RiverGAN: Fluvial Landform Generation Based on Physical Simulations and Generative Adversarial Network

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Abstract: Physical river models and simulations are used in the field of landscape architecture to study the complex and nonlinear process of river morphology, which is difficult to be studied by numerical simulations. However, the setup of physical simulations is usually sophisticated, costly and time-consuming. Thus, the physical models can only produce a limited number of simulation results for each study, which significantly limits the use of the physical simulation and the designers' imagination as well. In this research, we take the simulation of fluvial landscape on a hydromophological sand table as an example, to present a novel and alternative framework for faster, more accessible and iterative method for physical simulations for landscape designers. By using the methodological framework of Procedural Terrain Generation (PTG) with Generative Adversarial Network (GANs), we collected 500 pairs of mesh and texture data from a hydromorphological sand table for training a LightweightGAN model. The resulting 3D latent walk is visualized through a customized user interface and can be easily integrated into the creative workflow by landscape designers.

Keywords: Generative Adversarial Network, landscape architecture, Landform Generation, Procedural Terrain Generation, hydromorphology

1 Introduction

1.1 Physical Simulations in Landscape Architecture

From the 1960's on, ecological principles and systems thinking have become increasingly relevant to theories and practices of landscape architecture and have stimulated the shifts in design thinking from static and determinacy, to dynamic and indeterminacy (WALDHEIM 2006). Emerging physical modelling techniques combined with sensing and actuating devices have provided landscape designers advanced tools with which to challenge the traditional static modelling and simulating methods. The dynamics of such models are essential for designers in terms of understanding the complex and dynamic process of landscape evolution and landform morphology, as well as developing adaptive strategies between human interventions and the physical world (CANTRELL & HOLZMAN 2014).

Physical river models, for example, have long been used in both landscape design and engineering practice to study the hydrodynamics of river morphology, river meandering, tidal zones and delta formation, flood control strategies, land erosion and deposition process, etc. There are many strengths of using physical river models. First, the natural reproduction of complex nonlinear physical phenomena that are not fully understood can be easily simulated on physical models. Second, the simulation methods are well-established with a long tradition (CHERAMIE 2011), starting as early as the 1950s' pioneering work of the Mississippi Basin Model and San Francisco Bay Model. Third, the material and flow rates or wave conditions which occur on a large scale can be simulated on a small scale over a much shorter

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time period (SUTHERLAND & BARFUSS 2011), thus small changes to structures can be quickly implemented and effects can also be investigated quickly. Furthermore, the physical models show great potential for communicating complex and nonlinear phenomena, which serve as great platform for collaboration between different professions. Lastly, the opportunities for implementing physical river models in landscape practice also prove promising with the emerging technologies, such as the development of sensor technology to measure the time series of topography and flow (CANTRELL 2016), the computer power of real-time data processing, the responsive actuating devices (ESTRADA 2016), and composite modelling of tangible interface which integrate the numerical simulations into physical models (LIU 2020).

Although observations of material and dynamic processes are made easier by a greatly compressed time scale and expanded physical scale, there are also limitations to the physical hydraulic models. First, extracting data and projecting to the reality can be difficult because of many reasons, such as the unmatched scaling criteria of physical, material and temporal scales, the boundaries conditions, measuring resolutions, etc. Besides, the construction of physical river models usually requires experienced modelers, a large area and dedicate facilities, which can be costly and time consuming. Furthermore, the physical simulation is usually not reversible, which makes it difficult to iterate from the same settings. The models, especially site-specific models are usually destroyed after testing and analysis, while making adjustments to them or repeating the simulation process are even more difficult. Thus, the physical models can only produce a limited number of simulation results for each study, which significantly limited the use of the physical simulation and the designers' imagination as well.

