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Exploring and optimizing innovative structures in virtual reality

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Abstract

Innovative load-bearing structures often emerge from a fine balance between creative forms and engineering principles. Recent studies have advanced the structural design process by developing preference-based topology optimization methods. Such methods optimize material distribution for structural performance while integrating designers' preferences for certain geometric features. However, these methods face challenges in the subsequent exploration phases, including observing and editing complex 3D structural details vital for achieving diverse and satisfactory design options. This paper proposes a novel design exploration strategy by integrating virtual reality (VR) with topology optimization to create desirable 3D structures interactively and iteratively. Our strategy uses VR sculpting to offer immersive visualization, intuitive design exploration, and real-time feedback, with the sculpted models guiding and influencing material redistribution in topology optimization. This sculpting–optimization workflow can be repeated in multiple cycles, creating various innovative and efficient structures. Our parametric study demonstrates that adjusting the workflow parameters can control the formation of final structures toward performance-driven or preference-driven designs. We present several computational design examples that demonstrate practical applications of the proposed strategy and highlight its potential in solving real-world problems.

Keywords: structural design, virtual reality, topology optimization, subjective preference, Hangai Prize applicant

1. Introduction

Innovative load-bearing structures are typically designed not only to carry loads but also to possess unique geometric features that embody the creative ideas of their designers [1–4]. However, the emphasis on creative expression may result in neglect of structural efficiency and fundamental engineering principles. Many structural optimization techniques have been developed to achieve specific objectives while satisfying certain constraints. These techniques include topology optimization, an effective strategy to automatically create innovative and efficient structures through redistributing the underutilized material, typically performed for stiffness maximization [5].

The bidirectional evolutionary structural optimization (BESO) method [6] is a widely used topology optimization technique that allows inefficient and efficient materials to be simultaneously removed and added, respectively. In recent years, BESO has been increasingly used because of the availability of high-speed computers, efficient numerical algorithms, and limited material resources. Therefore, the BESO method has found diverse practical applications, including in additive manufacturing [7], architectural design [8–11], and furniture [12,13].

According to Xie [8], optimal structures based purely on structural performance may be of low value, as they cannot always satisfy all design requirements, such as aesthetic quality. Recent studies have attempted to generate satisfactory structures through topology optimization by considering subjective preferences (e.g., preferred geometric features) using generative adversarial networks [14], subdomains [9], or subjective weights [9]. These methods can yield multiple design options by adjusting parameters in a single design exploration. Then, designers must select a satisfactory design from these options. However, the selection process can be time-intensive, and finding solutions that satisfy all design requirements is often challenging [13]. Besides, relying on a single design exploration ignores that subjective preferences may be changed—often influenced by the solutions—leading to new inspirations [15]. Therefore, it is crucial for an effective design exploration process to allow designers the flexibility to update their subjective preferences [16,17].

Interactive topology optimization aims to involve the user in the optimization process, enabling real-time adjustments to design parameters, constraints, and aesthetic considerations. Hence, designers have more design freedom to guide topology optimization to generate desirable structures. Importantly, such interactive methods are particularly suited for accommodating evolving subjective preferences. However, the development of interactive topology optimization has predominantly focused on 2D structural designs, leaving its potential in 3D applications underexplored [13,18]. A significant barrier is the inherent complexity of visualizing and modifying 3D models. Designers without strong spatial awareness often struggle to interpret and interact with 3D structures on a 2D computer screen [19]. Additionally, 3D topology optimization typically includes internal geometric details that are not visible or editable from the outside, adding to the complexity of engaging with these details [18].

This paper proposes a novel design exploration strategy based on integrating virtual reality (VR) and topology optimization to create 3D structures aligned with evolving subjective preferences (see Figure 1). This integration provides a virtual design environment where designers can intuitively interact with and edit complex 3D geometries. In this environment, designers must first express their subjective preferences by sculpting a preferred model. This model is then translated into weights to guide the material redistribution process in a modified topology optimization algorithm for creating a 3D structure. Designers can further update subjective preferences by refining the current designs. Designers can efficiently explore multiple desired structures by iteratively updating subjective preferences and executing optimization. Section 2 describes the details of the proposed design exploration strategy. Section 3 introduces the modified topology optimization algorithm. Section 4 presents a parametric study and showcases potential practical applications of the proposed design exploration strategy, followed by a conclusion in Section 5.

