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Department of Computer Science
and Engineering
University of Minnesota
4-192 Keller Hall
200 Union Street SE
Minneapolis, MN 55455-0159 USA

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Generating Sokoban Puzzle Game Levels with Monte Carlo Tree Search

Bilal Kartal, Nick Sohre, Stephen Guy

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Bilal Kartal, Nick Sohre, and Stephen J. Guy
Department of Computer Science and Engineering
University of Minnesota
(bilal,sohre,sjguy)@cs.umn.edu

Abstract
In this work, we propose a Monte Carlo Tree Search based approach to procedurally generate Sokoban puzzles with varying sizes. We propose two heuristic metrics surrounding box path congestion and level terrain to guide the search towards interesting puzzles. Our method generates puzzles through the simulated game play itself, guaranteeing solvability in all generated puzzles. Our algorithm is efficient, capable of generating challenging puzzles very quickly (generally in under a minute) for varying board sizes. The ability to generate puzzles quickly allows our method to be applied in a variety of applications such as procedurally generated mini-games and other puzzle-driven game elements.

1 Introduction
Understanding and exploring the inner workings of puzzles has exciting implications in both industry and academia. One way we can deepen this understanding is by studying the computer generation of puzzle games. Many games have puzzles either at their core (e.g. Zelda: Ocarina of Time, God of War) or as a mini-game (e.g. lock picking and terminal hacking in Fallout4, Mass Effect 3). Generating these puzzles automatically could reduce bottlenecks in design, and help keep games new, varied, and exciting.

Here, we study the puzzle game of Sokoban. Developed for the Japanese game company Thinking Rabbit in 1982, Sokoban involves organizing boxes by pushing them with an agent across a discrete grid board. Sokoban is well suited for consideration for several reasons. A well-known game, Sokoban exhibits many interesting challenges inherent in the general field of puzzle generation. For example, the state space of possible configurations is very large (exponential in the size of the representation), and thus intractable for search algorithms to traverse. Consequently, ensuring generated levels are solvable can be difficult to do quickly. Furthermore, it is unclear how to characterize what makes an initial puzzle state lead to an interesting or non-trivial solution. While Sokoban has relatively straightforward rules, boards of similar size can present a challenge for human solvers.

In this paper, we propose a method to procedurally generate Sokoban puzzles. Our method produces a wide range of puzzles of different board sizes of varying difficulty as evaluated by a novel metric we propose (Figure 1). Beyond simply being able to generate more content for Sokoban enthusiasts, we can envision puzzles such as these used as inspiration or direct input to game elements that correspond well to puzzle mechanics. Furthermore, human designed puzzles only represent a small fraction of the possible puzzle space. Having efficient ways to generate puzzles can enable the exploration of never before seen puzzles.

Currently, the state of the art in Sokoban puzzle generation tends to use exponential time algorithms that require templates or other human input. As a result, these methods can take hours or even days to generate solvable puzzles even on small boards. Finding ways to address this issue can significantly enhance our ability to achieve the potential benefits of procedurally generating Sokoban puzzles.

Motivated by the challenges and current limitations of the field, we propose the use of Monte Carlo Tree Search (MCTS) for this problem. We show that the generation of
Sokoban puzzles can be formulated as an optimization problem, and apply MCTS guided by an evaluation metric to estimate puzzle difficulty. Furthermore, we model the search such that puzzles are generated by simulated game play. This alleviates current bottlenecks by eliminating the need to verify the solvability of candidate puzzles post-hoc. Overall, the contributions of this work are three-fold:

- We formulate the generation of Sokoban puzzles as an MCTS optimization problem.
- We propose a heuristic metric to govern the evaluation for the MCTS board generation and show that it produces puzzles of varying difficulty.
- Our method eliminates the need to check post-hoc for board solvability, while maintaining the guarantee that all of our levels are solvable.

The rest of this paper is organized as follows. Section 2 highlights background on related work on Sokoban puzzle game and Monte Carlo Tree Search. Section 3 presents our approach to the puzzle generation problem. In Section 4, we present results and analysis on the performance of our approach along with comparisons of both different bandit algorithms and generated game levels. Finally, Section 6 concludes the paper with limitations of our approach and future work.

