and Object instances in the environment. This representation supports linking explicitly to human spatial cognition.

- **Low-Level Representation (LLR)**: This is a JSON file that contains low-level information about all the blocks and entities in the environment. Among other uses, this representation can be consumed by a Minecraft mod to generate an environment procedurally, but with the actual PCG algorithms offloaded to the mcg library.

These specifications can then be used by other programs, some examples of which we describe in greater detail in section VII.

V. Approach

The mcg library provides a set of core components that can be extended and composed to design rich voxel-based task environments. In this section, we briefly describe these
components\(^2\) and the design philosophy behind them, followed by a tutorial on how to use the library.

A. Core classes

1) **Pos**: This class represents a point in the three-dimensional integer lattice \((Z^3)\) [19] - or in other words, a vector in a 3D Euclidean space with the constraint that its Cartesian components are restricted to integer values, reflecting the voxelated nature of the Minecraft environment.

2) **AABB**: An axis-aligned bounding box (AABB) is an elementary cuboidal structure that can be efficiently represented using a pair of 3D coordinates that correspond to vertices on opposite ends of one of its space diagonals. The AABB class instantiates an empty cuboidal space that effectively serves as a blank canvas to implement PCG algorithms in. For example, one could implement Perlin noise generation [20], [21] to add water blocks within an AABB made of grass to create a water body, or constrained growth algorithms [22], [23]. AABBs of different types can be defined using mcg by subclassing the AABB class, and can be manipulated, nested, and combined to produce complex structures (see Figure 3).

3) **Block**: This class represents a single Minecraft block with a given material and position. It allows for fine-grained placement of individual blocks in the game environment - for example, the diamond and gold treasure blocks in Figure 2.

4) **Entity**: This class represents an entity that is to be placed in the task environment. The constructor for this class takes two required arguments - the type and position (a Pos object\(^3\)) of the entity, and a set of optional arguments corresponding to the different equipment types that a Minecraft entity can have. We use this class to generate and place the wither skeletons and blazes in the dungeons in Figure 2.

5) **World**: This class represents the overall environment, and contains the lists of the AABBs, Blocks, Entities, Objects and Connections in it as class attributes.

6) **Object**: An object represents a Block with some additional semantics. An instance of this class contains information about an id, type, and Block associated with the Object. It is particularly useful in cases where a Block holds some semantic meaning, like the victim blocks in [11].

7) **Connection**: The Connection class represents a spatial connection between AABBs. It is meant to encompass a variety of structures that can fall under the semantic label of ‘connection’ - it can be used to represent both ‘point-like’ connections (e.g., a door between rooms) and ‘extended’ connections (e.g., a corridor that connects two locations). Some care must be taken with spatial translation, as the semantic building blocks of mcg are double-precision floating point numbers, we restrict them to be integers in mcg for simplicity.

\(^2\)The full documentation for the C++ API can be found at https://ml4ai.github.io/tomcat/cpp_api/index.html.

\(^3\)While Minecraft allows for the components of the Cartesian coordinates of Entity objects to be double-precision floating point numbers, we restrict them to be integers in mcg for simplicity.

Fig. 3: Axis Aligned Bounding Boxes (AABBs). We use AABBs as the semantic building blocks of mcg. They can be combined and nested into larger AABBs to form complex structures that are addressable as semantically meaningful components. In this figure, we show an example of a location hierarchy formed by nesting AABBs.
in AABB objects and World objects, a potential workaround for this issue would be to instantiate connections dynamically when AABB are moved around.

VI. TUTORIAL

In this tutorial, we showcase some of mcg’s capabilities and demonstrate how to use the classes described in section V. The goal of this tutorial will be to create a house with two rooms and a zombie in a purely programmatic manner.

A. World Setup

We start by creating an empty world. In a file named mcg_tutorial.cpp, we will add the following:

```cpp
#include "mcg/World.h"
using namespace std;

class TutorialWorld : public World {
public:
    TutorialWorld() {};
    ~TutorialWorld(){};
};

// Create the world and write the JSON output to file.
int main(int argc, char* argv[]) {
    TutorialWorld world;
    world.writeToFile("semantic_map.json", "low_level_map.json");
    return 0;
}
```

This minimal program will produce two files, semantic_map.json and low_level_map.json that correspond to the HLR and LLR respectively. The LLR is used by the WorldBuilder class in the ToMCAT Minecraft mod to construct the environment. At this point, the generated world will be empty.