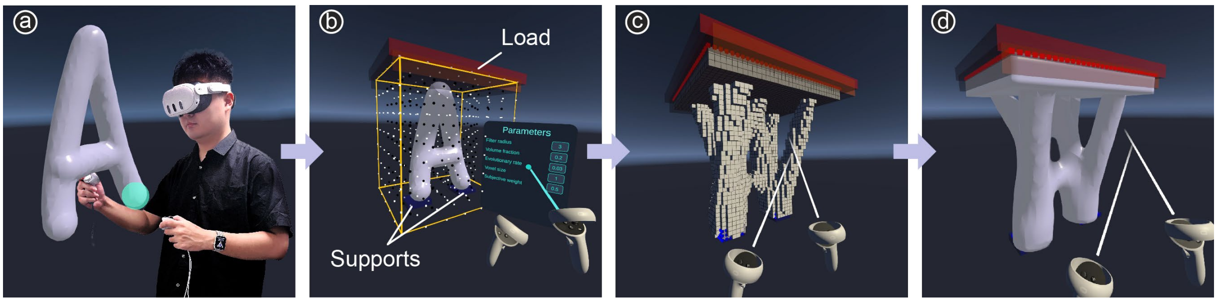

Figure 1: A single design cycle within the computational workflow of our proposed design exploration strategy: (a) Step 1: VR sculpting, (b) Step 2: initialization, (c) Step 3: topology optimization, and (d) Step 4: smoothing

2. Design exploration in virtual reality

In this study, we use the head-mounted display and two handheld controllers of the Meta Quest 3 VR device to observe and edit 3D geometries [20]. This VR device enables designers to perform operations based on body motion, offering an intuitive way to interact with the virtual environment. Importantly, the immersive environment is particularly beneficial for inexperienced designers, as it assists them in understanding complex 3D details and refining their subjective preferences.

This section describes the computational workflow of the proposed design exploration strategy. Four sequential steps are involved within a single design cycle (see Figure 2), including VR sculpting (Step 1), initialization (Step 2), topology optimization (Step 3), and smoothing (Step 4), detailed in Sections 2.1–2.4, respectively. Each cycle gives an optimal structure that aligns with the current subjective preferences. However, Steps 1–4 can be iteratively repeated to update subjective preferences, creating a series of desired structures that progressively match these evolving preferences. This design exploration strategy establishes a productive human–computer collaboration to improve the efficiency of design exploration and the quality of optimized structures (see Section 2.5). We have developed a digital design tool—virtual reality-based bidirectional evolutionary structural optimization (VR-BESO)—to implement the computational workflow. All examples presented in this paper have been created using VR-BESO. This newly developed software and its manuals have been made publicly available [21].

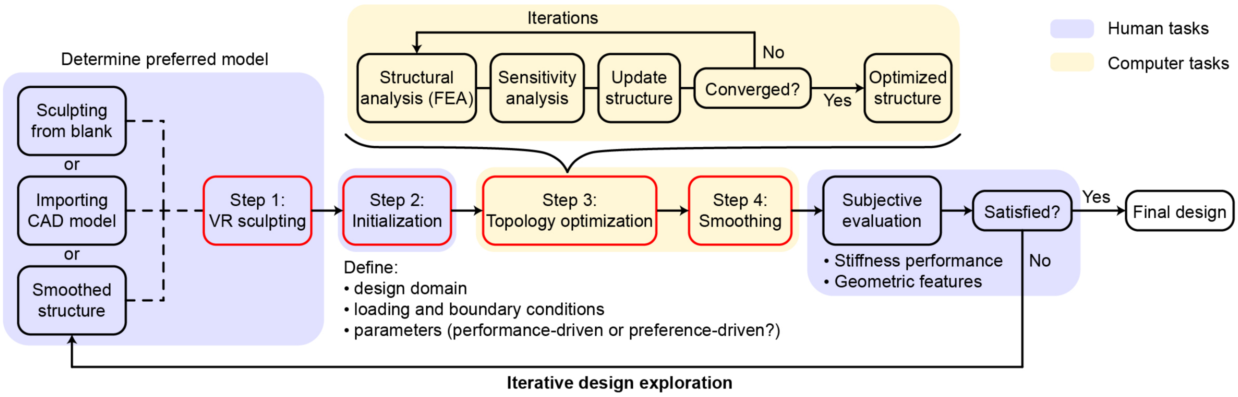

Figure 2: The computational workflow of the proposed design exploration strategy

2.1. Step 1: VR sculpting

Step 1 utilizes VR sculpting to help designers transform their creative ideas into tangible 3D geometries in a virtual environment, as shown in Figure 1(a). This process offers a direct and intuitive way for designers to express their subjective preferences. VR sculpting differs significantly from traditional flat-screen design interfaces, offering six degrees of freedom to simulate a real-life sculpting experience [22,23]. This technology typically includes various brush tools for drawing, building up, and removing material, offering extensive design freedom. Designers can shape their ideal geometries by waving the two handheld controllers, making the process accessible to those without 3D modeling experience.

