An Interactive Terrain Design Method Combining Augmented Reality Sandbox and Multi-objective Optimization Assistance

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Abstract: Virtual Reality (VR) concepts have been widely adapted to various disciplines and industries. The Augmented Reality Sandbox (AR-Sandbox) is an intuitive terrain visualization facility that realizes digital content projection onto the sand or clay surface and interactive operation. In this study, we developed an assistance tool to enhance AR-Sandbox's utility through the integration of the multi-objective optimization algorithm, enabling users to customize objectives including maximizing flow path length, minimizing maximum runoff velocity, and minimizing earthworks. Based on the non-dominated sorting genetic algorithm-II (NSGA-II) and multi-scenario plan references, this method aims to provide a more quantitative and efficient way than trial and error-based terrain-design processes.

Keywords: Augmented reality sandbox, multi-objective optimization, NSGA-II, terrain-design method, landscape architecture

1 Introduction

Virtual reality (VR) concepts have been commonly adapted to architectural design, landscape architecture and geoscientific disciplines and industries, notably in real situations with field trip restrictions or non-existent proposed projects (GAO et al. 2019, PORTMAN et al. 2015, REED et al. 2016). Augmented reality (AR) plays the role of digital content draped over actual objects within the spectrum between reality and virtuality (AKÇAYIR & AKÇAYIR 2017, EILOLA et al. 2023). The augmented reality sandbox (AR-Sandbox), an intuitive and effective terrain visualization facility, realizes digital content's free projection onto a physical sandbox (AFROOZ et al. 2018). AR-Sandbox allows users to interactively manipulate the sandbox and observe real-time changes of terrain reactions. It has proven highly effective in terrain making and knowledge popularization in landscape architecture, geoscience and hydrology (RHYS et al. 2019, TOMKINS & LANGE 2019).

Equipment updates and past research related to the AR-Sandbox have shown the evolution from invention, carrying of analysis tools to the lighter, more integrated version development (RATTI et al. 2004, HERMANSDORFER et al. 2020, PIPER et al. 2002, WELLMANN et al. 2022). The AR-Sandbox offers tangible feedback by scanning sand's shape and elevation. Users can carry out routine geo-analyses and assessments (e. g. slope, aspect, hydrological analysis) after instant terrain data importation. However, it is time-consuming and highly uncertain for users to manually modify the terrain until satisfactory analytic results and objectives are achieved. While the AR-Sandbox provides convenience in visualization and operation, the clarity and efficiency of the design process could be further improved by an 'assistant' that suggests users modify based on predictable development and analytical results. In practical implementation, terrain-design objectives are often conflictive, as enhanced benefits typi-

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cally imply more earthwork and higher investments. Achieving terrain modification with lower costs, rational earthwork and additional benefits (e. g., hydrological and ecological factors) faces challenges in identifying optimal results amidst conflicting objectives (XU et al. 2023).

Multi-objective optimization (MOO) employs optimization algorithms to search for Pareto front solutions, facilitating informed decisions among multiple conflicting objectives (DEB et al. 2002, MARLER & ARORA 2004, MIRJALILI et al. 2018, SHISHEGAR et al. 2018). MOO has shown feasibility in landscape planning and architectural design problem-solving (SHI et al. 2017, IBRAHIM et al. 2022, GAO et al. 2022, LIU et al. 2023). Therefore, MOO coupled with terrain-design is potential to be a accurate and efficient method compared to experience-based simulation and design processes. In response to the potential, this research aims to address the challenges and limitations related to the combination of AR-Sandbox and MOO in determining cost-benefit within the terrain design process. The objectives of this study are to:

1. Develop a framework that integrates MOO assistance with AR-Sandbox terrain-design procedures, considering hydro-morphometric analysis and earthwork factors (Fig. 1). It aims to explore the feasibility, efficiency and reliability of the obtained solution sets.

2. Quantify the comprehensive impacts of this MOO assistance in addressing the uncertainties and time-consuming nature of the AR-Sandbox terrain design.

