Towards Objective Metrics for Procedurally Generated Video Game Levels

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Abstract—With increasing interest in procedural content generation by academia and game developers alike, it is vital that different approaches can be compared fairly. However, evaluating procedurally generated video game levels is often difficult, due to the lack of standardised, game-independent metrics. In this paper, we introduce two simulation-based evaluation metrics that involve analyzing the behavior of a planning agent to measure the diversity and difficulty of generated levels in a general, game-independent manner. Diversity is calculated by comparing action trajectories from different levels using the edit distance, and difficulty is measured as how much exploration and expansion of the A* search tree is necessary before the agent can solve the level. We demonstrate that our diversity metric is more robust to changes in level size and representation than current methods and additionally measures factors that directly affect playability, instead of focusing on visual information. The difficulty metric shows promise, as it correlates with existing estimates of difficulty in one of the tested domains, but it does face some challenges in the other domain. Finally, to promote reproducibility, we publicly release our evaluation framework.

Index Terms—metrics, evaluation, procedurally generated content, planning.

I. INTRODUCTION

PROCEDURAL Content Generation (PCG) is a large field [1, 2] with many different approaches, ranging from genetic algorithms [3] to reinforcement learning [4]. A major problem, however, is the lack of comparable metrics between different games and works of literature. For example, Ferreira et al. [3] simply state that their method generates levels that are similar to the original Super Mario Bros. levels, without defining a similarity metric. It is therefore difficult to compare these results, as they usually measure different aspects, and often do not use the same units or methods of measuring.

We test our methods on a Maze game as well as Super Mario Bros. Our results indicate that our diversity metric displays desirable characteristics, such as invariance to visual changes that do not affect playability, as well as being less sensitive to the size or representation of the tested levels than the metrics we compare against. The difficulty metric correlates with existing measures in one of the tested domains, but fails to do so in the other.

II. RELATED WORK

How one chooses to evaluate generated levels for comparison between different methods is important in PCG. Many evaluation schemes, however, are mostly ad hoc and not easily transferable to other scenarios. For example, Khalifa et al. [4] use preset “goal” criteria to evaluate the level. These criteria stipulate that there should be a lower bound on the number of steps needed to solve a level, and that specific objects must occur a certain number of times (e.g. there must be 1 player, 1 door, etc.). Liapis et al. [8], who use an evolutionary approach, mainly report population-based metrics, such as how many individuals in the final population were feasible (i.e. playable and valid according to the game engine), and how diverse the feasible population is. Diversity between two tilemaps here is measured as the average number of non-matching tiles.

Most of the metrics are defined for a single level, measuring difficulty, and quality. Horn et al. [9] echo this sentiment and attempt to create a valid range of metrics that can be used to evaluate levels, but these have not been widely adopted. Most of the metrics are defined for a single level, measuring aspects like linearity (how well a level can be described by a straight line), density (how many platforms are stacked on top of each other in platform games), and leniency (how easy a level is). One metric that compares the diversity of levels is the compression distance, which measures the relative similarity between two levels from the same generator. The authors add that promising future work could be to use a simulation-based evaluation score, where an agent plays the generated level, and its behaviour is used to score the level.

Evaluating procedurally generated content is thus a major challenge, since different works adopt different game-
specific approaches, preventing fair comparisons and hindering progress in the field as a whole.

III. EXISTING AND PROPOSED METRICS

We now describe existing metrics and present our new simulation-based metrics. Our proposed metrics are general and evaluate the diversity and difficulty of generated levels without requiring game-specific configuration or human interaction. We compare them to the compression distance and leniency metrics respectively.

A. Existing Metrics

1) Compression Distance: Compression distance (CD) is a metric that measures the similarity between two strings by determining how much space is saved by compressing them as one concatenated string, compared to compressing them separately [10]. In the case of PCG, we simply use a string representation of the levels under consideration.

