Maze Generation from Video

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Abstract – Mazes are impressive and fascinating pieces of art. Previous works have shown that it is possible to accurately create a maze on top of an image while keeping the main features of the image in the features of the maze. Our objective is to continue their research and try to improve the model. Our research focused on…….
Using these methods, we were able to create our own algorithm to generate mazes sequences from videos.

Introduction

Maze generation is an area of computational geometry and algorithm design, with applications ranging from game development to procedural content generation. Traditionally, mazes have been generated using various algorithms that create intricate pathways and dead ends, challenging the solver to find the correct route from the start to the finish. The typical resources we could find on maze generation focus on static images or predefined patterns. However, an unexplored side of this field involves dynamic content, such as videos.

Unlike static images, videos provide a sequence of frames that capture motion and changes over time, which can be leveraged to create more complex mazes. Despite the potential, there has been limited research on this topic (only one academic paper, which was not published).

Maze generation from images usually involves algorithms like Reaction-Diffusion (RD) [1] to get patterns, A* or Dijkstra algorithm to turn it into a solvable maze [6].

But when it comes to videos, the process becomes more complex. Videos consist of a series of frames, each representing a static image at a different moment in time. The temporal dimension adds a layer of complexity, as the maze generation algorithm must now account for motion, changes in the scene, and possibly varying levels of detail across frames. This dynamic nature requires advanced techniques in image processing, such as optical flow analysis [x] or frame differencing to extract meaningful patterns that can be translated into maze structures.

The paper we found [2] on this subject explores the use of video data to create mazes by analyzing motion and changes within the frames. The approach involves detecting edges and features in the video frames, tracking their movement over time, and then using this information to construct a maze that evolves with the video content.

We could imagine using such generation processes in advanced video game scenarios where the environment adapts dynamically to the player's actions.

Literature review

Pedersen and Singh [3] created a model to transform simple shapes into organic labyrinths. However, this method often fails to preserve complex interior structures without detailed manual segmentation. Xu and Kaplan [4] developed procedural algorithms to generate maze templates. Their approach also requires careful image segmentation to maintain salient structures, which can be labor-intensive for complex images.

Reaction–diffusion systems, here modeled by the Gray-Scott model, describe changes in the concentration of chemical substances over space and time through local reactions and diffusion. Alan Turing theorized that these systems cause patterns seen in zebras, snakes, or corals.
In "Evolving Maze form Images", Wan, Liu, Wong, and Leung [1] introduce a novel RD simulator developed within the framework of cellular neural networks (CNN). Unlike traditional RD models, this simulator can evolve stripe patterns that resemble the source images, preserving the salient interior structures of the source images during the evolution process.

This method adapts to the underlying image, making it ideal for creating mazes that change over time and interact with user inputs. In "Moving Mazes", BOMMADEVARA and FLAHAUT extend RD simulation to moving images, ensuring frame coherence and smooth transitions by mapping corresponding walls between frames using geometric mean calculations. Their paper addresses the computational complexity of real-time maze creation for high-resolution videos and the challenge of balancing maze complexity with image fidelity.

[5] Flood-filling allows the detection of chambers in random patterns.

[6] a great path finding method using Dijkstra, to ensure of the solvability of the maze.

<u>Methods and technical details</u>   (basically all codes described)

1. Video processing

For our research we essentially used gif, as they are easier to split into frames. Videos would require an extra step – making sure the frame is clear enough to be processed – that we didn't have time to tackle. Our model processes square gif for simplicity but can be adapted to any video format.

2. Reaction-Diffusion process

$$\frac{dX_{i,j}^{(t)}}{dt} = -X_{i,j}^{(t)} + \sum_{k,l \in \eta(i,j)} a_{k-i,l-j} Y_{\tilde{k},\tilde{l}}^{(t)} + I_{i,j} \quad A = \begin{bmatrix} -0.25 & -1.0 & -1.5 & -1.0 & -0.25 \\ -1.0 & 2.5 & 7.0 & 2.5 & -1.0 \\ -1.5 & 7.0 & -23.5 & 7.0 & -1.5 \\ -1.0 & 2.5 & 7.0 & 2.5 & -1.0 \\ -0.25 & -1.0 & -1.5 & -1.0 & -0.25 \end{bmatrix}$$

With A the 5x5 kernel matrix. X(t) the state of the grid at step t, Y the response of the model to the X state, and I a constant input.

Y is calculated as follows:

$$Y_{i,j}^{(t)} = \frac{1}{2} \left[|X_{i,j}^{(t)} + 1| - |X_{i,j}^{(t)} - 1| \right]$$

A basic reaction diffusion model generates random patterns. Here, in order to make it look similar to the image, we take X(t=0) as the image converted to grayscale. We also make sur that the image is fed into the system at each step. This is done by setting I proportional to X(t=0)
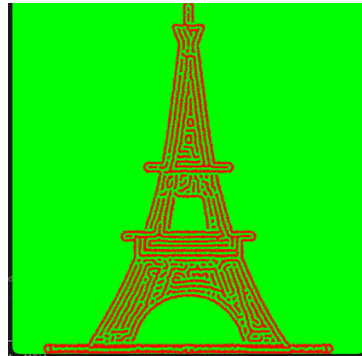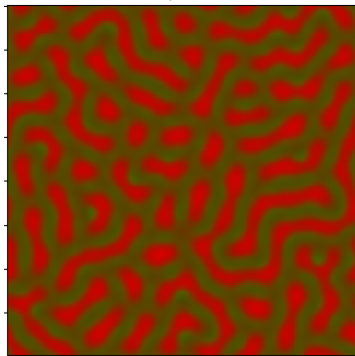
 basic, advanced

The next two steps are crucial in order to get a solvable maze. Indeed, the pattern we generated looks like a maze, but has no path, nor beginning/end.