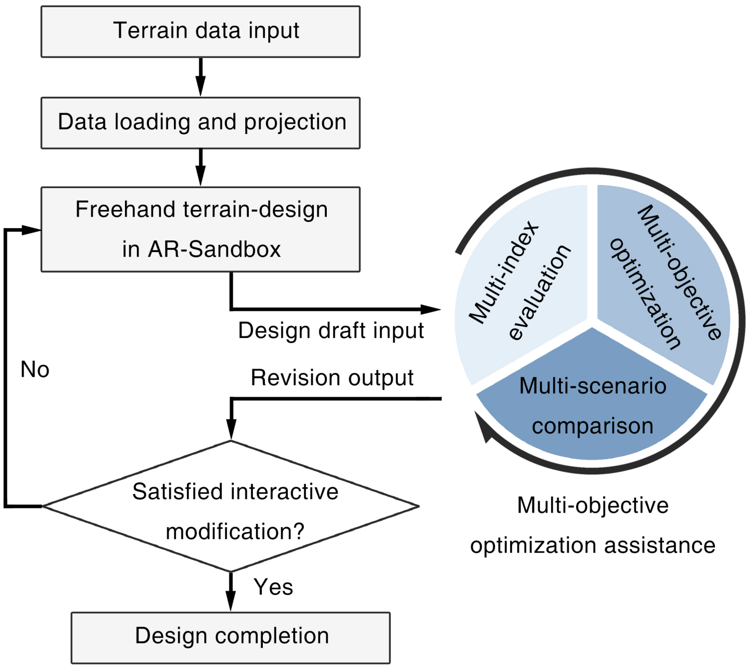

Fig. 1: Schematic framework of terrain design combining AR-sandbox and MOO assistance

2 Methodology

2.1 Workflow framework

This study uses the term ‘terrain design’ as it relates to surface grading or earthworks. The optimization of terrain design aims to enhance simulation performance with minimal earthwork modifications. This process primarily aids users in quantitatively evaluating and understanding the objectives of their proposed terrain, from the perspective including earthwork engineering and hydrology, and so on. In fact, complex terrain-design also relies on the multiple stakeholders’ ideas and aesthetic judgment. Therefore, referring to this workflow framework as a ‘terrain-design method’ might overstate its role. Clarifying the definition is crucial for understanding the objectives of this study.

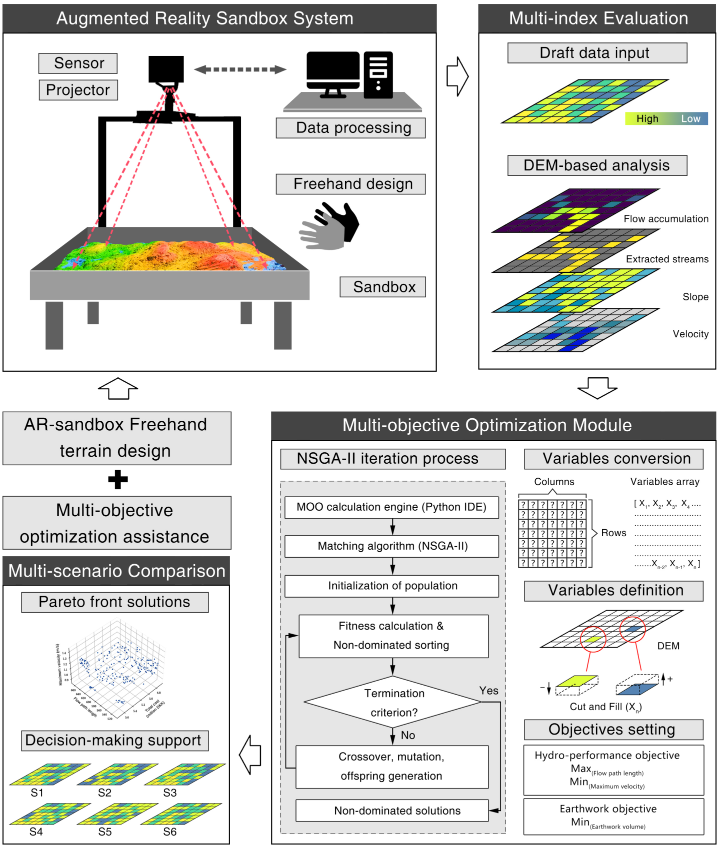

Fig. 2: Methodology flowchart

The proposed method involves several stages as follows (Fig. 2):

1) Terrain Data loading and projection: using the Rhino platform with the Grasshopper plug-in SandWorm to combine sensors and projection equipment to complete the construction of the AR-Sandbox (HERMANSDORFER et al. 2020).