2 Background

There have been many applications of Procedural Content Generation (PCG) methods to puzzle games, such as genetic algorithms for Spelunky [Baghdadi et al., 2015], MCTS based Super Mario Bros [Summerville et al., 2015], and map generation for Physical TSP [Perez et al., 2014b]. Other approaches propose search as a general tool for puzzle generation [Sturtevant, 2013], and generation of different start configurations for board games to tune difficulty [Ahmed et al., 2015]. Some even dynamically adapt to player actions, as proposed in [Stammer et al., 2015]. We refer readers to the survey [Togelius et al., 2011] and the book [Shaker et al., 2014] for a more comprehensive and thorough discussion of the field.

2.1 Sokoban Puzzle

The Sokoban game board is composed of a two-dimensional array of contiguous tiles, each of which can be an obstacle, an empty space, or a goal. Each goal or space tile may contain at most one box or the agent. The agent may move horizontally or vertically, one space at a time. Boxes may be pushed by the agent, at most one at a time, and neither boxes nor the agent may enter any obstacle tile. The puzzle is solved once the agent has arranged the board such that every tile that contains a goal also contains a box. We present an example solution to a Sokoban puzzle level in Figure 2.

Previous work has investigated various aspects of computational Sokoban including automated level solving, level generation, and assessment of level quality.

Sokoban Solvers

Previously proposed frameworks for Sokoban PCG involve creating many random levels and analyzing the characteristics of feasible solutions. However, solving Sokoban puzzles has been shown to be PSPACE-complete [Culberson, 1999]. Some approaches have focused on proposing approximate solutions to reduce the effective search domain [Botea et al., 2002; Junghanns and Schaeffer, 2001; Cazenave and Jouandeau, 2010].

Recently, the authors in [Pereira et al., 2015] propose an approach that uses pattern databases [Edelkamp, 2014] for solving Sokoban levels optimally, finding the minimum necessary number of box pushes (regardless of agent moves). The authors in [Perez et al., 2014a] applied MCTS for solving Sokoban levels, but concluded that pure MCTS performs poorly.

Level Generation

While there have been many attempts for solving Sokoban puzzles, the methods for their procedural generation are less explored. To the best of our knowledge, Murase et al. [Murase et al., 1996] proposed the first Sokoban puzzle generation algorithm. Their algorithm firstly creates a level by using templates, and proceeds with a search based solver to check for solvability. If solvable, the algorithm uses a heuristic based evaluation function to select interesting levels. More recently, the authors [Taylor and Parberry, 2011] proposed a similar approach, using templates to generate empty rooms and enumerating box locations in a brute-force manner. Their method is able to generate compelling levels that are guaranteed to be solvable. However, the run-time is exponential, and the method cannot be used to generate levels with more than a few boxes.

Level Assessment

There have been several efforts to assess the difficulty of puzzle games. One example is the very recent work in [van Kreveld et al., 2015], which combines features common to puzzle
games into a difficulty function, which is then tuned to user study data. Others consider Sokoban levels specifically, comparing heuristic based problem decomposition metrics with user study data [Jarůšek and Pelánek, 2010], and using genetic algorithm solvers to estimate difficulty [Ashlock and Schonfeld, 2010]. More qualitatively, the authors in [Taylor et al., 2015] conduct a user-study and conclude that computer generated Sokoban levels can be as engaging as those designed by human experts.

2.2 Monte Carlo Tree Search (MCTS)

Monte Carlo Tree Search is a best-first search algorithm that has been successfully applied to many games [Cazenave and Saffidine, 2010; Pepels et al., 2014; Jacobsen et al., 2014; Frydenberg et al., 2015; Mirsoleimani et al., 2015; Steinmetz and Gini, 2015] and a variety planning domains such as multi-agent narrative generation [Kartal et al., 2014] and multi-robot patrolling [Kartal et al., 2015]. The authors in [Bauters et al., 2016] show how MCTS can be used for general MDP problems. More recently, the authors [Zook et al., 2015] adapted MCTS such that it simulates different skilled humans for games enabling faster gameplay data collection to automate game design process. We refer the reader to the survey on MCTS [Browne et al., 2012].