1.2 Machine Learning and Surrogate Modelling

Machine learning methods provide an alternative way of simulation, which avoids the costly model construction and time-consuming simulation process. In many engineering problems, the outcome of simulation cannot be easily measured or compute. When a simulation takes a long time to complete, tasks such as design optimization, what-if analysis and design space exploration become impossible since they require many simulation evaluations. One way to solve this problem is by constructing approximation models, also known as surrogate models, to mimic the behaviour of the simulation model while being cheaper and easier to evaluate. The surrogate models are constructed using data-driven and bottom-up method. Designers can quickly construct surrogate models from existing simulation results, and explore the impact of different evaluation criteria by constructing several models from the same set of data (WORTMANN et al. 2015). The methods are widely applied in the simulation of built environment, such as wind simulation (MOKHTAR et al. 2020, LIN et al. 2019), energy simulation (SEBESTYEN & TYC 2020, DUERING et al. 2020), structural simulation (SINKE et al. 2019, ZHENG et al. 2019), etc. In these studies, computational or physical simulations are usually run multiple iterations to generate enough datasets for training a machine learning model. Methods such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN) and Generative Adversarial Network (GAN) are used for training. The trained models can then use given input conditions to generate simulated results in a significantly faster way (ZHENG 2019), thus can provide the opportunity of an iterative optimization and design process. The faster computing process also allows generating large amount of visualization results in a limited time, which allows the designers to explore through and select from.

1.3 Terrain Generation with Generative Adversarial Network

Procedural Terrain Generation (PTG) is the algorithmic generation of terrain that is widely used in video games to produce infinite real-life terrain without adding expense of labour. PTG is traditionally done with designed algorithms that generate heightmaps and textures. In landscape design, many off-the-shelf tools can be used to procedurally and algorithmically manipulate terrain by adding or removing attractors, vector fields and forces. These tools, such as Docofossor (HURKXKENS & BERNARD 2019) and Bison, are imbedded into 3D modelling software Rhino and Grasshopper so designers can easily integrate into their design workflow. 2D-based simulation methods such as Cellular Automata are used to simulate changing of landforms such as erosion, deposition, and morphology. Other generation algorithms such as agent-based modelling (DORAN & PARBERRY 2010), evolutionary algorithms (RAFFE et al. 2012), erosion algorithms (OLSEN 2004) and more recently generative networks in deep learning, such as the GAN (GOODFELLOW et al. 2014), are also used in PTG. Compared with other algorithms, GAN shows great potential to learn algorithms to automatically generate terrain without the need to manually write algorithms to do so (BECKHAM & PAL 2017). GAN in Procedural Content Generation is successfully applied in the design of built environment domains such as urban design (TIAN 2020) and architecture design (RODRIGUES et al. 2015), and shows great potential to be integrated into the landscape design process (CANTRELL et al. 2021).

2 Methodology

2.1 Dataset Preparation

We developed a novel workflow (Fig. 1) to create a braided river terrain dataset from a hydromorphology table. The physical simulation part of this project is built upon the EmRiver4 table. This small interactive water table used by professional hydrologists is imported into the field of landscape architecture to help students in design studios better understand hydromorphological process, and to facilitate the production of responsive design strategies.

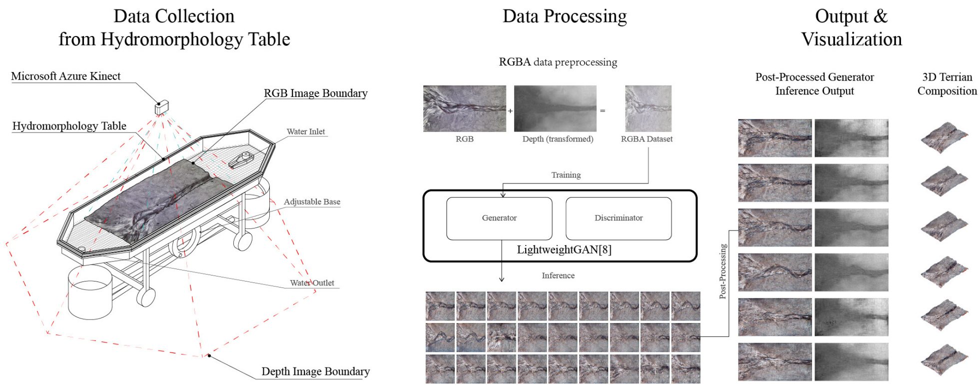

Fig. 1: Workflow of data collection, processing, training, output and visualization