2) Freehand draft design: manipulating the sand or clay terrain to propose a preliminary terrain mesh for analysis and optimization.

3) MOO assistance: transforming terrain mesh as grid raster with elevation numbers, then generating the digital elevation model (DEM) to the external computational platform for assisted analysis and optimization (**Fig. 3**). The MOO assistance module comprises three components:

   - Multi-index evaluation: providing an initial assessment of the draft based on various parameters (e. g., slope, aspect, flow path, runoff velocity);
   - Multi-objective optimization: employing the non-dominated sorting genetic algorithm-II (NSGA-II) to customize optimization objectives (incl. maximizing flow path length, minimizing maximum runoff velocity, minimizing earthwork volume) based on project-specific needs (Blank and Deb 2020; Deb et al. 2002). Every terrain raster is regarded as an optimization variable. The raster elevation varies within a certain limit, which means modification volume range, to obtain better analysis results and cost-effectiveness;
   - Multi-scenario comparison: visualizing and comparing different scenarios generated through optimization results for understanding the trade-offs and preference of different choices.

4) Iterative design process: based on quantitative analysis and comparison findings, users can further refine the terrain through manual operation. This iterative process continues until the users deem the design complete and optimal for the project requirements.

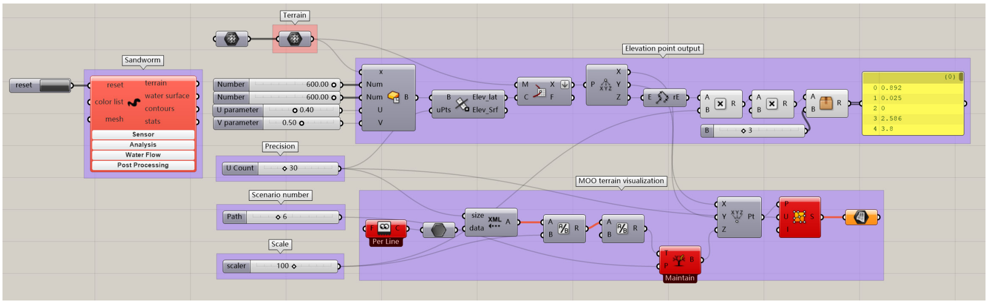

Fig. 3: A diagrammatic grasshopper workflow of AR-Sandbox scanning terrain data transformation

2.2 Multi-objective Optimization Setup

The NSGA-II is a widely adopted algorithm that effectively addresses MOO problems (DEB et al. 2002). The loop procedure encompasses several steps. First, generating a random population with a predetermined number of individuals (n). Second, assessing each individual and sort the population by fitness calculation and non-dominated sorting. Crossover and mutation, based on the parent population, apply to new candidates for the offspring population. The selection and prioritization process for the new generation incorporates both existing and newly formed individuals. It then continues this process, selecting solutions from successive generations until it meets the end conditions.

The Pymoo library and the Whitebox workflow (WbW) are employed to provide a built-in implementation of the NSGA-II and related topographic and hydro-morphometric analysis modules (BLANK & DEB 2020, LINDSAY 2016). All code has been open-sourced and is available at the GitHub repository.

2.3 Optimizing Accuracy and Scale

Since the precision limit of manual operation and clay material is around 3-5 cm, which means that manual operation cannot realize the corresponding rebuild even if the high-precision optimization results are provided. Therefore, MOO tools are effective with the appropriate site size or height difference and scale of the AR-Sandbox. The operation table we used, with a size of 60 cm × 60 cm, was viewed as grids region and provides the user with two versions which are standard precision (30 × 30) and high precision (60 × 60). **Table 1** shows the suggested scales and the actual mesh data size for the optimization. In summary, due to the limitations in size and precision of the sandbox, medium and small-scale sites are more suitable for the framework implementation, e. g. single plot, block and street.