MCTS proceeds in 4 phases as presented in Figure 3. Each node in the tree represents a complete state of the domain. Each link in the tree represents one possible action from the set of valid actions in the current state, leading to a child node representing the resulting state after applying that action. The root of the tree is the initial state, which is the initial configuration of the Sokoban puzzle board including the agent location. The MCTS algorithm proceeds by repeatedly adding one node at a time to the current tree. Given that actions from the root to the expanded node is unlikely to find a complete solution, i.e. a Sokoban puzzle for our purposes, MCTS uses random actions, a.k.a. rollouts. Then the full action sequence, which results in a candidate puzzle for our domain, obtained from both tree actions and random actions is evaluated. For each potential action, we keep track of how many times we have tried that action, and what the average evaluation score was.

Exploration vs. Exploitation Dilemma

Choosing which child node to expand (i.e., choosing which action to take) becomes an exploration/exploitation problem. We want to primarily choose actions that had good scores, but we also need to explore other possible actions in case the observed empirical average scores don’t represent the true reward mean of that action. This exploration/exploitation dilemma has been well studied in other areas.

Upper Confidence Bounds (UCB) [Auer et al., 2002] is a selection algorithm that seeks to balance the exploration/exploitation dilemma. Using UCB with MCTS is also referred to as Upper Confidence bounds applied to Trees (UCT). Applied to our framework, each parent node $p$ chooses its child $s$ with the largest $UCB(s)$ value according to Eqn. 1. Here, $w(.)$ denotes the average evaluation score obtained by Eqn. 2, $\hat{\pi}$ is the parent’s updated policy that includes child node $s$, $p_s$ is visit count of parent node $p$, and $s_v$ is visit count of child node $s$ respectively. The value of $C$ determines the rate of exploration, where smaller $C$ implies less exploration. $C = \sqrt{2}$ is necessary for asymptotic convergence of MCTS [Kocsis and Szepesvári, 2006].

$$UCB(s) = w(\hat{\pi}_s) + C \times \frac{\ln p_s}{s_v} \tag{1}$$

If a node with at least one unexplored child is reached ($s_v = 0$), a new node is created for one of the unexplored actions. After the rollout and back-propagation steps, the selection step is restarted from the root again. This way, the tree can grow in an uneven manner, biased towards better solutions.

Variations in Selection Methods: There are several other selection algorithms that can be integrated to MCTS. In this work, as a baseline, we employed UCB algorithm. However, considering a possible relationship between the variance of tree nodes and agent movement on the board, we also experimented with UCB-Tuned [Auer et al., 2002], and UCB-
V [Audibert et al., 2007] for Sokoban puzzle generation using our evaluation function shown in Eqn. 2.

UCB-Tuned and UCB-V both employ the empirical variance of nodes based on the rewards obtained from rollouts with the intuition that nodes with high variance need more exploration to better approximate their true reward mean. UCB-Tuned purely replaces the exploration constant of the UCB algorithm with an upper bound on the variance of nodes, and hence requires no tuning, whereas UCB-V has two additional parameters to control the rate of exploration.

3 Approach Overview

One of the challenges for generating Sokoban puzzles is ensuring solvability of the generated levels. Since solving Sokoban has been shown to be PSPACE-complete, directly checking whether a solution exists for a candidate puzzle becomes intractable with increasing puzzle size. To overcome this challenge, we exploited the fact that the game could be generated through gameplay itself. To do so, we decompose the puzzle generation problem into two phases: puzzle initialization and puzzle shuffling. Puzzle initialization refers to assigning the box start locations, empty tiles, and obstacle tiles. Puzzle shuffling consists of performing sequences of Move agent actions (listed in section 3.1) to determine goal locations. In a forward fashion, as the agent moves around during the shuffling phase, it pushes boxes to different locations. The final snapshot of the board after shuffling defines goal locations for boxes.