The table is equipped with a controllable water pump and adjustable tilted base metal bed, filled with synthetic sediment of varying colors, sizes and densities. Upon each simulation epoch, the sediments are initially placed as a flat terrain on the bed of the hydromorphology table. When simulation begins, the water pump is used to pump water. As the simulation progresses, the sedimentary terrain is reshaped with the wash of the water body. As the simulation is running, a Microsoft Azure Kinect sensor mounted above the hydromorphology table can capture real-time data of changing material composition and river shape simultaneously from top. The material composition is represented with (512, 512, 3) images and the terrain is represented with (512, 512, 1) black-and-white depth images. The device is calibrated so that both the center and the size of the two images are aligned. Then we concatenate the depth channel into the RGB images as an alpha channel as RGBA images. 10 epochs of 1-hour physical simulations are run with the same initial setup conditions, from which we sampled RGBA images with a minimum time interval of 1-minute to guarantee the diversity of input data. The final training dataset consists of 502 pairs of a top-view RGBA image. A sample of the dataset is shown in Figure 2.

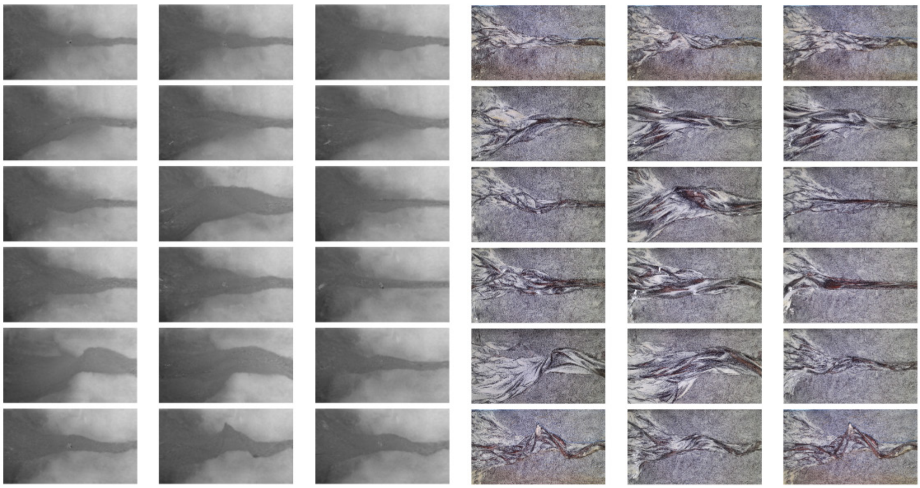

Fig. 2: Sample RGB texture data and depth data collected with Microsoft Azure Sensor

2.2 Data Training

LightweightGAN, a state-of-the-art (SOTA) GAN toolkit for fast, high-fidelity and few-shot image synthesis is used as the surrogate model for fluvial pattern generation. With skip-layer channel-wise excitation mechanism (SLE) and self-supervised regularization on the discriminator, LightweightGAN works in similar ways to StyleGAN, LightweightGAN achieves SOTA performance compared to StyleGAN on most personal devices.

Specifically, a LightweightGAN model is fit on our fluvial terrain dataset to generate RGBA images that represent river terrain textures and depth. The generative model for 100,000 epochs were trained and latent walk videos were created from the toolkit.