In Step 1, designers can import external 3D geometries created with other computer-aided design (CAD) software (e.g., Rhinoceros). This capability is important as it allows designers to bypass the need to start sculpting from blank. Instead, they can begin by modifying and refining preexisting designs. The imported design is first converted into an editable model using advanced surface reconstruction techniques [24]. Designers can then utilize VR sculpting tools to add new features or remove unwanted parts, guided by their artistic intuitions or preferences. This capability conserves time that would otherwise be spent sculpting models from blank and allows designers to concentrate on refining their subjective preferences.

2.2. Step 2: Initialization

While VR sculpting (Step 1) significantly eases the expression of subjective preferences, there is a risk that excessive design freedom might lead designers to focus too much on creative ideas and neglect fundamental engineering principles. Structural optimization becomes a crucial step in the design exploration process to ensure that the sculpted models have practical value. Before executing this optimization, the initial settings must be established to clearly define the design optimization problem.

In Step 2 (see Figure 1(b)), the initial task is to determine the size of the design domain (i.e., the space in which materials can be redistributed). Designers can use the handheld controllers to adjust the dimensions of this design domain to align with specific design requirements; the adjusted bounding box is marked by a cubic frame in Figure 1(b). Subsequently, designers must define the support and load conditions. In Figure 1(b), a uniformly distributed load is applied on top of the design domain, represented by the rectangular box, and a fixed support is set at the base, represented by two dark boxes. Finally, Step 2 concludes by inputting optimization parameters through a virtual number pad. Detailed explanations of these parameters, including the filter radius, volume fraction, evolutionary rate, voxel size, and subjective weight, will be provided in Section 3.

2.3. Step 3: Topology optimization

Step 3 (see Figure 1(c)) performs a modified topology optimization method based on the BESO framework (see Section 3). Initially, the sculpted model is transformed into subjective weights by computing a distance field (see Section 3.2). These weights are then incorporated into the sensitivity analysis; they play a pivotal role in the optimization procedure determining materials' addition or removal. Notably, the "subjective weight" parameter is introduced to adjust the importance level of subjective preferences. Introducing this parameter allows designers to control the formation of final structural topologies toward being performance-driven or preference-driven. This feature indicates that our topology optimization enables the sculpted models to be computationally modified and refined into high-performance structures. Moreover, the topology optimization in this study is implemented based on an efficient code [25]. Its optimization efficiency allows designers to obtain an optimized structure without a long wait. This significantly improves designers' interactive experience.

2.4. Step 4: Smoothing

Our topology optimization is based on finite element analysis (FEA), requiring the continuous design domain to be discretized into finite element meshes to represent the given materials. Therefore, optimization results possess zig-zag boundaries formed from straight element edges. These boundaries, and hence the design resolution, are determined by the number of elements used. A resolution that is not sufficiently fine could affect how designers perceive and define their subjective preferences. Step 4 is an additional smoothing step to improve the aesthetic quality of the optimization result obtained from Step 3 (see Figure 1(d)).

The authors previously developed the smoothing algorithm utilized in this study based on a pre-built lookup table [26]. Notably, the smoothed model can be exported to external CAD software. This capability grants designers considerable flexibility: they can further modify the design for various purposes, including as a new input for Step 1, for rendering, or to meet specific manufacturing requirements.

2.5. Iterative design exploration

A single design exploration may not fulfill all design requirements, as designers often develop new preferences during the exploration process [13]. Our proposed design exploration strategy offers flexibility by allowing designers to modify the results from Steps 1–4 and redesign through these steps again. This iterative approach ensures that the evolving subjective preferences are continually updated.