B. Creating a room

We will now add single room to this world. To do so, define a class called Room that extends AABB, and whose constructor takes a string identifier and a Pos object that represents the top left corner of the room.

```cpp
#include "mcg/AABB.h"
class Room : public AABB {
public:
    Room(string id, Pos& topLeft) : AABB(id) {
        // Set the base material to be 'log'
        this->setMaterial("log");
        // Define the object's boundaries
        Pos bottomRight(topLeft);
        bottomRight.shift(5, 4, 5);
        this->setTopLeft(topLeft);
        this->setBottomRight(bottomRight);
    }
};
```

This will give us a room made of logs with a 6×6 block base and a height of 5 blocks. Finally, modify the TutorialWorld constructor to place a Room instance at (1, 3, 1). The constructor should now look as follows:

```cpp
tutorialWorld() {
    Pos topLeft(1, 3, 1);
    auto room1 = make_unique<Room>("room_1", topLeft);
    this->addAABB(move(room1));
}
```

C. Adding details

We will now add some details to this room - namely, a floor, roof, windows, and a zombie (see Figure 4). This is accomplished by adding the following to the Room constructor.

```cpp
// The floor should be made of planks
this->generateBox("planks", 1, 1, 0, 4, 1, 1);
// Add windows made of glass
this->generateBox("glass", 0, 5, 1, 1, 1, 1);
this->generateBox("glass", 5, 0, 1, 1, 1, 1);
this->generateBox("glass", 1, 1, 1, 1, 0, 5);
// Add a roof (will be made of logs)
this->hasRoof = true;
// Add a zombie
mt19937_64 gen; // Random number generator engine
Pos randomPos = this->getRandomPos(gen, 1, 1, 1, 2, 1, 1);
auto zombie = make_unique<Entity>("zombie", randomPos);
this->addEntity(move(zombie));
```

D. Multiple rooms

Finally, we will combine two Room instances to create a house. To do this, we create a second Room instance and add both rooms to an enclosing AABB. This is done by adding the following code to the TutorialWorld constructor:

```cpp
Pos topLeft(1, 3, 1);
auto room1 = make_unique<Room>("room_1", topLeft);
auto room2 = make_unique<Room>("room_2", topLeft);
room2->shiftX(5);
```

Note that the coordinates passed to the generateBox method are relative to the AABB itself, so we do not need to respecify them when placing a second room.

4To actually view the generated environment in Minecraft, you can use the script tools/run_mcg_tutorial that is included in the repository.

5By the 'top left' corner of an AABB, we mean the corner with the lowest values of the X, Y and Z coordinates.

6We set the y-coordinate to 3 to match the level of the ground in the Minecraft world.
auto house = make_unique<AABB>("house");
house->addAABB(move(room1));
house->addAABB(move(room2));
this->addAABB(move(house));
...

Figure 4: This figure shows the TutorialWorld Room with all the details added in subsection VI-C. It now has a floor made of planks, windows on three sides, a roof, and a zombie.

Figure 5 shows the completed TutorialWorld with a house that has two rooms. The code for this tutorial along with instructions on how to compile and run it can be found in the libs/mcg/examples/mcg_tutorial folder.

Figure 5: This figure shows the completed TutorialWorld house. It has two rooms, each with the details added in subsection VI-D.

VII. APPLICATIONS

The machine-readable high-level and low-level representations that are simultaneously produced by mcg can be consumed by a number of downstream applications. We divide them into two broad categories: agents and non-agents.

As mentioned earlier, mcg is being developed as part of the ToMCAT project [7], which is in turn part of DARPA’s Artificial Social Intelligence for Successful Teams (ASIST).

program [24]. The testbed developed for the program [12] publishes real-time measurements of each participant’s state, environment, and actions in Minecraft to an MQTT message bus [25], along with data from other sources such as physiological sensors and pre and post-task questionnaires.

The term ‘agent’ is a fairly overloaded one. However, in this paper, we use the term to refer to programs that the various ASIST performer teams are developing that subscribe to topics on the message bus, process it in a streaming manner, and publish their outputs back to the message bus, where they can potentially be used by other, downstream agents.

In contrast, we use the term ‘non-agents’ to mean software components that are not primarily designed to process streams of information. The potential applications and their relation to the high and low level representations are shown in Figure 6.

A. Non-agents

1) mcgen: The mcgen program is being developed for ToMCAT experiments, and is representative of generator executables that can be built using mcg. The environments shown in Figure 1, Figure 2, and Figure 7 are all generated using mcgen.