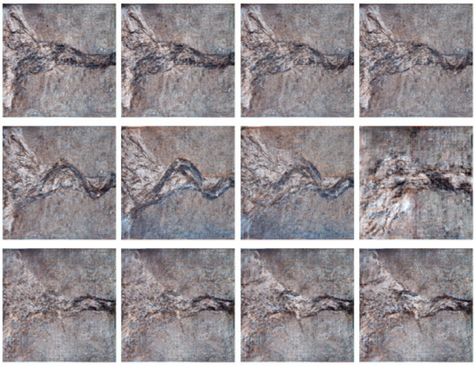

Fig. 3:
Processed training data by dimensiona stacking using OpenCV

2.3 Visualization

For procedural content generation with deep learning, inference visualization is crucial for the designers' workflow. Therefore, a user interface was also developed for visualizing 3D latent walk. Specifically, the latent walk video generated from Section 2.2 is ported to a static Three.js web interface for mapping the RGBA image to a textured mesh.

The toolkit can be easily integrated into the creative workflow with landscape architects and is available as an open-sourced toolkit at https://github.com/Archolic95/LandformGAN.

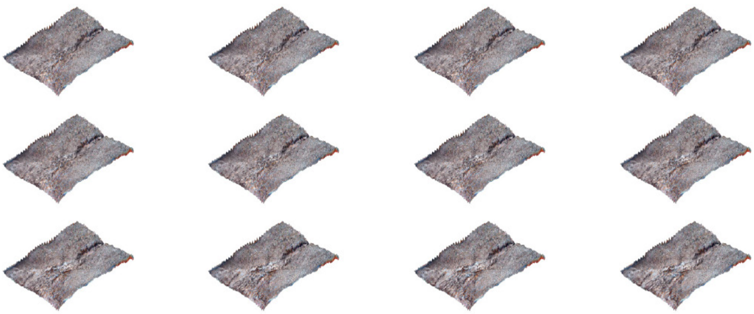

Fig. 4: 3D visualization of generated fluvial landform

3 Conclusion and Future Work

In this paper, we present a novel method for building a surrogate model for fluvial landform simulation, by using Generative Adversarial Network and physical simulations. Our method provides a faster, more accessible and intuitive way for fluvial morphodynamic modelling. Furthermore, as uncertainty and dynamics are important features in landscape modelling, the inherent less-deterministic and more-holistic character of Machine Learning offers promising possibilities and creativities for landscape architects to explore.

However, GAN models usually require large amount of input data (more than 500) to generate relatively satisfying results, and physical fluvial simulation usually takes more than one hour to run each iteration. Due to limited time, we were only able to test the simplest setup, with an initial straight channel, without any other influence parameters. Thus, the generated landform is not constrained by any parameters but produced directly from random noise input. The power of a surrogate model is not that obvious in this experiment. For future work, we need to include in the input dataset more constrained parameters, more simulation scenarios and more testing iterations. Different types of GAN algorithms should be used accordingly.

3.1 Conditional Input

Here, we would test putting obstacles in the stream and recording the process as the landform reaches stable patterns. By labelling the location of the obstacles as input and the landform pattern as output, we should be able to train a conditional GAN to build a surrogate model. This surrogate model should be able to generate stable fluvial landform in real-time by giving location of obstacles. Thus, designers could easily use it to test strategies of placing in-stream structures, without setting up complex physical or computational simulations.

3.2 Coastal Scenario

In this paper's experiment, we only tested the morphology of a simple channel. The EmRiver4 table used in this experiment can be used to simulate more than braided river morphology and delta formation, but can also simulate the water behaviour in coastal areas, such as storm surge and sea level rise. If we can run enough simulations of coastal scenarios, we should also be able to build a surrogate model by using the same GAN algorithms.

3.2 Time-series Simulation

In this experiment, we extracted 502 frames from 10 videos to train the GAN model. We treated the 502 pairs of training data equally and looked over the time sequence of the data. For future work, if time allows us to run more iterations and collect more videos, we will test video-based GAN such as MoCoGAN HD and DVDGAN with the same data collection pipeline to build surrogate models. Thus, the formation of simulated scenarios, such as the formation of braided river and delta formations can be simulated with minimal input and setup.

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