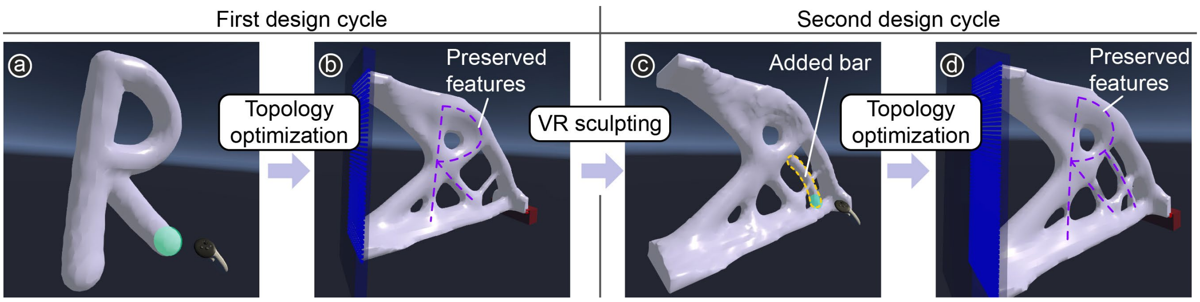

Figure 3: Iterative design exploration: (a) sculpting a preferred model, (b) obtaining an optimal topology via a single design cycle, (c) adding a bar to the current design through VR sculpting, and (d) generating a new optimal design

The iterative design exploration is demonstrated more clearly in Figure 3. Figures 3(a) and 3(b) represent the sculpted models before and after optimization, respectively. Designers can manually add or remove specific parts from the optimization result, as shown in Figure 3(c). These modifications significantly influence the subsequent topology optimization, as shown in Figure 3(d). Designers can also undertake a series of iterative design explorations by alternately updating the preferred geometric features and executing topology optimization. This process is repeated until the subjective preferences are refined to achieve a final design that best meets all requirements.

2.6. Effective design exploration explained

Unlike traditional single-design exploration strategies (see Figure 4(a)), our proposed strategy (see Figure 4(b)) eliminates the extensive evaluation tasks involved in selecting a design from a wide array of often unsatisfactory options. Our new approach empowers designers to participate in and guide the design process effectively.

In fact, our key contribution is to establish a productive human–computer collaboration by integrating VR sculpting and topology optimization. This collaboration enables user preferences to directly guide topology optimization, fostering the creation of innovative structures. Topology optimization ensures the structural performance of these innovative structures. This synergistic relationship effectively leverages the unique strengths of human insight and computational power, thereby enhancing the efficiency of design exploration and the quality of optimized structures.

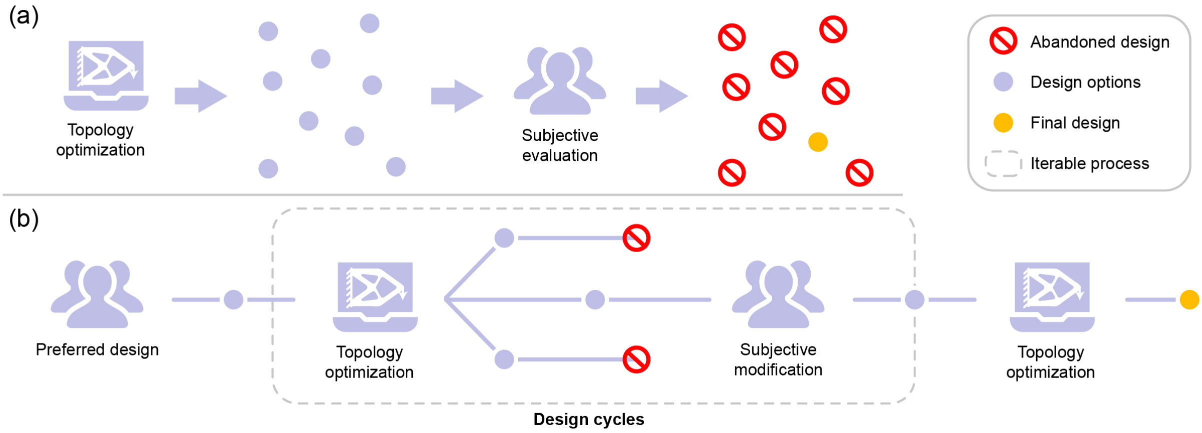

Figure 4: (a) Single design exploration versus (b) the proposed iterative design exploration