2) mcgviz: mcgviz is a Python script included with mcg, that takes the HLR and LLR output by mcg to produce visualizations of the environment. Using the HLR, it can construct either a graph structure (e.g. Figure 7a) or a ‘blueprint’ style visualization showing a top-down view of the AABBs in the generated environment (see Figure 7b). It can also combine the LLR and HLR to provide a more detailed map with individual colored patches corresponding to the different types of blocks in the environment.

3) ToMCAT mod: The ToMCAT mod is a Minecraft mod that builds upon the Malmo mod [2] with additional functionality for human-machine teaming research. Currently, the
LLR produced by mcg is consumed by the ToMCAT mod to construct the in-game environment (see Figure 7c).

B. Agents

1) LocationMonitor: The LocationMonitor agent developed by IHMC [26] for the ASIST program uses a ‘semantic map’ - that is, the HLR output by mcg - to construct an internal representation of named locations (e.g. rooms, hallways) with their boundaries and connections to other named locations. Using this internal representation, it monitors the player’s position (in Cartesian coordinates) and publishes a message to the message bus whenever a player goes from one named location to another.

2) PyGL-FoV: PyGL-FoV [27] is an agent that uses observations of the Cartesian coordinates of the player, the pitch and yaw of the gaze vector of their Minecraft avatar, and a low-level representation of the environment to compute whether certain blocks of interest are visible on the player’s screen at any given time.

3) Dialog Systems: There is growing interest in using Minecraft as an environment to develop dialog-enabled artificial agents [3], [7], [28]. Dialog systems such as the ToMCAT DialogAgent8 rely on a taxonomy of concepts to ground natural language extractions to. In order to ground to specific locations that are referred to by participants (especially if they have been provided a blueprint with the location labels beforehand), the taxonomy will need to incorporate location names - the HLR produced by mcg can be used to automate the construction of the spatial portion of the taxonomy.

4) Planning and Plan Recognition Systems: The HLR produced by mcg contains information about named locations and their connections to each other - it can be used to automatically construct portions of formal planning domain and problem specifications related to spatial information. For example, the connectivity information in the HLR can be used to automatically generate a number of predicates such as connected(L1, L2) (i.e., AABBs L1 and L2 are connected), and the hierarchical relations in the HLR can be used to construct predicates such as contains(L1, L2) (i.e. the AABB named L1 contains the AABB named L2).

5) Probabilistic Modeling Systems: Probabilistic models of participants performing tasks in Minecraft (e.g., [29]) can also make use of the HLR produced by mcg to construct initial concise internal representations of the task environment.

In general, developing AI agents with machine social intelligence will require some kind of explicit high-level environment representation to reason about the beliefs, desires, and intentions of their human partners. mcg treats this high-level representation as a first-class citizen in its generation framework.

VIII. CONCLUSION

In this paper, we laid out the motivations for incorporating procedural content generation into human-machine teaming experiments, and presented our open-source C++ library, mcg, which integrates low-level content generation with high-level semantics in order to support human-machine teaming research. The library provides a set of core components that can be extended and composed to construct detailed voxel maps while simultaneously generating machine-readable representations of the environment that can be used by downstream programs.

A. Limitations

1) Aesthetic concerns: It is worth noting that generating a structure with non-rectilinear geometry - for example, something like the Sydney Opera House [30] - will be more difficult to do procedurally than manually. In general, if
aesthetic appeal is a significant concern (like it is in the GDMC settlement generation competition [31]), an AABB-based procedural generation approach is likely not an ideal one. However, in the context of controlled human-machine teaming experiments, we expect that the fine-grained control, reproducibility, and scalability afforded by mcg will outweigh the aesthetic benefits of manual environment generation.

2) Programming overhead: Another potential concern with a procedural generation approach to Minecraft task environment creation is that it is easier to train people to manually modify Minecraft environments than to write programs to generate the environments procedurally. This is not an insignificant concern, especially when considering that human-machine teaming experiments are often designed in collaboration with researchers who are not used to writing C++ programs. However, our stance is that the benefits of using a PCG approach (and the downsides of manual environment creation) are significant enough to warrant investing in procedural generation.

B. Future work

We intend to continue to develop mcg as a part of the ToMCAT project. Along with making it easier to use and better documented, we will implement additional AABB-based algorithms to enable researchers to create rich, yet controlled voxel-based virtual task environments for human-machine teaming research.

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