The normalised compression distance (NCD) is defined as

\[ \text{NCD}(x, y) = \frac{C(xy) - \min\{C(x), C(y)\}}{\max\{C(x), C(y)\}} \]

where \( C(x) \) is the length of the string \( x \) after compressing it, and \( xy \) is simply the concatenation of \( x \) and \( y \). The intuition is that strings that are very similar will have a low NCD value as compressing them together can take advantage of their similarities. On the other hand, strings that are very different will have a higher distance, as compressing them as one string does not offer much benefit over compressing them separately. For clarity, we refer to this metric (using gzip as the compression algorithm) simply as CD.

Shaker et al. [6] apply this to platformer levels by generating a feature for every column in the map, which is determined by various aspects, like an increase or decrease in platform height, the start or end of a gap, the existence of enemies and other blocks, as well as their combinations. This string of features is then used as the string representation of a level. For the Maze Game, we simply flatten the map, and thereby obtain a binary string that represents the level, where zeros and ones represent free space and walls respectively.

2) Leniency: Leniency is a metric that measures how lenient a level is to a player’s mistakes. Originally defined for platformers by Smith et al. [5], it was determined by averaging the leniency score for each of the potential challenges in a level, and normalising that to a value between 0 and 1. These challenges could be a gap or an enemy (with a leniency value of \( l = -1 \)), a jump without an associated gap (\( l = 1 \)), and various other elements. We follow the approach of Shaker et al. [6], who use leniency in the context of Super Mario Bros. by slightly adapting the metric described above.

For the Maze game, it is not immediately obvious how to apply this metric, since there are no inherent challenges. We therefore elect to calculate leniency as the fraction of paths that result in dead ends. For each unfilled tile \( t \), we find the shortest path from the start \( s \) to \( t \). We then fill in this path and determine if there is still a path from \( t \) to the goal \( g \). Tile \( t \) is labelled as a dead end only if no such path exists.

B. A* Diversity

We assume that diverse levels require diverse solutions [11], and we thus look at the differences in solution characteristics between two levels to calculate their diversity.

To measure the diversity between two levels, we simply run our A* agent separately on each level, and consider the actions that the agent performed as integers specifying a single discrete action (like moving to the right in the Maze game). We use these action strings to evaluate how different the levels are, using the Levenshtein (or edit) distance [12], so that trajectories of different lengths can be compared. We normalise this distance by dividing it by the length of the longer string.

This diversity metric measures levels that can be solved using closely-related approaches as similar, and other levels that have drastically different paths as diverse. This method thus focuses on the characteristics of a level that actually affect the playability, instead of being distracted by different (but potentially irrelevant) visual information.

There might be some potential problems with this metric, however. Specifically, we use actions to distinguish levels, and some actions might not affect the environment, such as walking into a wall [11]. This is mitigated by using an agent that rarely performs unnecessary actions. A second possible shortcoming is that multiple actions might result in roughly the same path (e.g., moving to the right in Super Mario Bros. is often equivalent to jumping right), leading to noise in the metric. Again though, using the same agent in all cases leads to consistent and comparable actions.

We further compute the correlation between this edit distance-based metric and a similar one that uses the average Manhattan distance between corresponding positions, which should be less affected by small differences in actions. We find a high correlation (Pearson’s \( r > 0.7, p < 0.05 \)), indicating that this phenomenon does not have a large effect.

Finally, we re-emphasise that this method is not constrained to only use A*, and it can be used with any game-playing agent, such as an evolutionary controller or reinforcement learning agent.

C. A* Difficulty

We measure the difficulty of a level as the number of nodes that the A* agent expands that are not along the optimal path, divided by the total number of reachable states. The justification for this is that levels that are more difficult and contain more dead ends will require more exploration, and thus more expansion of the search tree. On the other hand, easier levels, where there is a simple unobstructed path between the start and the goal, will require much less searching, as the heuristic will lead the agent directly to the goal.