3. Modified topology optimization

3.1. BESO framework

The modified topology optimization method is developed based on the BESO framework. The BESO method requires a design domain, Ω, to be discretized into N elements (voxels) according to the input elemental size (voxel size). Its compliance minimization (i.e., stiffness maximization) problem can be formulated as:

$$\begin{gathered} min: C = \frac{1}{2}\boldsymbol{U}^T\boldsymbol{K}\boldsymbol{U} \\ s.t.: V^* = \textstyle\sum_{i=1}^{N} v_i\, x_i \\ x_i = x_{min}\ or\ 1 \end{gathered} \tag{1}$$

where C is the mean compliance value (an inverse measure of stiffness). $\boldsymbol{U}$ and $\boldsymbol{K}$ represent the global displacement vector and the global stiffness matrix, respectively. V^* and v_i are the target structural volume and the i-th elemental volume, respectively. Each element, e_i, has a design variable, x_i, to determine whether the element is solid ($x_i = 1$) or void ($x_i = x_{min} = 0.001$). In the BESO framework, x_i is calculated by the relative ranking of sensitivity numbers. The i-th sensitivity number, α_i, is defined by:

$$\alpha_i = -\frac{1}{p}\frac{\partial C}{\partial x_i} = \begin{cases} \frac{1}{2}\boldsymbol{u}_i^T\boldsymbol{k}_i\boldsymbol{u}_i, & \text{when } x_i = 1 \\ \frac{x_{min}^{p-1}}{2}\boldsymbol{u}_i^T\boldsymbol{k}_i\boldsymbol{u}_i, & \text{when } x_i = x_{min} \end{cases} \tag{2}$$

where $\boldsymbol{k}_i$ is the elemental stiffness matrix, $\boldsymbol{u}_i$ is the i-th elemental displacement vector, and $p = 3$ is the penalty exponent.

To improve numerical stability, filtering and history-averaging techniques are employed, which require a parameter, r_{min}, to determine the size of the filter [6]. The final structural topology is obtained by iteratively conducting FEA, sensitivity analysis, and updating structures until all criteria are satisfied. The changed volume in each iteration can be controlled by the evolutionary ratio, ER. More details of the BESO method can be found in Huang and Xie [6].

3.2. Subjective weights

Subjective weights represent the sculpted model in our optimization, obtained by computing a distance field. For a given sculpted model, M, we calculate the subjective weight, ω_i, as follows:

$$\omega_i = \begin{cases} d(c_i, \partial M), & \text{if } c_i \in M \\ 0, & \text{if } c_i \notin M \end{cases} \tag{3}$$

where c_i is the centroid of e_i, ∂M represents the boundary of M, and $d(c_i, \partial M)$ is the distance between c_i and ∂M. Following Equation (3), the modified sensitivity number that is finally used in the modified topology optimization method, $\bar{\alpha}_i$, is defined as:

$$\bar{\alpha}_i = \lambda^2 \hat{\omega}_i + (1 - \lambda^2)\hat{\alpha}_i, \quad \lambda \in [0,1] \tag{4}$$

where $\hat{\omega}_i$ and $\hat{\alpha}_i$ represent the normalized subjective weight and the normalized sensitivity number of e_i, respectively. Importantly, λ is a design parameter from 0 to 1 that controls the influence of the subjective weights. Subjective weights may dominate the formation of the optimal topology [9,13]. Therefore, we employ the λ^2 term so the influence of $\hat{\omega}_i$ is more gradual.

4. Results and discussion

4.1. Parametric study

Our parametric study investigated the effect of varying the parameter λ on the formation of the resulting structural topology. Here, our design optimization problem is the classic 3D short cantilever [6]. The design domain is 80 mm long × 20 mm wide × 50 mm tall, discretized into 80,000 cubic elements. A point load $F = -1$ N is applied at the center of the free end. A fixed boundary condition is assigned behind the whole cantilever. The material used in this study is assumed to be isotropic and linear elastic, with Young's modulus of $E = 1$ MPa and Poisson's ratio of $v = 0.3$. BESO parameters are: $ER = 2\%$, $V^* = 15\%$, and $r_{min} = 3$ mm. The preferred geometric features are represented by the "preferred model" shown in Figure 5(a), which was initially created through VR sculpting and then refined in the Rhinoceros CAD software.