3. Flood-filling and chamber detection

We define as chambers every white space enclosed by walls. In order to identify the chambers on our pattern, we use a flood-filling algorithm [5]. The flood fill process begins by adding an initial point to a stack, which serves as the queue for points to be processed. During the main loop, the algorithm continues to process points from the stack until it's empty. Each point is first checked to ensure it's within the grid boundaries and hasn't been previously marked or doesn't match the target value. If valid, the point is marked with a specified marker and its neighboring points (left, right, up, down) are added to the stack for further processing. This method is particularly effective for detecting chambers or distinct regions within a grid or image, as it allows the identification and segmentation of contiguous areas sharing similar properties. The process concludes when the stack is empty, returning a list of all points marked during the operation, effectively mapping out the detected chambers.
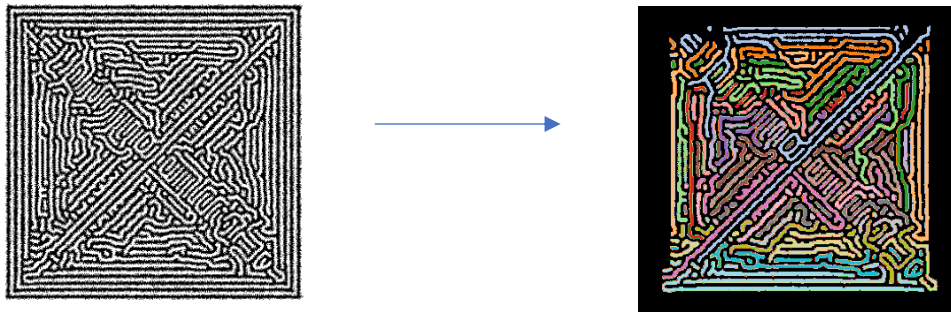
4. Dijkstra algorithm and maze processing

Once we have localized every chamber, we represent them on a graph based on their coordinates (Fig. 7. a). The start/end points are chosen randomly, the only condition being that they need to be on the extremities of the figure and as far away as possible.

Dijkstra algorithm works by iteratively selecting the node with the smallest known distance from the start node, then exploring its neighboring nodes to update their shortest distances. Each time a node is visited, the shortest path to that node is potentially updated if a shorter path is found via the current node. This process repeats until we reach the end node, or all possible paths are exhausted. The result is the shortest path through the graph, navigating efficiently through the maze from start to finish based on the weighted edges that may represent distance or difficulty of passage between chambers. Every edge here weights the same, thus giving us the shortest path. In order to produce more randomness and get longer paths, we could adjust the weight of some edges.

Then we break some parts of the walls between two consecutive chambers in the path returned by Dijkstra. This created one unique chamber: the path from start to finish (Fig. 7. b).

At the point, we only created one path, and a quite obvious one, looking at the result (Fig. 7. b).

In order to "hide" the main path, we need to create many others. To do so, we can break random walls, or created other paths (with Dijkstra) connecting completely random chambers.
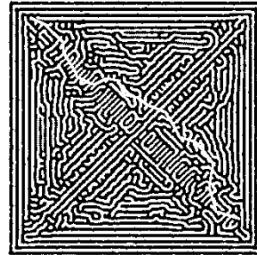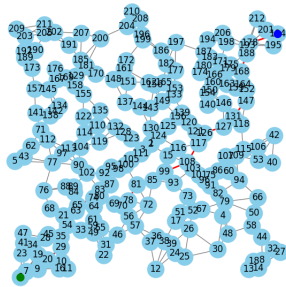
Ajouter image maze complet (c)

Modifications and improvements

Time comparisons

Differences with [2]

-Pipeline and multithreading (5th part of technical details)
Efficiency

It was important for us to get an optimized process. We chose to use C++ for the Reaction-Diffusion step as it requires a great number of calculations. (Give the numbers)
Python for the global pipeline, easier to use and is efficient to centralize the data.

Observation and future works

When studying the case of frame coherence, our fellow IPP predecessors [2] thought about using a CNN for the remapping. We attempted that by training a model.

From an innovation point of view, the first step was generating on images, then on a series of image. We could now only expect it to expand on 3D environments. [3] and [10] Explain how we could develop a RD-simulator for 3D structures.

Conclusion

In conclusion, our research extended maze generation from static images to dynamic videos. Using techniques like reaction-diffusion and optical flow analysis, we developed an algorithm that creates intricate maze sequences from video frames while maintaining visual coherence.

Building on previous studies, we addressed challenges unique to video data, ensuring solvable and visually appealing mazes through flood-filling for chamber detection and the Dijkstra algorithm for pathfinding. Our optimized process, using C++ and Python, demonstrates the feasibility of short-time maze generation.

Future work could explore 3D environments and more sophisticated pathfinding algorithms, further enhancing our model's applicability. + speed
Overall, we tried our best to offer a robust framework for dynamic, video-based mazes.

References

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[7]

[8]

[9]

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[11]