Table 1: AR-Sandbox size and corresponding scale site

	AR-Sandbox Size: 60cm * 60cm	**Standard precision: 2cm * 2cm**	**High precision: 1cm * 1cm**
Scale	**Maximum site area**	**Unit resolution (SP)**	**Unit resolution (HP)**
1:10	6m * 6m	0.2m * 0.2m	0.1m * 0.1m
1:20	12m * 12m	0.4m * 0.4m	0.2m * 0.2m
1:50	30m * 30m	1m * 1m	0.5m * 0.5m
1:100	60m * 60m	2m * 2m	1m * 1m
1:200	120m * 120m	4m * 4m	2m * 2m

Note: The sandbox size indicated is the maximum operating area, and terrain operations may be accomplished partially at the user's discretion.

3 Case Validation

We invited two students from the University of Copenhagen to test the framework. They chose the scale of 1:100 and followed the workflow to initially complete a terrain draft (Fig. 4). Standard precision mode was chosen for the test. Fig. 5 shows the pre-analysis for evaluating the draft terrain. Then they stipulated the optimization constraints which the volume of earthwork should not exceed 450 m^3. After draft data input and MOO calculation, the visualization results of the draft were successfully obtained along with 20 reference scenarios. The optimization and visualization process required approximately a few minutes of computation to yield 200 generations (populations size = 20) in the Windows 10 environment (AMD Ryzen 7 5800h 3.20 GHz CPU, 16 GB memory).

Fig. 6 illustrates the final Pareto front revealing the relationships among the three objectives. The earthwork volume (m^3) converged between 376.98 and 441.07. The flow path length (grid number) converged between 158 and 232 with an original value is 110. The maximum runoff velocity (m/s) converged between 0.72 and 1.25, compared to the original value of 1.13. Users can drag sliders to select different solutions and visualize them in Rhino platform. The result values of the three objectives for each solution can be checked so that users can quickly compare them with those of the terrain draft. The visualization of the selected solutions is visible as a real-time reference, i. e. the orange mesh in Rhino, for the user's interactive modification and imitation.

Fig. 4: Procedures for practical operation using terrain-design method combining AR-sandbox tool and MOO assistance. Student project by: Yu Liu, Ziming Wang.