We use five different λ to generate topologically different solutions, including 0.1, 0.3, 0.5, 0.7, and 0.9. Each solution is compared with two reference designs (Ref. 1 and Ref. 2). Ref. 1 (see Figure 5(b)) is the original BESO result obtained without considering subjective preferences ($\lambda = 0$); it considers only structural performance. Ref. 2 (see Figure 5(c)) is the extreme preference-driven design ($\lambda = 1$), obtained by redistributing the given materials to the preferred model. We use the compliance ratio, C^*, and overlapping rate, P, to quantify the differences in structural performance with Ref. 1 and shape with Ref. 2, respectively. Specifically, C^* is defined as C_B/C_A, where C_A and C_B represent the compliance values of the given solution and Ref. 1; P is defined as V_P/V^*, where V_P is the volume fraction of the overlapping part with Ref. 2, as shown in Figure 5(d), respectively [13,27].

Topology optimization results are summarized in Figure 5(e), with the evolutionary histories shown in Figure 5(f), and measurement results of C^* and P are detailed in Figure 5(g). Our findings show that increasing λ from 0.1 to 0.9 leads to a noticeable rise in C^* and P. This suggests that a lower λ tends to produce structures with performance characteristics more aligned with Ref. 1, while a higher λ results in structures with shapes closer to Ref. 2. Therefore, designers can adjust λ according to their specific design requirements, effectively guiding the formation of the final structures toward being either performance-driven or preference-driven.