IV. RESULTS

We investigate two tilemap-based games. The first is a simple Maze game where each tile can be a wall or empty space, and the goal is to find a path between the top left corner and the bottom right corner. We use the Manhattan distance to the goal as the A* heuristic here. The second game we consider is a simplified version of Super Mario Bros., with
only Goombas as enemies, and no powerups. We use the A* agent by Robin Baumgarten\textsuperscript{2} [13], where the heuristic is based on the estimated time to reach the rightmost point of the screen. Example levels can be seen in Fig. 1.

We evaluate levels generated using a variety of methods: PCGRL [4], a genetic algorithm approach [3], and a method that uses NeuroEvolution of Augmenting Topologies [14] combined with novelty search [15] to evolve level generators. This latter method was also used to generate levels of different sizes, as it proved the fastest and generated mostly solvable levels.

A. Diversity

When comparing these two diversity metrics, we find a few specific characteristics and major flaws of compression distance:

1) Compression distance is sensitive to the exact string representation used, and there is a marked difference between simply flattening the Super Mario Bros. levels and using a more game-specific feature representation.
2) The compression distance increases with the size of the level, while the variance decreases. Larger levels are thus all marked as having approximately the same diversity score, regardless of their actual content.

To illustrate these shortcomings, we consider the distribution of diversity scores, i.e. if we have 100 levels, there are \( \frac{(100)(99)}{2} = 4950 \) pairwise comparisons, and we consider all of these values for 5 different random seeds.

Fig. 2 shows that the compression distance is quite sensitive to the exact representation used. We consider three different representations: firstly “Normal”, as described above and detailed by [6, 16]. Secondly, we use “Concatenated”, which is similar to Normal, but we instead concatenate the strings representing the platform height and the enemy placement respectively [16]. Finally, we consider “Flat”, where we simply flatten the 2D array of tiles. We find that the correlation between these methods, especially for the Flat representation, is not very large. Normal and Concatenated are better correlated, however, as they are related. Our method, however, does not suffer from this problem, as it is completely independent of the representation used.

\textsuperscript{2}https://github.com/amidos2006/Mario-AI-Framework/tree/master/src/agents/robinBaumgarten

Fig. 3 shows that as the level size increases, the mean of the compression distance becomes larger, while its variance reduces. By contrast, the A* diversity metric shows less dramatic changes when the level size increases. We also note that our metric marks many pairs of levels as being identical (i.e. A* diversity = 0), as the same set of actions solved both levels, which is something that the compression distance does not do. We see a similar effect for Super Mario Bros. in Fig. 4, but it is much more pronounced when using the flat representation.

Finally, to illustrate that compression distance also considers visual information that does not affect the playing experience of the level, we generate a set of 30 × 30 levels with one unchanging path from the start to the end. The rest of the tiles, which are unreachable, are randomly set. A few of these levels can be seen in Fig. 5, with results shown in Fig. 6. Compression distance does not make a distinction between arbitrary visual differences and differences in playable area, and thus assigns most pairs of levels high diversity, whereas the A* diversity metric marks all levels as identical.

Thus, compression distance has some undesirable characteristics that make it less suitable as a comparable, objective metric. Concretely, it is very dependent on the specific string representation used, as well as the size of the levels under consideration. By contrast, the A* diversity metric is independent of the level representation used, and is less affected by
4

(a) The compression distance values become increasingly meaningless as the level size increases.

(b) By contrast, the A* Diversity is not as affected by the level size.

Fig. 3: Distributions of diversity metrics for the Maze domain. Each colour represents the metric values from pairwise comparisons over 5 seeds and 100 levels per seed for different level sizes. Only solvable levels that were generated using one specific method were considered (to fairly compare against the A* metric, which requires solvability), but the compression distance trend also holds for random levels.

changes such as level size.