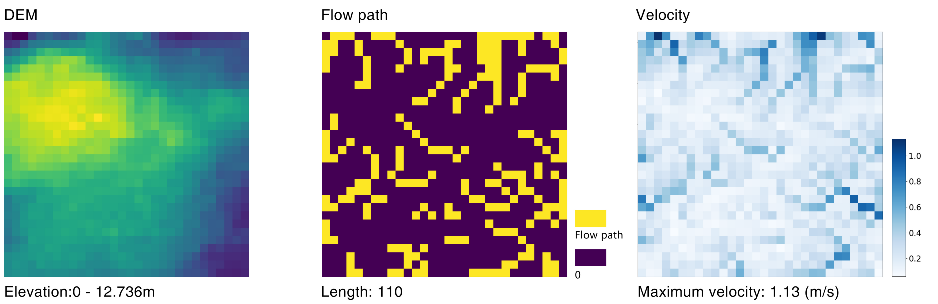

Fig. 5: Pre-analysis of terrain draft DEM data

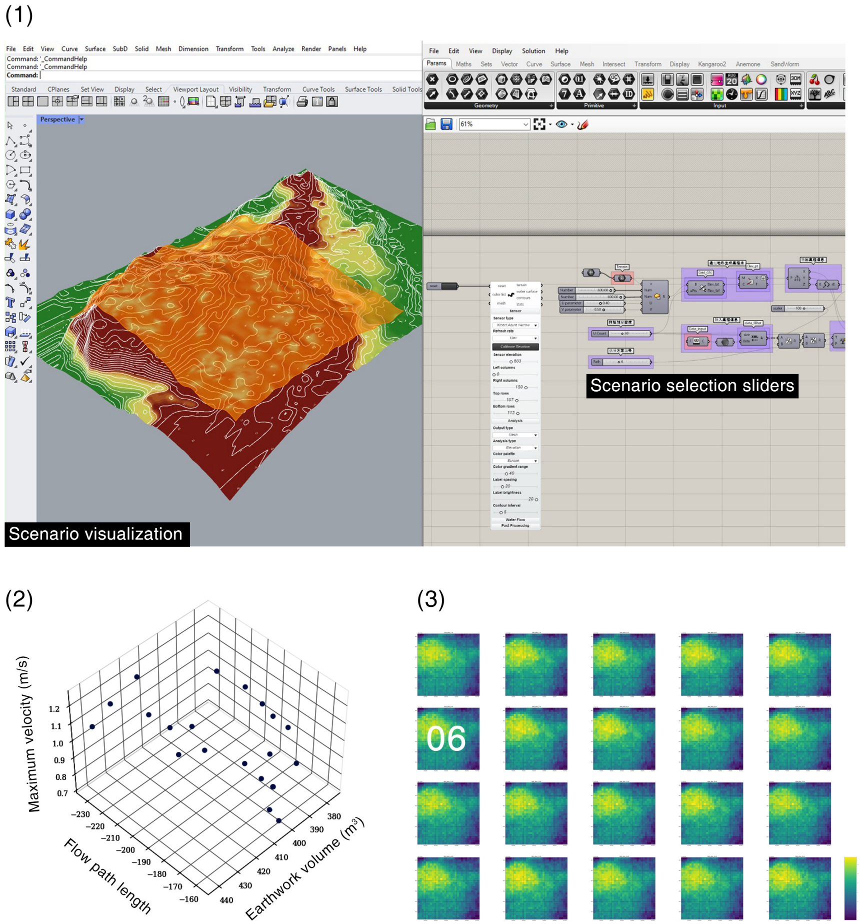

Fig. 6: Solution selection and visualization of MOO results. (a) Interactive operation interface (randomly chose solution 06 as the example); (b) Pareto front solutions distribution; (c) visualization of 20 solution terrains.

4 Discussion

In most of the current cases, the AR-sandbox facilitates interaction through haptic operation and visualization of terrain with contour lines, graphics colors and hydrological simulations. The practical application for landscape architects has been constrained by the lack of advanced design assistance and optimization capabilities. In response to this limitation, this study presents an innovative approach to enhance AR-Sandbox's utility through the integration of MOO functions, resulting in a terrain design process tailored to address complex grading objective challenges.

The presented interactive method offers several advantages. First, the integration of MOO assistance allows users to consider multi-factors simultaneously during freehand operation.

This is helpful in complex terrain design scenarios, where multiple objectives need to be balanced. Second, unlike 2D drawing or 3D virtual modeling, the method offers a more intuitive and collaborative approach that facilitates communication between designers and non-professionals through the understandable tangible model and real-time visualizations. Third, the MOO assistance system provides users with reference solution sets rather than an absolute quantitative result. The balance between a creative idea and quantitative analysis is enhanced, while enhancing the functionality and practicality of their designs.

Nevertheless, to ensure practical support for terrain design implementation and optimization assistance replicability, it is important to acknowledge this study's limitations and how they may have affected the results. The optimization module is limited to a few optimization goals, focusing primarily on hydrology and cost-effectiveness. Different DEM-based analysis functions could be integrated into the optimization system. However, expanding optimization objectives could further enhance the effectiveness of the assistance system, but would require increased processing power and more efficient optimization algorithms. Another limitation is that the size of sandbox has resulted in a restricted size area and optimization precision. Furthermore, we have not yet been able to replicate real-world terrain accurately in our system, which is crucial for practical applications beyond educational or hypothetical scenarios. In the future, 3D printing or advanced scanning and reconstruction tools that could potentially be integrated to rebuild the actual terrain.

Based on students' feedback, they appreciated the system's innovation and utility in terrain design, yet noted its relatively high learning threshold for beginners, and that the tool's flexibility and customization options require improvement. In conventional landscape architecture education, students usually practice terrain-design as a space and aesthetic endeavor, with minimal attention to slope and drainage. Participant students reflected that they were not used to splitting the terrain-design into such precise objectives for generation, but at the same time, they were generally satisfied with the generated results and assistant functions. Hence, the logic and precision offered by MOO may overwhelm some, and resonate more with students inclined towards quantitative reasoning.

5 Conclusions

This research presents an innovative and effective approach to terrain design, to our knowledge, coupling augmented reality and multi-objective optimization. This method enhanced AR-Sandbox by integrating a MOO assistance tool, facilitating collaboration between professionals and non-professionals and aiming to offer a balance of aesthetic idea and quantitative assessment. With further development and expanded optimization objectives, this approach has the potential to impact the fields of landscape design and geospatial technology, offering a more versatile and efficient way to approach terrain design in both educational and professional settings.

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