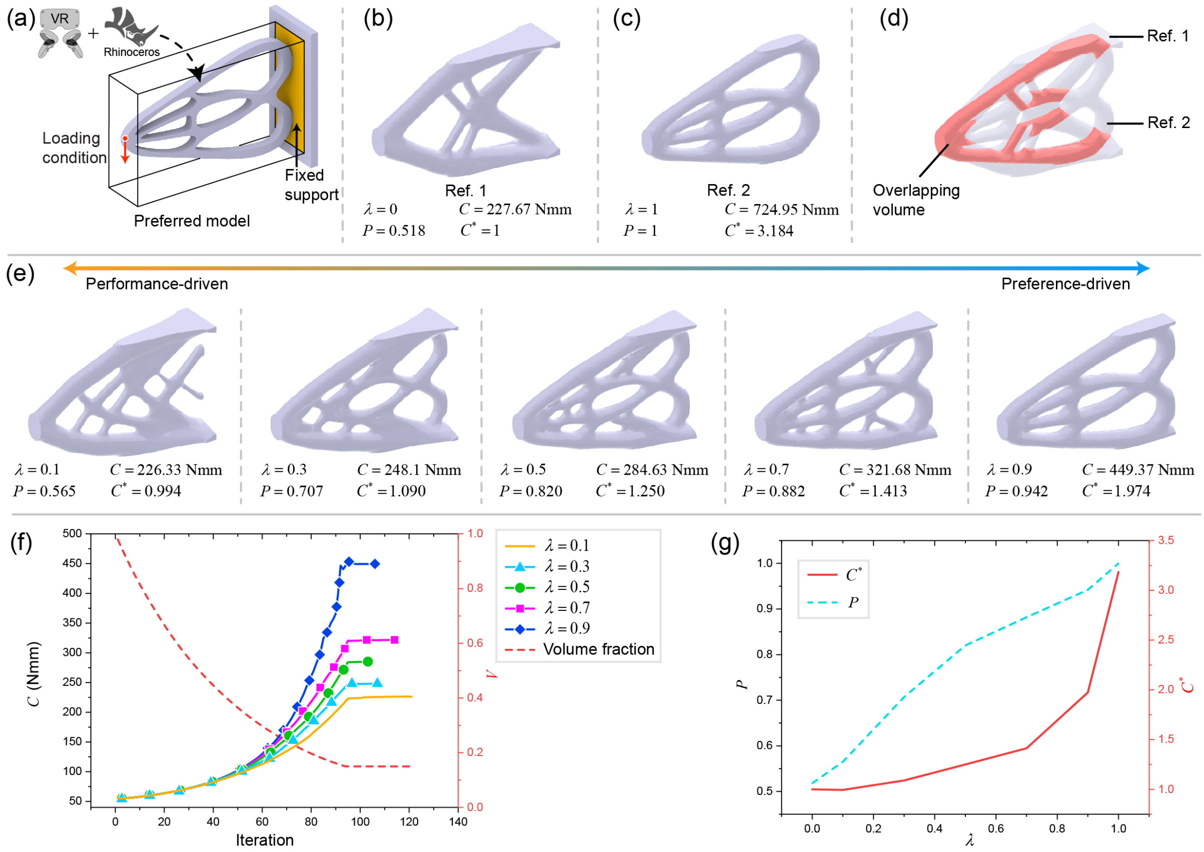

Figure 5: Investigation of the influence of λ on optimization results using the 3D cantilever example: (a) initialization and the preferred model created by VR sculpting and Rhinoceros, (b) extreme performance-driven design (Ref. 1), (c) extreme preference-driven design (Ref. 2), (d) measuring similarity between Ref. 1 and Ref. 2 by calculating their overlapping volume, (e) five designs obtained using different λ, (f) evolutionary histories, and (g) variation of C^* and P with respect to λ

4.2. Potential practical applications

Figure 6 uses a 3D pavilion to demonstrate the potential practical applications of our proposed design exploration strategy. The designed domain (see Figure 6(a)) is 6,000 mm × 6,000 mm × 4,000 mm, discretized into 14,400 cubic elements. A total vertical load of 10,000 N is uniformly distributed over the 300 mm thick passive solid domain [28], and two rectangular fixed supports are applied at the base. BESO parameters are: $V^* = 15\%$, $r_{min} = 300$ mm, and $ER = 2\%$. Figure 6(b) shows the BESO result without considering subjective preferences (i.e., $\lambda = 0$). Our goal is to utilize VR to include subjective preferences in this design while preserving a high level of structural performance.

Figure 6(c) presents the outcomes of the initial design exploration, showcasing three innovative structures (solutions A–C). These structures consider a capitalized letter "A" as the preferred model, created through VR sculpting and refined using Rhinoceros CAD software. Moreover, each structure is optimized using different values of λ (0.2, 0.5, and 0.8). In this design cycle, solution B may be the preferred design based on its stiffer performance (i.e., lower compliance) than solution C while maintaining the essential geometric features. Solution A is not comparable because it sacrifices the preferred geometric features, specifically the horizontal bar, for better structural performance.

In the second design cycle (see Figure 6(d)), we wish to improve the structural performance while preserving the preferred model. In the next round of optimization, we modify solution A, which performed best in the previous design cycle, to include our new subjective preferences through VR sculpting. Specifically, we add a horizontal bar to complete the letter "A" and remove four slender bars from the roof support based on our subjective assessment.