B. Difficulty

We next analyse the A* difficulty metric, comparing it to the preexisting leniency metric. When comparing the leniency of a collection of levels with their A* difficulty score, we find a Pearson’s correlation coefficient of $-0.17$ ($p = 3.4 \times 10^{-30}$) over $\pm 4000$ levels for the Maze, and we find no statistically significant correlation over $\pm 2500$ levels for Super Mario Bros. We next investigate whether there exists a correlation between the original Super Mario Bros. levels and the metrics above; in particular, whether later levels imply a higher difficulty (lower leniency) than earlier levels. We use the implementation\(^3\) from Horn et al. [9] to measure the leniency of a subset of 10 of the original levels, but we find no statistically significant correlation between the level index and difficulty for either leniency or the A* metric. This might indicate that later levels are not necessarily more difficult than previous ones, but rather just different due to, for example, new enemies or features. During this experiment, we also found that some levels were not solvable by the A* agent, since it usually took a greedy path to get to the rightmost point of the screen, and some levels had barriers that needed to be surpassed with backtracking.

We next perform a similar experiment on the Maze domain using mazes generated according to a desired difficulty,\(^4\) which we treat as a ground-truth label. We seek to determine whether our metric is able to distinguish easy mazes from harder ones by generating 20 levels (of size $40 \times 40$) for each of the 5 difficulty categories ranging from “very easy” to “very difficult”.

The results are shown in Fig. 7, where we observe a general increase in A* difficulty as ground-truth difficulty increases, although “moderate”, “difficult” and “very difficult” are marked as similar by our metric. The $p$-values indicate that “very easy” and “easy” levels indeed have lower A* difficulty scores than “moderate”, “difficult” and “very difficult”. By contrast, the leniency score increases with the ground-truth difficulty. This is unexpected, as a higher leniency actually implies a lower difficulty, and suggests that the leniency measure does not always correspond to human notions of difficulty.

To determine whether these results generalise, we perform the same experiment using a different maze generator.\(^5\) While noisier, the results still indicate a similar trend in that the easiest difficulty is rated by the A* difficulty metric to be easier than the hardest one. The results for leniency are similar to what is shown in Fig. 7b, although there is much less variance in the leniency scores, with all difficulties, except for the most difficult one, being marked as similarly lenient.

V. DISCUSSION, FUTURE WORK AND CONCLUSION

We introduce two general agent-based metrics that measure the diversity and difficulty of levels. These metrics do not require any game-specific knowledge or intricate feature representations, but simply a game engine and an agent. Our diversity metric is more expressive than compression distance for the Maze game, and is not as dependent on the size of the levels, or the string representation used.

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\(3\)http://sokath.com/fdg2014_pcg_evaluation/

\(4\)http://www.glassgiant.com/maze/

\(5\)https://github.com/mwmancuso/Personal-Maze
Fig. 4: Illustrating the diversity metrics as level size increases in the Super Mario Bros. domain. (a–c) For all level representations, the compression distance displays sensitivity to the level size. Further, for a fixed size of levels, the different representations display drastically different distributions, mirroring Fig. 2’s results. (d) Our diversity metric is robust to increases in level size.

Fig. 5: Example levels that are visually similar while playing identically. The solution path (shown in green) is identical for all levels.

Promising avenues for future work also include comparing the A* diversity metric to the KL-Divergence based score introduced by Shu et al. [18] or against human judgements of diversity. A learning-based approach could also be used to measure difficulty, where the difficulty is proportional to how long an agent (e.g. a reinforcement learning agent) needs to learn before being able to solve a level [19]. Different types

Fig. 6: Showcasing the diversity metric values for levels that only differ visually in the Maze domain. Compression distance rates all levels as diverse, despite the fact that they are functionally identical.
of agents can even be used to approximate different levels of player skill [20].

Overall, we believe that the metrics proposed here are a step towards standardising the evaluation of procedural content generation—an important step in accelerating research in the field.

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