We apply MCTS by formulating the puzzle creation problem as an optimization problem. As discussed above, the search tree is structured so that the game can be generated by simulated gameplay. The search is conducted over puzzle initializations and valid puzzle shuffles. Because puzzle shuffles are conducted via a simulation of the Sokoban game rules, invalid paths are never generated. In this way our method is guaranteed to generate only solvable levels.

The main reasons for choosing MCTS for Sokoban puzzle generation is its success in problems with large branching factors and its’ anytime property. MCTS has been applied to many problems with large search spaces [Browne et al., 2012]. This is also the case for Sokoban puzzles as the branching factor is in the order of $O(mn)$ for an $m \times n$ puzzle.

Anytime algorithms return a valid solution (given a solution is found) even if it is interrupted at any time. Given that our problem formulation is completely deterministic, MCTS can store the best found puzzle after rollouts during the search and optionally halt the search with some quality threshold. This behaviour also enables us to create many puzzle levels from a single MCTS run with varying increasing scores.

3.1 Action set

Our search tree starts with a board fully tiled with obstacles, except for an agent which is assumed to start at the center of the board. At any node, the following actions are possible in the search tree:

1. Delete obstacles: Initially, only the obstacle tiles surrounding the agent are available for deletion. Once there is an empty tile, its surrounding obstacle tiles can also be turned into an empty tile (this progressive obstacle deletion prevents boards from containing unreachable hole shaped regions).

2. Place boxes: A box may be placed in any empty tile.

3. Freeze level: This action takes a snapshot of the board and saves it as the start configuration of the board.

4. Move agent: This action moves the agent on game board. The agent cannot move diagonally. This action provides the shuffling mechanism of the initialized puzzle where the boxes are pushed around to determine box goal positions.

5. Evaluate level: This action is the terminal action for any action chain; it saves the shuffled board as the solved configuration of the puzzle (i.e. current box locations are saved as goal locations).

These sets of actions separate the creation of initial puzzle configurations (actions taken until the level is frozen) from puzzle shuffling (agent movements to create goal positions). Before move actions are created as tree nodes during MCTS simulations, the agent moves randomly during rollouts. As search is deepened, agent moves become more non-random.

Once Evaluate level action is chosen, before we apply our evaluation function to the puzzle, we apply a simple post-processing to the board. We turn all boxes that are placed to the board but never pushed by the agent into obstacles as this doesn’t violate any agent movement actions. By applying evaluation function after post-processing, we make sure our heuristic metrics’ values are correctly computed.

The proposed action set has several key properties which make it well suited for MCTS-based puzzle generation. In contrast to our approach, interleaving puzzle creation and agent movement requires the MCTS method to re-simulate all actions from the root to ensure valid action sequences, which would render the problem much more computationally expensive and MCTS less efficient.

3.2 Evaluation Function

MCTS requires an evaluation function to optimize over during the search. For game playing AI, evaluation functions typically map to 0 for loss, 0.5 for tie, and 1 for winning sequence of actions. For Sokoban puzzle generation, this is not directly applicable as we do not have winning and losing states. Instead, we propose to use a combination of two metrics, i.e. terrain and congestion, to generate interesting Sokoban levels. Our approach seeks to maximize the geometric mean of these two metrics as shown in Eqn. 2. This provides a good balance between these two metrics without allowing either term dominate. Parameter $k$ is employed to normalize scores to the range of 0 to 1.

$$ f(P) = \frac{\sqrt{\text{Terrain} \times \text{Congestion}}}{k} $$

(2)

These two components of our evaluation function are intended to guide the search towards boards that have congested landscapes with more complex box interactions.
Figure 4: Our method works in an anytime fashion, improving the quality of generated puzzles over time. The red line corresponds to the performance of UCB-V for 5x5 board generation over time. The first two levels, i.e. generated instantaneously by MCTS, are trivial to solve. As time passes and the puzzle scores increase, more interesting puzzles (such as the last two shown above) are found. The anytime property of MCTS proves to be useful as a single MCTS run can generate a variety of levels.