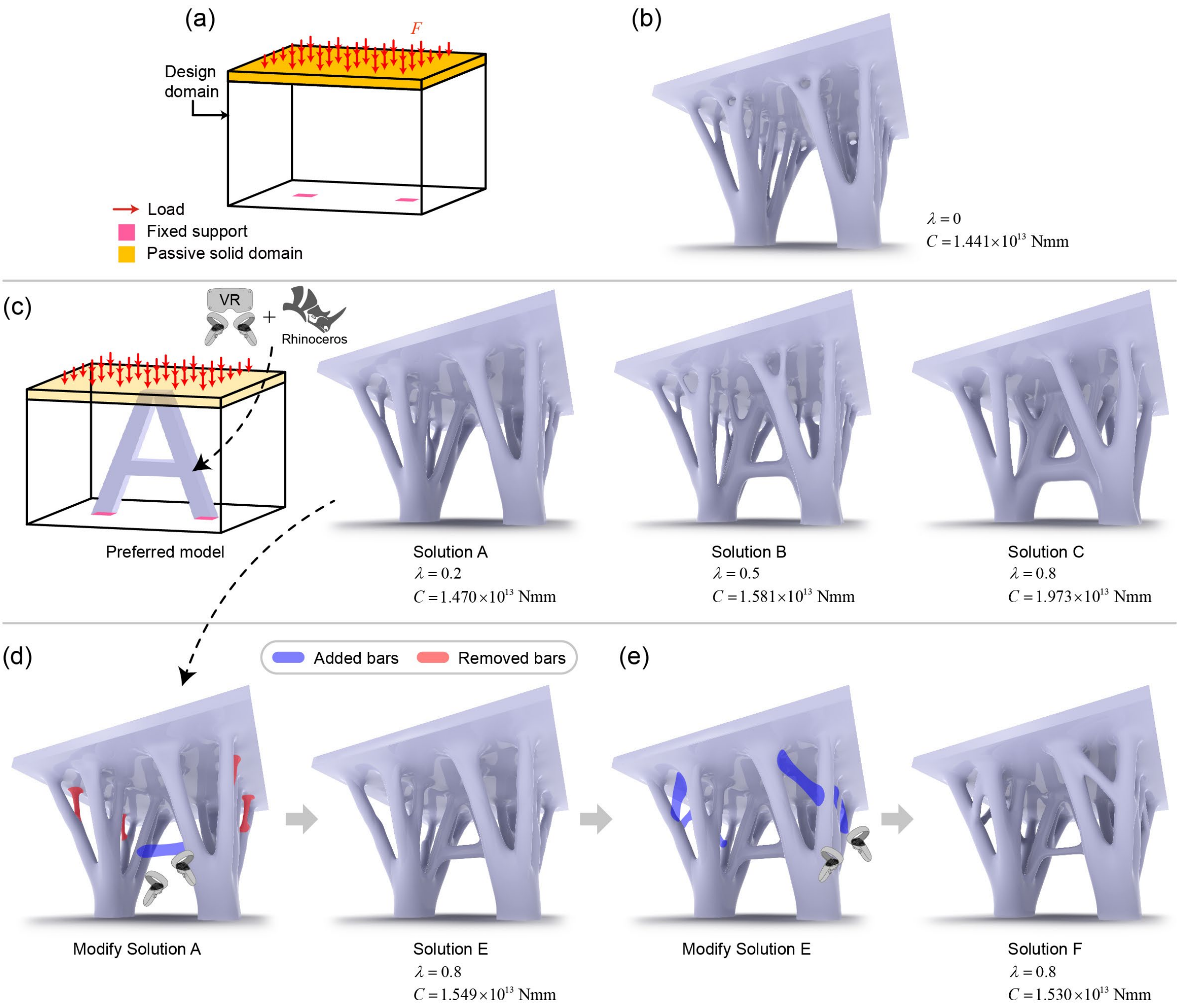

Figure 6: Pavilion example: (a) initialization, (b) reference design generated by the BESO method, (c) the preferred model created by VR sculpting and Rhinoceros and the results of the first design cycle, (d) the second design cycle, and (e) the third design cycle

During optimization, we use $\lambda = 0.8$, a relatively high value, to ensure that the newly updated geometric features effectively influence the outcome. The optimization result (solution E) includes all these new modifications. Solution E has better structural performance (i.e., lower compliance) than the best-performing structure from the previous design cycle (solution B). Both solutions incorporate the preferred model and emerge as strong contenders for the final design.

After a thorough subjective evaluation of the shapes of solutions B and E within the VR environment, we conclude that solution B appears overly complex, while solution E seems overly simplistic. Therefore, a third design cycle (see Figure 6(e)) is performed. For this new round, the preferred model is modified by adding eight bars to link some of the neighboring roof support bars of solution E. The optimization result, solution F, achieved with $\lambda = 0.8$, not only presents a more visually appealing design but is also stiffer than both solutions B and E. Based on these improvements, solution F is selected as the final design for the 3D pavilion example.

Figure 6 demonstrates the benefits of an iterative design exploration approach grounded in human–computer collaboration. Designers influence the formation of optimization results by inputting their preferred geometric features. The results can spark new inspirations, guiding designers to refine their subjective preferences. With each design cycle, designers have more opportunities to achieve a final structure that meets functional (i.e., stiffness) requirements and aligns with their artistic intuitions.

5. Conclusion

We have developed a novel design exploration strategy integrating VR and topology optimization. We show that VR provides designers with an intuitive, interactive, and immersive platform for observing and editing 3D geometries. Designers can use VR sculpting to transform their creative ideas directly into 3D models. The sculpted models can represent their subjective preferences and influence material redistribution in the topology optimization process. Importantly, we emphasize that the sculpting–optimization workflow can be repeated in multiple cycles, creating various innovative and efficient structures that reflect designers' subjective preferences. Our newly developed digital design tool, VR-BESO, which implemented the proposed exploration strategy and generated all examples in this paper, is publicly available. Our findings indicate that by adjusting a specific parameter, the optimization process can control the generated structural form toward being either performance-driven or preference-driven. This flexibility enables the optimized structures to meet engineering principles and aesthetic preferences. Further, the results highlight the potential practical applications of the proposed iterative design exploration strategy. This strategy, coupled with VR-BESO, can effectively harness the strengths of human creativity and computational power to enhance the efficiency of design exploration and the quality of optimized structures.

Acknowledgments

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