### Congestion Metric

The motivation for the congestion metric is to encourage puzzles that have some sort of congestion with respect to the paths from boxes to their goals. The intuition is that overlaps between box paths may encourage precedence constraints of box pushes. We compute this by counting the number of boxes, goals, and obstacles in between each box and its corresponding goal. Formally, given an \( m \times n \) Sokoban puzzle \( P \), and given \( b \) boxes on the board, let \( b^s \) denote the initial box locations, and let \( b^f \) denote the final box locations. For each box \( b_i \), we create a minimum area rectangle \( r_i \) with corners of \( b^s_i \) and \( b^f_i \). Within each rectangle \( r_i \), let \( s_i \) denote the number of box locations, let \( g_i \) denote the number of goal locations, and let \( o_i \) denote the number of obstacles. Then:

\[
Congestion = \sum_{i=1}^{b} (\alpha s_i + \beta g_i + \gamma o_i).
\]  (3)

where, within our evaluation function, \( \alpha \), \( \beta \), and \( \gamma \) are scaling weights.

### Terrain Metric

The value of Terrain term is computed by summing the number of obstacle neighbors of all empty tiles. This is intended to reward boards that have heterogeneous landscapes, as boards having large clearings or obstacles only on the borders make for mostly uninteresting puzzles.

### 4 Results

In this section, we firstly present a comparison between different selection algorithms. Then, we report the anytime performance of our algorithm. Lastly, we present a set of levels generated by our approach.

#### 4.1 Experimental Design

All experiments are performed on a laptop using a single core of an Intel i7 2.2 GHz processor with 8GB memory. Search time is set to 200 seconds for all results and levels reported in this work. Given the simple game mechanics of Sokoban puzzles, our algorithm on average can perform about 80K MCTS simulations per second for 5x5 tile puzzles.

For our experiments, we set \( C = \sqrt{2} \) for UCB which is presented in Eqn. 1. For the two parameters involved with UCB-V, we use those suggested in [Audibert et al., 2007]. For the congestion metric (Eqn. 3), we used the following weights for all boards generated: \( \alpha = 4 \), \( \beta = 4 \), and \( \gamma = 1 \).

The normalization constant of \( k = 200 \) is employed for all experiments.

We ran our experiments for 5 runs of varying random seeds across each board size generated (5x5 to 10x10). Boards were saved each time the algorithm encountered an improvement in the evaluation function.

#### 4.2 Computational Performance

Our method was able to produce approximately 700 candidate puzzles (about 100 per board size) on a single processor over a period of 6 hours. Because of the anytime nature of our approach, non-trivial puzzles are generated within a few seconds, and more interesting puzzles over the following minutes (see Figure 4). The anytime behaviour of our algorithm for different puzzle board sizes is depicted in Figure 5.
We compare the results of different MCTS selection methods in Figure 6. While UCB-Tuned has been shown to outperform these selection algorithms for other applications [Perick et al., 2012], our experiments reveal a slight advantage for UCB-V. Although all selection methods perform statistically similarly, UCB-V slightly outperforms other techniques consistently across different tested board sizes.

Compared to other methods that are exponential in the number of boxes, our method is a significant improvement on the run time. Our algorithm is capable of quickly generating levels with a relatively large number of boxes. As can be seen in Figure 7, puzzles with 8 boxes or more are found within a few minute time span. Previous search-based methods may not be able to generate these puzzles in a reasonable amount of time given the number of boxes and board size.

Figure 5: Anytime behavior of MCTS algorithm for varying board sizes is depicted; here each line corresponds to the average of the best score found so far by UCB-V across 5 runs with different seeds, grouped by the size of boards being generated. We have chosen UCB-V for display as it outperformed other methods for our domain. MCTS quickly finds trivially solvable puzzles within a second. Given more time, more interesting puzzles are discovered.

Figure 6: Different MCTS selection algorithms are compared. UCB-V slightly outperforms UCB and UCB-Tuned algorithms. All algorithms were provided the same search budget. The results are obtained by averaging 5 runs with different seeds.

4.3 Generated Levels

Our algorithm is capable of generating interesting levels of varying board sizes. Figure 7 showcases some examples. Our algorithm does not require any templates, generating the levels from an initially obstacle-filled board. Figure 4 shows how board quality evolves over time. Lower scoring boards are quickly ignored as the search progresses towards more interesting candidates. The leftmost board depicted in Figure 4, while only 5x5 tiles, presented a challenge for the authors, taking over a minute to solve. As MCTS is a stochastic search algorithm, we obtain different interesting boards when we initialize with different random seeds.

5 Discussion

The difficulty of a Sokoban puzzle is not easily quantified (even knowing the optimal solution would not make determining relative difficulty easy). Some properties of the scores produced by our evaluation function are worth noting. In general, higher scores led to higher congestion (more box path interactions) and a larger number of required moves. This does lead to more challenging and engaging puzzles as the score values increase. However, there are other aspects of difficulty that are not explicitly captured by our metrics. A level that requires more moves than another doesn’t necessarily mean it is more difficult to recognize the solution (e.g. having to move 3 boxes 1 space each vs 10 boxes 1 space each). Examples exist in which a very challenging level has a much lower score than a “busier” but otherwise menial one. Additionally, the box path interactions in our challenging puzzles usually correspond to determining a small number key moves, after which the puzzle is easily solved. In contrast, human designed puzzles can require the player to move boxes carefully together throughout the entire solution.

A key motivation of our work is the ability to use our generated levels for games that have puzzle mechanics as an integral part of gameplay. Here, the ability to generate the puzzles behind these elements could make the entire game experience different on every play through. Additionally, levels of varying difficulties could be generated to represent mini-games corresponding to various skill levels. For example, one could imagine the reskinning of Sokoban puzzles as a “hacking” mini-game where the difficulty can be tuned to the desired challenge based on contextual information.

The properties of our algorithm in particular make it well suited to the aforementioned applications. Since the speed of our method could allow new puzzle to be generated for every instance, players could be prevented from searching for solutions on game forums (if that property is desired). Additionally, an evaluation metric that corresponds well to puzzle difficulty could allow the game to dynamically present puzzles of various difficulty to the player based on their character’s profile (e.g. “hacking skill”) or other contextual information. Finally, the anytime nature of the algorithm allows for the generation of multiple levels of varying difficulty in a single run, which could be stored for later use in the game.

6 Conclusion

In this work, we have proposed and implemented an MCTS approach for the fast generation of Sokoban puzzles. Our algorithm requires no human designed input, and is guaranteed to produce solvable levels. We developed and utilized heuristic evaluation function that separates trivial and uninteresting levels from non-trivial ones, enabling the generation of challenging puzzles. We have shown, with examples, that our method can be used to generate puzzles of varying
sizes. In the future we seek to improve our evaluation metric (and as a result the density of high quality puzzles) via user studies, feature selection techniques, and metric tuning, in addition to increasing the performance of our method with parallelization techniques.

Limitations: While our method can be used as is to generate interesting levels, there are areas in which the method could potentially be improved. No formal validation of our evaluation function for selecting interesting levels (congestion and terrain metrics) has been performed. While we have presented levels that were challenging to us, we have not tested the validity of these metrics statistically.

Future Work: We plan to pursue the extension and improvement of this work in two main directions. One is to deepen our knowledge of what makes puzzles interesting and challenging to play, while the other is improving the performance of the algorithm. Currently, our evaluation function remains unvalidated. This could be addressed by conducting a user study to collect empirical annotations of level difficulty, as well as other characteristics. Having humans assess our puzzles would allow the testing of how well our evaluation function corresponds to the puzzle characteristics as they are perceived. To begin overcoming the challenge of better understanding puzzle difficulty, we must expand our notion of what makes a puzzle engaging or challenging. This could be achieved by using machine learning methods to identify potentially useful features on both human designed and generated puzzles with annotated difficulty. To increase the scalability and performance of our approach, we plan to parallelize MCTS potentially with the use of GPUs for increased speed.

References


